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RESEARCH ARTICLE

Multiple Fault Detection in an Automobile Engine Using Single Sensor System

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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 150 cc two-stroke (TS) automobile 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 six different types of faults and the classification of the same is carried out. The signal normalization, conditioning, 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 an 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 an ANN based classifiers are more appropriate than statistical classifiers. It is also observed that the magnitude of Mean Square Error (MSE) is under permissible limit and percentage Average Classification Accuracy (% ACA) is also reasonable.

Keywords: Automobile Engine, Statistical Classifiers 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 and Isolation (FDI) 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 find 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 (FDI) 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 150 cc 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 signal normalization, 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 six different types of faults that are Air Filter Fault (FF), Spark Plug Fault (SP), Rich Mixture Fault (RM), Gudgeon Pin Fault (GP), 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 and it can be used as one type of tool to know the status of the engine. Therefore, the proposed FDI system will be used as a guide for maintaining the vehicle in good condition that will save our time and inconvenience and based on this 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

Two Stroke Engine	Microphone	Sound Recorder
Peak power : 8.0 HP at 5500 RPM	Unidirectional Cardioid	AD/DA conversion : 24 bits, 44.1 kHz
Peak torque : 1.35 Kg-m At 3500 RPM	*Frequency : 50Hz - 18KHz*	*Format : WAV*
Engine Type : 5-port single Cylinder, 2stroke	*Impedance : 32 Ohm*	*Bit Rates : 64/96/128/ 160/192 /256/320 kbps*
Transmission : 4-speed gear box, Clutch : Wet multi-disc type	*Sensitivity : 62 dB*	*Frequency Response : 20 Hz to 20 kHz*
Compression ratio: 6-10	*Connector : 3.5 mm*	*USB Interface*
Operating cycle : 2 stroke spark Ignition, 150 cc engine	*Impedance : 1K ohm*	

2. Methodology

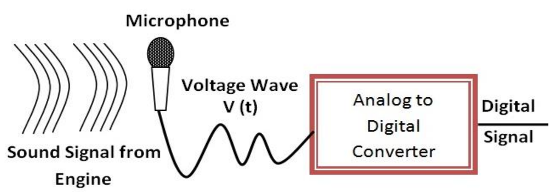

Fig 1: Signal Capturing System

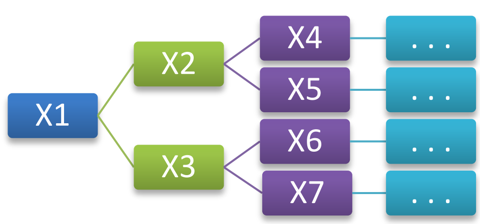

Fig 2: Signal Decomposition Technique

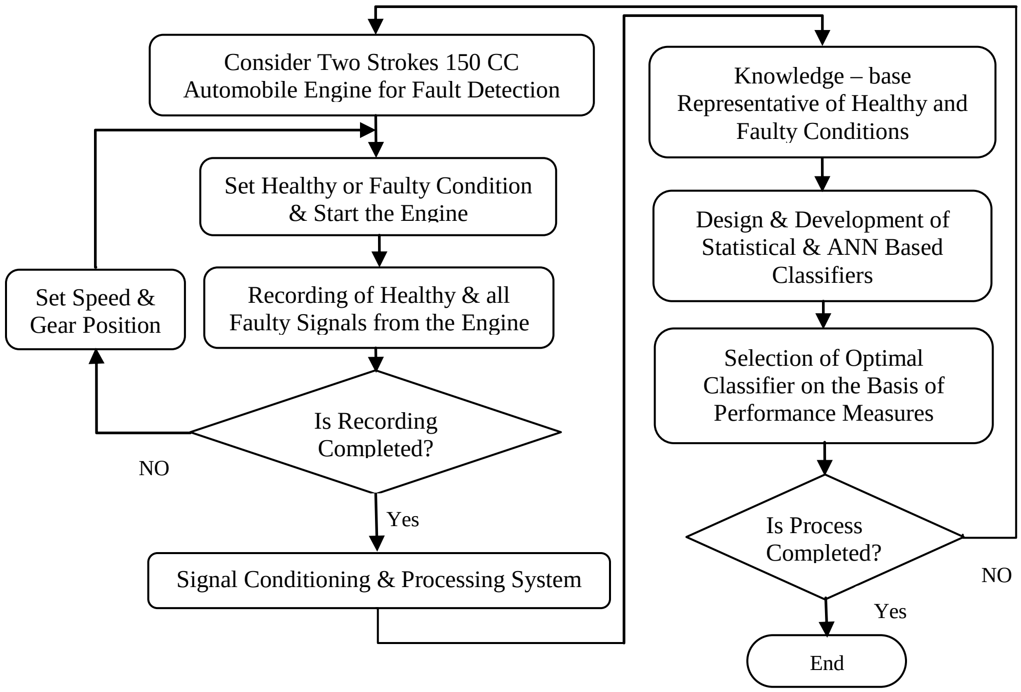

Fig 3: Working of Proposed FDI System

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 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 normal condition and signals are recorded at different speed and different gear positions. The two stroke 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 six 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 details of working of Fault Detection system is shown in Fig 3.

3. Observations of Recorded Signals and Pattern of Features

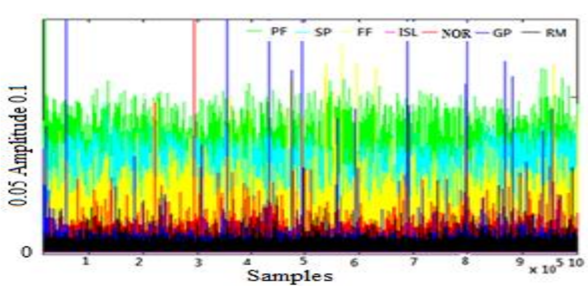

Fig 4: Two Stroke Engine' Signal Plot

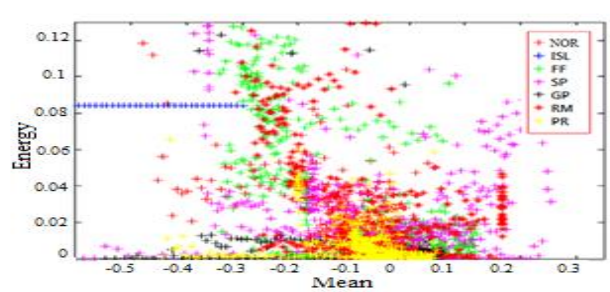

Fig 5: Scatter Plot for Mean Vs Energy

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 of TS engine in healthy (Normal) condition and faulty conditions signals are plotted as shown in Fig 4. It is noticed from the signal plot that the most of the signals are overlapped and their nature is found to be highly complex. The amplitude of the normal signal and rich mixture fault is very less as compared to the other faulty conditions signals. Similarly, the amplitude of the signal for spark plug and piston fault is found to be greater than the other faulty and normal signals.

The extracted features are Mean, Energy, Maximum Value, Minimum Value, Standard Deviation, Variance and Mode for six different types of faults and out of which Mean and Energy is plotted as shown in Fig 5. It is observed from the scatter plot that the most of the features are overlapped and the decision boundaries are not linearly separable. Therefore, it is necessary 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.

4. Classification of Faults Using Statistical Classifiers

Initially, the statistical analysis is carried out for TS engine using XLSTAT. The classification and regression trees have been employed to classify the faults. The knowledge base comprising of 7 inputs and one categorical output has been applied to statistical classifiers. The performance of statistical classifier using *CHAID Pearson, CHAID Likelihood, Exh- CHAID Pearson, Exh- CHAID Likelihood, C&RT Gini, C&RT Towing and Quest* has been observed for TS 150cc automobile engine.

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	% ACA for GP
CHAID & Exh. CHAID	*Pearson*	*75.00%*	*87.50%*	*90.00%*	*97.50%*	*75.00%*	*87.50%*
CHAID & Exh. CHAID	*Likelihood*	*75.00%*	*87.50%*	*90.00%*	*97.50%*	*75.00%*	*92.50%*
C&RT	*Gini*	*82.50%*	*87.50%*	*80.00%*	*92.50%*	*75.00%*	*85.00%*
C&RT	*Towing*	*62.50%*	*75.00%*	*65.00%*	*92.50%*	*70.00%*	*62.50%*
Quest		*75.00%*	*50.00%*	*52.50%*	*95.00%*	*50.00%*	*85.00%*

The Process Flow Diagram for Statistical Classifiers is shown in Fig 6. The size of each feature matrix is 20×8 including seven inputs and one categorical output. Therefore, knowledge base consists of 40 rows and 8 columns. The performance of all above statistical classifiers is observed for six different types of faults and the classification accuracy has been depicted in the following Tables 2,

It is observed form the Table 2 that for FF-Fault the maximum %ACA is 82% for *C&RT (Gini)* classifier. For SP fault the maximum %ACA 87.5% for *CHAID & Exh. CHAID (Pearson), CHAID & Exh. CHAID (Likelihood) and C&RT (Gini)* classifiers. For PR fault the maximum %ACA is 90.0 % for *CHAID & Exh. CHAID (Pearson) and CHAID & Exh. CHAID (Likelihood)* classifiers. For ISL fault the maximum %ACA is 97.5 % for *CHAID & Exh. CHAID (Pearson) and Quest* classifiers. For RM fault condition the maximum %ACA is 75.0 % for *CHAID & Exh. CHAID (Pearson), CHAID & Exh. CHAID (Likelihood) and C&RT (Gini)* classifiers. In case of GP fault condition, the maximum %ACA is 92.5 % for *CHAID & Exh. CHAID (Likelihood)* classifiers.

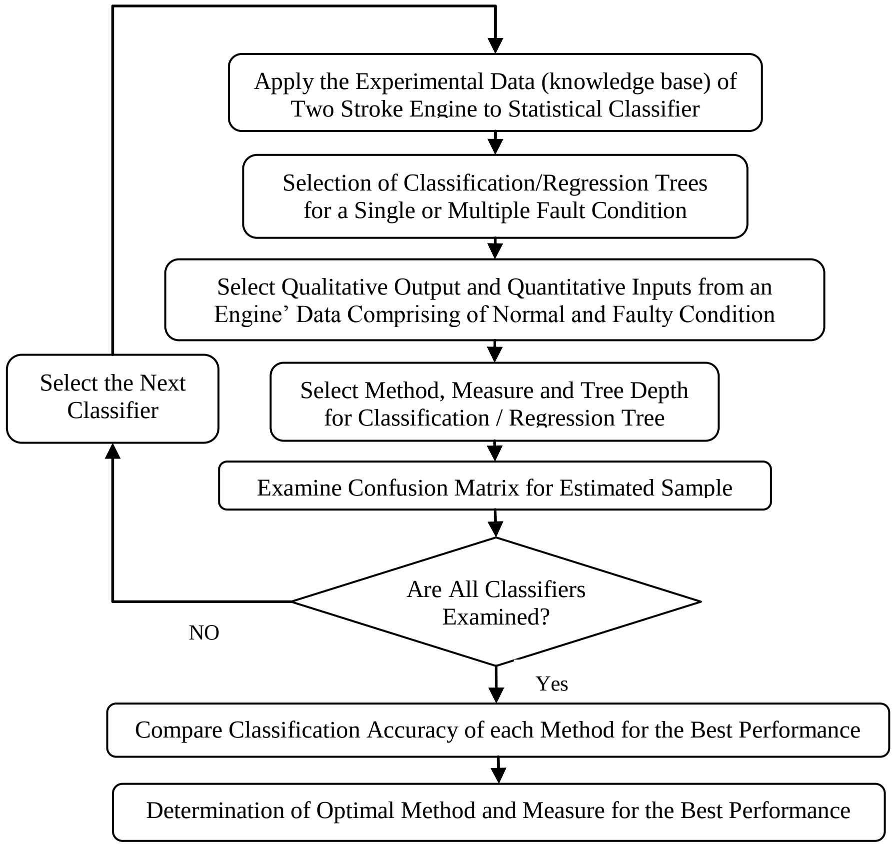

Fig 6: Process Flow Diagram for Statistical Classifiers

4.1 Classification of Combined Six Faults Using Statistical Classifiers

The feature matrix containing the features of healthy and six different fault signals is applied to the Statistical Classifier. The size of each feature matrix is 20×8 including seven inputs and one categorical output. Therefore, knowledge database consists of 140 rows and 8 columns. The performance of all statistical classifiers has been observed and results are depicted in Table 3 with the percentage Classification Accuracy of each method. It is observed that the classification accuracy of *CHAID and Exhaustive-CHAID-Pearson* is found to be better than the other classifiers. Therefore, the performances of these two classifiers are observed for variation of tree depth which is continued for *CHAID Pearson* and *Exh-CHAID Pearson* for tree depth varying from 5 to 10; the performance of its shown in Table 4. The performance has been observed with respect to CHAID-Pearson and Exhaustive-CHAID-Pearson. It has been seen that the percentage Classification Accuracy increases with increase in tree depth and the Maximum %ACA is found to be 81.5% for tree depth 10. The analysis is pursued by using ANN based Classifiers for possibility of improvement in performance in subsequent section.

Table 3: Performance of Statistical Classifier for Combined Six Faults in a TS Engine

Faults	*CHAID (Pearson)*	*Exh. CHAID (Pearson)*	*CHAID & Exh. CHAID (Likelihood)*	*C&RT (Gini)*	*C&RT (Towing)*	*Quest*
FF	*3.13*	*47.81*	*0.00%*	*50.00%*	*40.00%*	*0.00%*
GP	*95.94*	*95.00*	*85.00%*	*40.00%*	*45.00%*	*100.00%*
ISL	*95.00*	*95.00*	*80.00%*	*35.00%*	*60.00%*	*0.00%*
NOR	*0.00*	*0.00*	*0.00%*	*55.00%*	*45.00%*	*0.00%*

PR	*98.75*	*79.06*	*65.00%*	*10.00%*	*50.00%*	*0.00%*
RM	*98.75*	*98.75*	*35.00%*	*35.00%*	*0.00%*	*0.00%*
SP	*14.06*	*24.06*	*0.00%*	*30.00%*	*25.00%*	*0.00%*
Total % ACA	*57.95*	*62.81*	*37.87%*	*36.43%*	*37.86%*	*14.29%*

Table 4: Performance of Statistical Classifier for Combined Six Faults in a TS Engine

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

5. Classification of Faults using ANN Based Classifiers

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 percentage Classification Accuracy 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 six different types of faults and one state indicating healthy condition, the number of neurons in the output layer must be seven (Six neurons corresponding to six 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. The detail working of ANN Based Classifiers and selection of optimal classifiers for Classification of Faults in a TS Engine is given in the form of flowchart Fig 7.

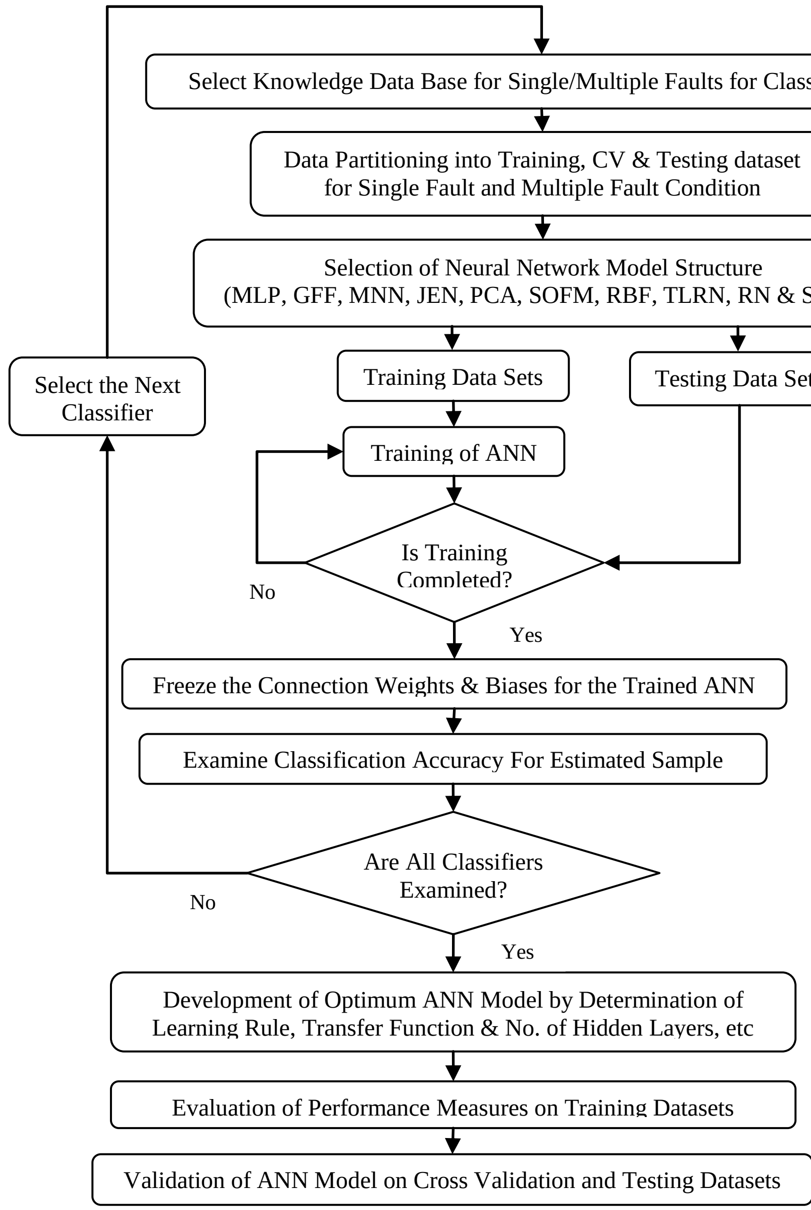

Fig 7: Working of ANN Based Classifiers for Classification of Faults in a TS Engine

5.1 Classification of Single Fault in a Two Stroke Engine

The classification accuracy of all ten types of ANN based classifiers has been observed for each type of fault. Initially, a single frame of normal and faulty recorded signal is considered. The size of the feature matrix for single frame with a single fault is 40×8 with seven inputs and one categorical output. This knowledge base is then applied to each ANN based classifier by selecting the proper data partitioning scheme (2:1:1)**.** Three data partitions, namely, Training, Cross Validation (CV) and Testing were used with different tagging order. Each ANN based classifier was retrained three times with different random initialization of connection weights and biases. The performance of all ten types of ANN based classifier has been shown in following Table 5 and Table 6. Further, analysis is continued for considering the combined three faults togather in two groups. In one group, the combined three faults are PR, SP & GP and in second group FF, RM & ISL. Afterward, the combined six faults are considered for classifications which is explained in the following sections.

Table 5: Performance of ANN Based Classifiers for Single Fault (GP, SP & PR) with Single Frame

ANN	Gudgeon Pin Fault			Spark Plug Fault			Piston Ring Fault		
	Testing	*CV*	*Training*	*Testing*	*CV*	*Training*	*Testing*	*CV*	*Training*
MLP	*83.3333*	*90.0000*	*100.0000*	*80.0000*	*83.3333*	*85.4167*	*79.1667*	*77.5000*	*95.8333*
GFF	*80.0000*	*90.0000*	*88.8889*	*80.0000*	*78.5714*	*79.1667*	*79.1667*	*66.6667*	*81.2500*
MNN	*75.0000*	*90.0000*	*100.0000*	*80.0000*	*54.7619*	*85.4167*	*79.1667*	*66.6667*	*81.2500*
JEN	*75.0000*	*90.0000*	*75.2525*	*60.0000*	*61.9048*	*77.0833*	*50.0000*	*66.6667*	*58.3333*
PCA	*70.8333*	*90.0000*	*100.0000*	*60.0000*	*52.3810*	*79.1667*	*79.1667*	*70.8333*	*89.5833*
RBF	*75.0000*	*90.0000*	*100.0000*	*80.0000*	*61.9048*	*85.4167*	*79.1667*	*54.1667*	*89.5833*
SOFM	*80.0000*	*70.0000*	*100.0000*	*80.0000*	*61.9048*	*77.0833*	*79.1667*	*58.3333*	*85.4167*
TLRN	*45.8333*	*90.0000*	*75.2525*	*40.0000*	*69.0476*	*60.4167*	*62.5000*	*58.3333*	*62.5000*
RN	*75.0000*	*70.0000*	*83.3333*	*40.0000*	*92.8571*	*37.5000*	*50.0000*	*58.3333*	*45.8333*
SVM	*83.3333*	*90.0000*	*100.0000*	*80.0000*	*61.9048*	*91.6667*	*70.8333*	*54.1667*	*95.8333*

Table 6: Performance of ANN Based Classifiers for Single Fault (RM, ISL & FF) with Single Frame

ANN	Rich Mixture Fault			Insufficient Lubricants			Air Filter Fault		
	Testing	*CV*	*Training*	*Testing*	*CV*	*Training*	*Testing*	*CV*	*Training*
MLP	*61.9048*	*79.1667*	*83.3333*	*100.0000*	*100.0000*	*100.0000*	*85.7143*	*83.3333*	*94.4444*
GFF	*69.0476*	*54.1667*	*68.6869*	*90.9091*	*100.0000*	*100.0000*	*78.5714*	*62.5000*	*85.3535*
MNN	*47.6191*	*54.1667*	*57.5758*	*89.9091*	*92.8571*	*100.0000*	*78.5714*	*62.5000*	*85.3535*
JEN	*61.9048*	*45.8333*	*63.1313*	*90.9091*	*100.0000*	*100.0000*	*78.5714*	*62.5000*	*84.3535*
PCA	*54.7619*	*37.5000*	*83.3333*	*95.4546*	*92.8571*	*100.0000*	*78.5714*	*62.5000*	*68.6869*
RBF	*50.0000*	*50.0000*	*50.0000*	*90.9091*	*100.0000*	*95.4546*	*78.5714*	*79.1667*	*84.3434*
SOFM	*45.2381*	*70.8333*	*77.7778*	*100.0000*	*95.4546*	*95.4546*	*78.5714*	*79.1667*	*79.7980*
TLRN	*61.9048*	*70.8333*	*84.3434*	*83.3333*	*90.9091*	*79.7980*	*40.4762*	*54.1667*	*41.9192*
RN	*47.6191*	*91.6667*	*68.6869*	*100.0000*	*90.9091*	*95.4546*	*71.4286*	*62.5000*	*68.6869*
SVM	*61.9048*	*75.0000*	*78.7879*	*100.0000*	*100.0000*	*100.0000*	*83.3333*	*70.8333*	*89.8990*

5.2 Classification of Combined Three Faults PR SP and GP

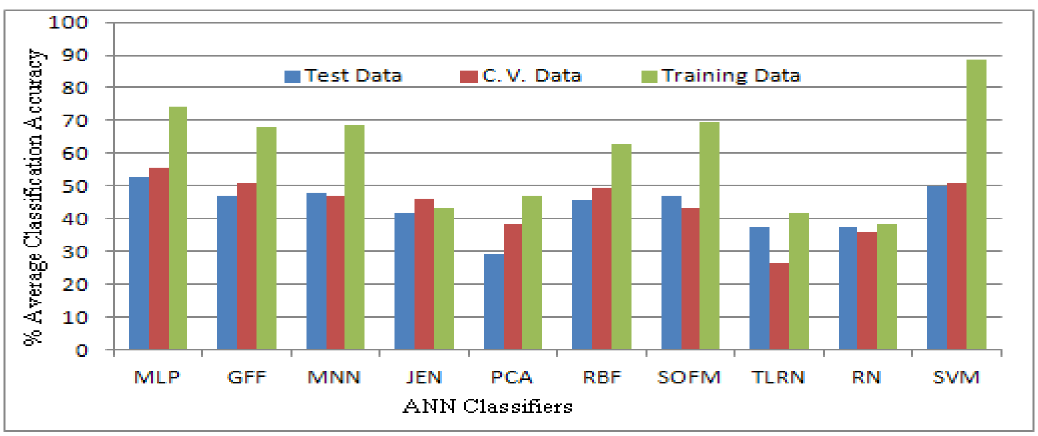

Fig 8: Performance of ANN Based Classifiers for Combined Faults (PR, SP & GP)

5.3 Classification of Combined Three Faults FF, RM and ISL

In this case, remaining three faults are combined i.e. Air Filter Faults (FF), Rich Mixture Faults (RM) and Insufficient Lubricant Faults (ISL). The performance of all ten types of ANN based classifiers is observed for single frame and the result is shown in Fig 9. It is observed that the performance of MLP and SVM based classifier is found to be reasonable amongst all ten types of ANN based classifiers.

The design of 1 & 2HL-MLP was further improved by varying the number of Epochs, different variants of standard back propagation Learning Rule Algorithms such as STEP, Momentum (MOM), Conjugate Gradient (CG), Levenberg Marquardt (LMQ), Quick Propagation (QP) and Delta-Bar-Delta (DBD). For two hidden layer MLP, the % ACA is found to be Maximum for Learning Rule – Momentum, Transfer Function TANH – AXON, with Learning rate 1.0 and momentum 0.7, as portrayed in Table 15.

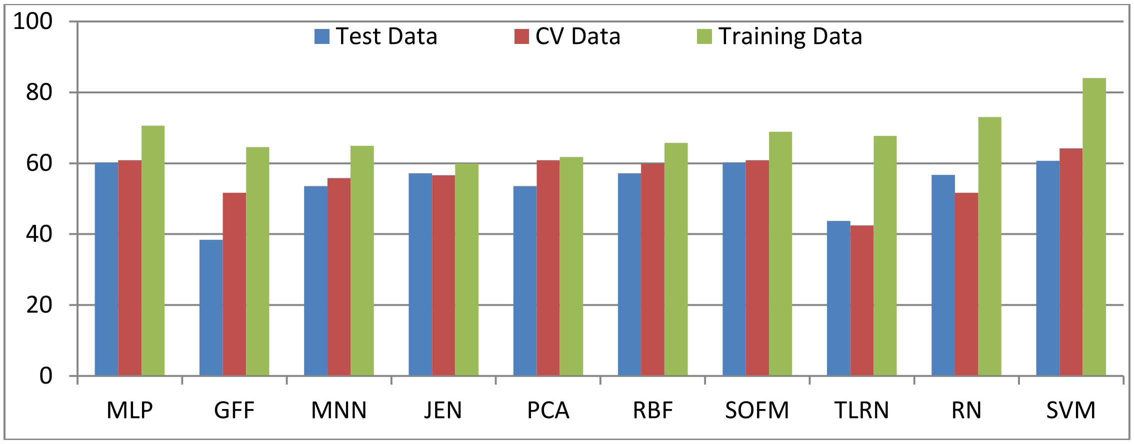

Fig 9: Performance of ANN Based Classifiers for Combined Faults (FF, RM & ISL)

5.4 Classification of Combined Six Faults PR, SP, GP, FF, RM and ISL

Further, analysis is continued for combined six faults; in this case FF, RM, ISL PR, SP and GP are combined and the signals are divided into 1 to 512 frames, by using signal decomposition scheme. The performance of all ten types of ANN based classifiers is shown in Fig 10. The dataset was split into three different partitions in the ratio of 2:1:1, first part of the data was used for training the network, the second part of the data was used for cross validation and the third part of the data was used for testing the network.

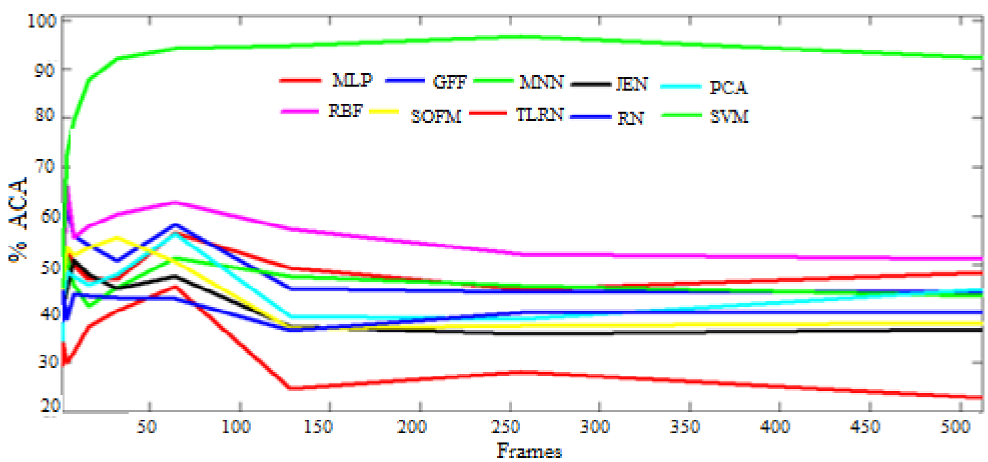

Fig 10: Performance of ANN Based Classifier for Combined Six Faults

From the Fig 10, it is observed that the Classification Accuracy for all classifiers is Maximum for 64-frames except for SVM based classifier. In case of SVM based classifier, the Classification Accuracy is Maximum for 256-frames. It is also observed that, further increase in frame number does not seem to improve the result. It is also observed from the plot, that the classification Accuracy of SVM based classifier is consistently high for all different types of frames. Looking to this scenario, the SVM based classifier is further investigated as explained in subsequent section.

5.5 Design of SVM Based Classifier for Combined Six Faults

Further, analysis of SVM based classifier is continued with 256 frames for combined six faults along with normal signal i.e. for PR, SP, GP, FF, RM, ISL and NOR. The size of feature matrix is 71,680×8, i.e. 71,680 rows and 8 columns for seven inputs and one categorical output. The Kernel Adatron algorithm is specifically used for Support Vector Machine. The dataset was divided into three partitions in the ratio of 2:1:1, first part of the data was used for training the network, the second part for cross validation and the third part for testing the network. The performance of SVM based classifier observed for different epochs is plotted in Fig 11. It is observed from the plot that the % Average Classification Accuracy of SVM is above 96% for Test, CV and Training datasets and it is Maximum at 200th Epoch.

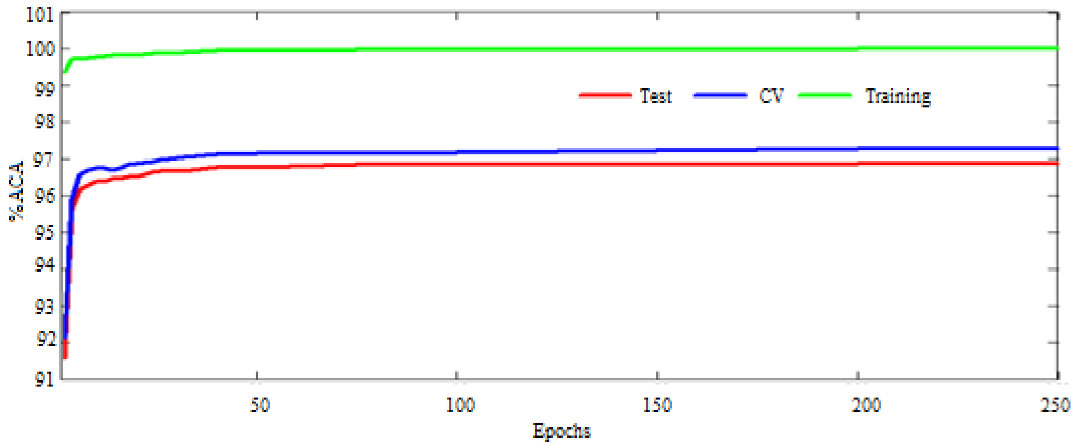

Fig 11: Performance of SVM Based Classifier for 256-Frames

The following are the observations from the above classification of faults:

- The %ACA for both MLP and SVM based classifiers for forward tagging order is found to be greater than that of the reverse tagging order and also the performance of #2HL MLP based classifier is found to be superior to #1HL MLP based classifier as shown in Table 7, Table 8 and Table 10.
- The performance of SVM based classifier is superior to #1 & 2#HL MLP based classifier as shown in Table 7 and Table 10 in case of,
  - Combined three faults PR+SP+GP and
  - Combined Six Faults PR+SP+GP+FF+RM+ISL.
- The performance of MLP classifier is superior to SVM based classifier as shown in Table 8
  - Combined three faults FF+RM+ISL.
- The %ACA for #1 & #2HL-MLP based classifier is found to be Maximum for Transfer Function – TANH AXON and Learning Rule – back propagation with Momentum as shown in Table 9.
- The %ACA of both classifiers for ISL single fault is found to be 100% and for GP, the %ACA for both classifiers is same as shown in Table 5 and Table 6.

Finally, the classification is also carried out for combined six faults. The performance of MLP and SVM based classifiers is compared as shown in Table 10. It is found that the classification accuracy for SVM based classifier is better than the one and two Hidden Layer MLP based classifier.

Table 7: Comparison of MLP & SVM Based Classifiers for Combined Faults PR-SP-GP

	Forward Tagging				Reverse Tagging			
	PE	*Testing*	*CV*	*Training*	*PE*	*Testing*	*CV*	*Training*
1HL-MLP-64-Frame	*45*	*82.77598*	*83.17492*	*84.68425*	*50*	*81.02367*	*81.35268*	*88.1591*
2HL-MLP-64-Frame	*35-25*	*87.04025*	*87.04025*	*87.04025*	*35-20*	*77.45224*	*80.97784*	*89.00994*
SVM-64-Frame	*EP-45*	*94.14392*	*95.2622*	*99.52898*	*EP-90*	*81.46802*	*75.05209*	*100*

Table 8: Comparison of MLP & SVM Based Classifiers for Combined Faults FF-RM-ISL

ANN	Forward Tagging				Reverse Tagging			
	PE	*Testing*	*CV*	*Training*	*PE*	*Testing*	*CV*	*Training*
1HL-MLP-8-Frame	*35*	*86.7142*	*86.3625*	*86.9450*	*65*	*81.2118*	*77.9397*	*89.8988*
2HL-MLP-8-Frame	*40-35*	*87.7018*	*88.3644*	*93.1249*	*40-75*	*83.5512*	*82.2900*	*93.4986*
SVM-8-Frame	*EP-100*	*83.09018*	*82.08398*	*99.68354*	*Ep-60*	*83.4482*	*78.2515*	*99.3654*

Table 9: Optimal Parameters for MLP Based Classifier for Combined Faults FF-RM-ISL

1HL-MLP NN with Epochs - 4000			2HL-MLP NN with Epochs - 2000		
Parameter	*HL-1*	*Output Layer*	*HL-1*	*HL-2*	*Output Layer*
PEs	*45*	*4*	*35*	*25*	*4*
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*

Table 10: Comparison of MLP & SVM for Combined Six Faults (PR, SP, GP, FF, RM & ISL)

ANN	Forward Tagging				Reverse Tagging		
	PE	Testing Data	CV Data	Training Data	Testing Data	CV Data	Training Data
1HL-MLP-64-Frame	45	76.67063	78.35813	80.87097	71.3802	72.13649	71.6929
2HL-MLP-64-Frame	35-45	80.5196	81.50319	83.48509	69.56522	74.35897	73.68421
SVM-256-frame	EP-80	96.3	95.4672	100.00	93.89306	94.42516	99.63336

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 Artificial Neural Networks 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 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 two-stroke. The %ACA for combined six faults for SVM based classifier is found to be 96.3%, 95.46% and 100% for Test data, CV Data and Training Data sets respectively. However, SVM based classifier is seen to be more appropriate classifier for two-stroke 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 database for respective faults.

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