International Journal of Current Engineering and Technology
ISSN 2277 - 4106

Available at http://inpressco.com/category/ijcet

Research Article

Model Based Approach for Fault Detection and Isolation in a Four Stroke Engine Using an Acoustic Signal

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Accepted 15 September 2013, Available online 01 October 2013, **Vol.3, No.4 (October 2013)**

Abstract

The paper deals with the problem of fault detection in an automobile engine employing an artificial neural network (ANN). The Fault Detection and Isolation (FDI) is not an easy task for an inexperienced mechanic or driver because it needs a lot of knowledge and experience. Many times, the trial and error approach is seen to be applied to detect the fault and because of that, the engine may get more damaged instead of getting repaired. To overcome such type of problem, the new approach has been suggested to diagnose the fault correctly without opening the engine. Therefore, this paper presents the model based technique to detect the Air Filter Fault (FF) and Spark Plug Fault(SP) in a Four Strokes Engine using a single sensor. The Hero Honda Passion Four Stroke (HHPFS) engine is used for experimentation. The Artificial Neural Networks have been employed to classify the faults correctly. Performances of Multilayer Perception Neural Network (MLP NN) and Support Vector Machine (SVM) have been compared on the basis of Average Classification Accuracy (ACA) and finally, the optimal Neural Network has been designed for the best performance.

Keywords: *Automobile Engine, Artificial Neural Network, Classification Accuracy, MLP & SVM.*

1. Introduction

The machines are made by the engineers to make our life easier. The modern world has completely changed our lives by providing us with new technology and advancements. With the development of digital signal processing and Artificial Intelligence techniques, knowledge-based diagnosis systems for automobile engine repair are becoming more important for the automobile industry. On the one hand, because more automobiles are in use in the world each year, the maintenance work becomes more strenuous. Also, because the structure of automobiles is becoming more complex, it is impossible for an expert to master all the repair and diagnosis techniques.

The major causes of the failure of the engines are normal mileage wear and tear; poor maintenance; lubrication problems; excessive overheating. In any vehicular system, various input and output parameters of the engine are related to one another in a non-linear manner. As long as these relations do not get disturbed, the vehicle provides optimum performance. However, the characteristics change in due course of time while the vehicle is in use. It is also known that due to the changes in parameters the sound variations of the engine will also get changed and these variations can be used for fault detections.

The literature published in the related areas has been reviewed for last two decades. Fault detection, using numerical techniques based on mathematical system models is a well-established subject and a lot of survey papers and books have been written, such as Gertler (1988) and Baseville (1988), observer based nonlinear estimation (Yong-Wha, 1998), Patton (1991), Patton (1998), Chen and Patton (1999), Patton, Frank and Clark (2000), Basseville (2003), Kinnaert (2003), Basseville (2003) and Yu et al (1999) In this case, faults can be detected by comparing the data collected with the appropriate valid mathematical models. The use of models enables the estimation of variables and parameters which are influenced by the fault. An important wide coverage of the various diagnostic techniques in dynamic systems was presented in the multi-authored book of Patton, Frank and Clark (1989) and also by Marcin Witczak (2006).

To overcome the difficulties of using mathematical models, and making FDI algorithms more applicable to real systems, the neural network can be used to both generate residuals and isolate faults (Chen & Patton, 1999). Research work on neural networks in fault detection processes has been carried out during the last few years. Recent work includes Chen et al (1998), Dimla et al (1998), Boudaoud and Masson (1998), real

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time supervision using production sensors and additional sensors installed (Nyberg and Stutte, 2004) and neural networks (Gomm et al., 2000), Papadimitropoulos et al (2003), E. G. Laukonen, et al (1995) proposed the fault detection and isolation in an internal combustion engine using fuzzy logic and also by Yingping et al (2008).

Narendra, (1996), Ren and Chen (1999) proposed a new type of neural network in which the dynamic error feedback was used to modify the inputs of the network. Han and Frank (1997) and also Du & Swami (2006) proposed a parameter estimation based FDI using neural networks in which physical parameters are estimated by applying the neural network universal approximation property applied to the measured I/O data. The deviations from normal values are then used for fault diagnosis

2. Methodology

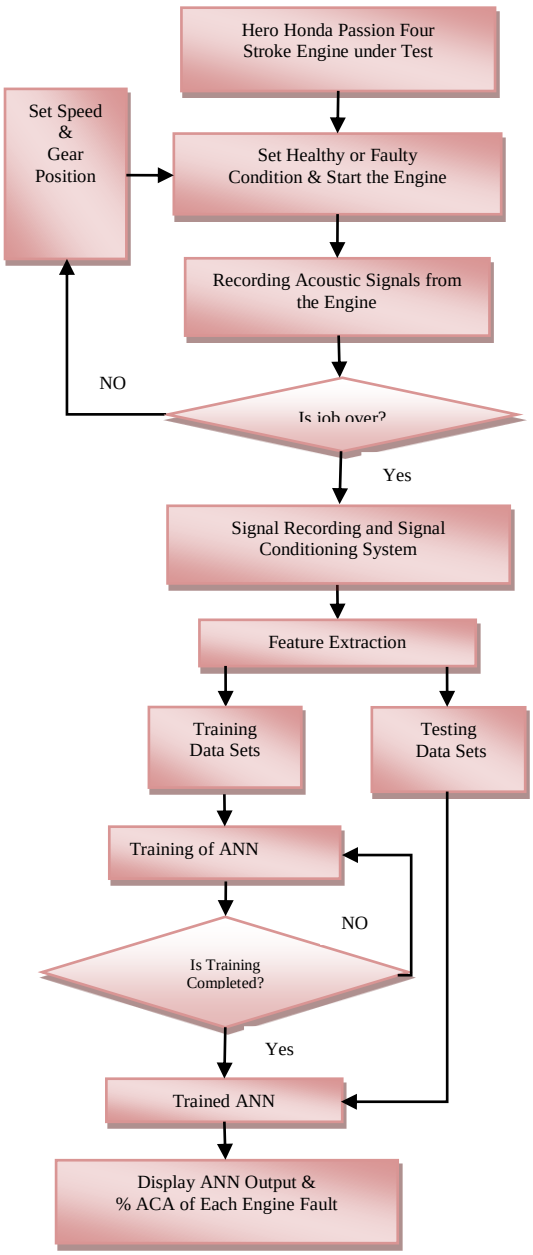

Fig 1: Working of proposed FDI model

The methodology adopted is explained in Fig 1. Initially, the engines were started in healthy condition and four different signals were recorded by using an MP3 sound recorder in wave format. The signals are 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. Therefore, the total 20 signals are recorded in each gear position. Later, one-by-one, fault is created in an automobile engine and the process of recording the signals is continued for two different faults. Finally, there will be a collection of total 60 recorded signals. The faults considered for analysis are Air Filter Fault (FF) and Spark Plug fault (SP) (with extended gap). The normalization, signal conditioning and Analog to Digital conversion have been carried out by using the algorithm written in MATLB R2010B. The Specifications of an Automobile Engine, Microphone and MP3 Sound Recorder are given in Table 1 and Table 2 respectively.

Table 1: Specifications of HHPFS Engine
Displacement : 97.50cc
Maximum Power : 7.37 HP (5.4 kW) @ 8000 RPM
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

Table 2 : Specification of Microphone and MP3 Recorder	
Microphone - Unidirectional	MP3 Sound Recorder
Type: Cardioids, Very high quality, low noise	AD/DA conversion: 24 bits with 44.1 kHz
Frequency: 50Hz -18KHz	BitRates:64/96/128 /160/192/256 kbps
Impedance : 32 Ohm	
Sensitivity : 62 dB	Freq. :20Hz to 20 kHz
Connector : 3.5 mm	
Impedance : 1K ohm	Format : WAV
Low power consumption	Interface : Mini-B type connector

The experimentation is carried out at "Automobile Engineering Laboratory, Mechanical Engineering Department, Babasaheb Naik College of Engineering, Pusad. District-Yavatmal. (M.S.)" and "Research laboratory of Dept of Applied Electronics Sant Gadge Baba Amravati University, Amravati".

The absolute values of recorded signal with healthy and Air Filter Fault signal are plotted as shown in Fig 2 and with Spark Plug Fault signal depicted in Fig 3, respectively. From the signal plot, it is found that the most of the signals are overlapped. The pattern of the signal is found to be repetitive but highly complex. Therefore, frequency response is also observed by computing the Fast Fourier Transform (FFT) of the normal and faulty signal.

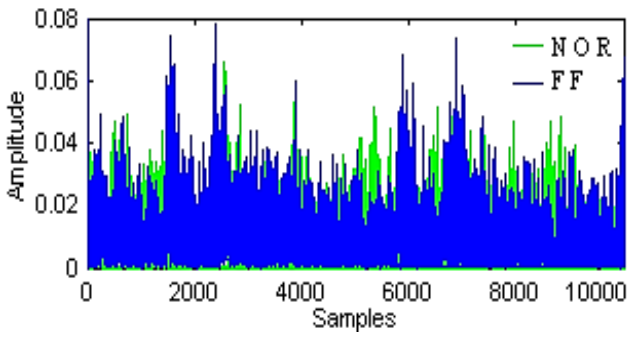

Fig 2: Signal Plot for Normal & Filter Fault

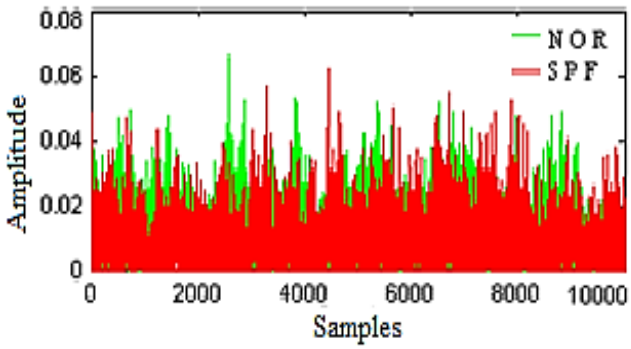

Fig 3: Signal Plot for Normal & Spark Plug Fault

3. Fast Fourier Transform

The absolute value of the FFT of healthy, Air Filter Fault (FF) and Spark Plug Fault (SPF) signals has been plotted as shown in Fig 4 and Fig 5, respectively. From the FFT plot, it is observed that the frequency components of normal and faulty signal are found to be completely overlapped. Therefore, the important features have been extracted for the further analysis of the faults.

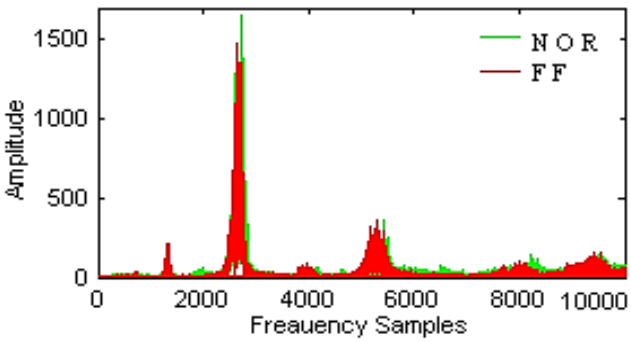

Fig 4: FFT Plot for Normal & Filter Fault

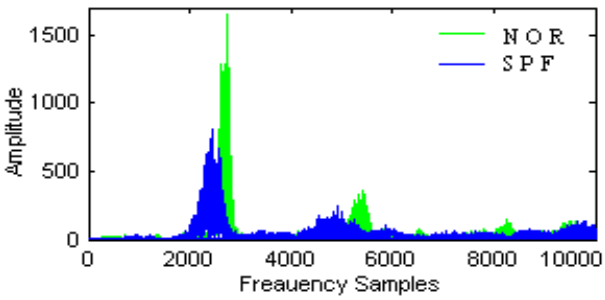

Fig 5: FFT Plot for Normal & Spark Plug Fault

4. Feature Extraction

The five sets of signals were recorded in different speed and different gear positions at 1200 RPM, 1500 RPM, 1800 RPM, & 2100 RPM for approximately one minute duration. Therefore, each set consists of total 20 signals. Further, each signal is divided into 64 frames with each frame comprising of 1000 samples. The normalization, signal conditioning and feature extraction of each frame have been carried out using the algorithm written in MATLAB. The extracted seven features are Mean, Mode, Energy, Maximum Value, Minimum Value, Standard Deviation and Variance. The scatter plots for Minimum Vs Maximum and Mean Vs Energy are shown in Fig 6 and Fig 7 respectively.

It is observed from the scatter plot, that most of the parameters for filter fault and spark plug fault are found to be overlapped and they are not linearly separable. The decision boundaries are also highly complex and not linearly separable and therefore, Artificial Neural Networks, such as, MLP and SVM have been employed to estimate such a complex decision boundary with a view to separate out the faults. The required data partitioning scheme are explained in the following section.

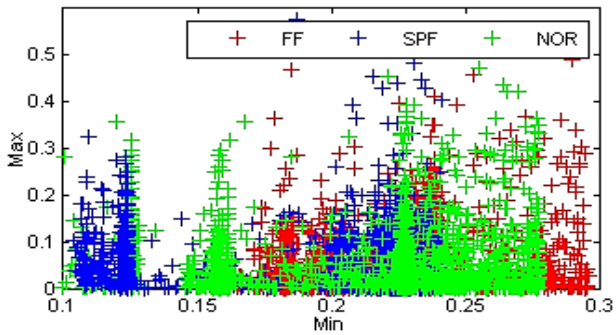

Fig 6: Scatter Plot for Normal and Faulty Signal

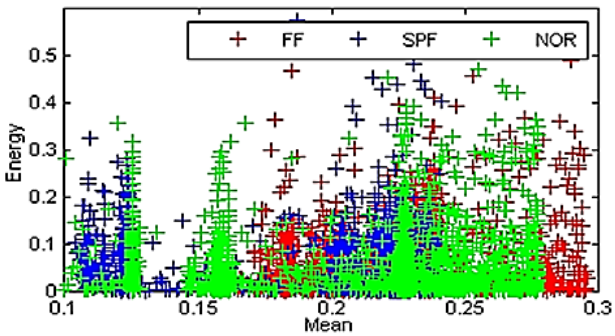

Fig 7: Scatter Plot for Normal and Faulty Signal

5. Data Partitioning

As there are 20 signals in each healthy and faulty condition and there are 64 frames of each signal, the size of each feature matrix will be 64 x 20 x 8 with 7 inputs and one categorical (symbolic) output. The size of feature matrix will be 3840 x 8, after combining two faults and healthy signal. These 3840 sets of features are then used as inputs to the neural network for the classification of the

fault in an automobile engine. Three different data partitions were used with different tagging orders. In the forward tagging order, the top 50 % samples (1:1920) are used for training, the middle 25 % samples (1921:2880) for cross validation, and the bottom 25 % samples (2881:3840) for testing of the classifier. In the reverse tagging order, the bottom 50 % samples (1921:3840) are used for training, the middle 25 % (961:1920) for cross validation, and the top 25 % samples (1:960) for testing of the classifier.

6. Experimentation

6.1 Design of Multilayer Perceptron Neural Network (MLP NN) Classifier

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

6.2 Single Hidden layer MLP NN Classifier

A single hidden layer MLP NN is designed to give optimal performance on the basis of the best ACA. The dataset of 3840 records was divided into three partitions in the ratio 2:1:1, first part of the data was used for training the network, the second part of the data were used for cross validation and the third part of the data were used for testing the network. The network with 7 inputs and one categorical output (translated into 3 outputs as there are three different classes of faults) with TANH-AXON transfer function (TF) and Momentum Learning Algorithm (LR) was trained three times and tested for classification accuracy for test, cross validation, and training data sets. The process was repeated with varying hidden layer Processing Elements (PEs) from 2 to 100 for default epochs set to 1000. It is found that the maximum ACA is observed for PE equal to 30. After that, by maintaining 30 PEs and by varying Epochs from 100 to 5000, again ACA is observed. The Maximum ACA is obtained for Epochs equal to 4000.

The MLP was further refined by changing the Learning Rule Algorithms such as STEP, Momentum (MOM), Conjugate Gradient (CG), Levenberg Marquardt (LMQ), Quick Propagation (QP) and Delta-Bar-Delta (DBD). It is found that the maximum ACA is obtained for Transfer Function - TANH-AXON and for Learning Rule – Error Back-propagation with Momentum, along with the step size 1.0 and 0.1 for hidden layer and for output layer, respectively and also the momentum rate is 0.7 for both hidden layer and output layer. The performance of one hidden layer MLP NN has been shown in Table 3.

6.3 Two Hidden layers MLP NN Classifier

The 2 HL-MLP was trained three times by giving faulty and healthy feature matrix derived from an automobile engine as input to the neural network. A total dataset of size 3840 x 8 was divided into three parts in the ratio 2:1:1, first part used as training data set, second as cross validation and third as testing data set. As the number of hidden layers in a neural network increases, the complexity of computation also increases. Here the network is designed by setting L1 PE of 5 and varying L2 PE from 5-100 in the increment of 5. Then step-by-step, the L1 PE was also varied from 5-100 in steps of 5 varying simultaneously the L2 PE. Separate networks were designed to compare the performance of MLP NN while L1 & L2 PE are varied. After training the network three times with each set of PEs, the network was tested for test, cross validation and training data set. The performance of the network was recorded as percentage classification accuracy and MSE for various data sets. Further, the network was also refined by varying the Epochs 100 to 5000 for best classification accuracy.

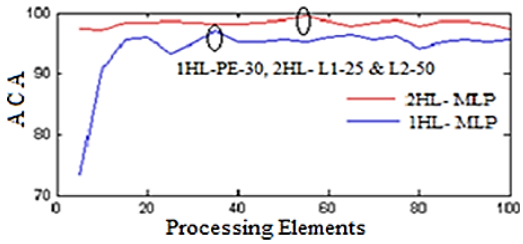

Fig 8: PE Vs % ACA for 1HL and 2HL MLP

The Fig 8 shows the comparison between the classification accuracy of 2 hidden and 1 hidden layers MLP. Table 4 shows the performance of two hidden layer MLP. Table 5 portrays the optimal parameters for 1 and 2 hidden layer MLP. Further, the analysis is continued using SVM as explained in the next section.

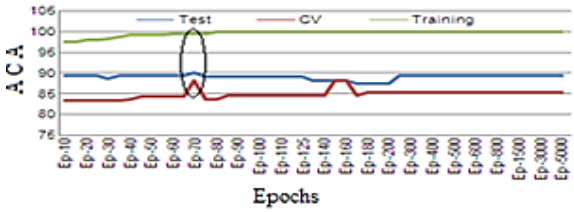

Fig 9: Performance of SVM NN for Epochs vs. ACA

7. Design of Support Vector Machine NN Classifier

The Kernel Adatron algorithm is specifically used for Support Vector Machine, which is designed to give optimal performance on the basis of the best ACA. The dataset of 3840 x 8 records was divided into three parts in the ratio 2:1:1, first part of the data was used for training the network, the second part of the data were used for cross validation and the third part of the data were used for testing the network. A total dataset of size 3840 x 8 with 7 inputs and 1 symbolic output (translated into 3 outputs as there are three different classes of faults) were trained for three times by giving healthy and faulty feature matrix derived from an automobile engine as input to the network. The SVM is trained and tested by varying the Epochs from 10 to 5000. The performance of SVM is shown in Fig 9 and Table 6.

Table 3: Performance of one Hidden Layer MLP-PE-30-Epochs-4000

Performance	Test Dataset			CV Dataset			Training Dataset		
	Sym (FF)	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*
MSE	0.050	0.048	0.056	0.009	0.043	0.030	0.016	0.011	0.003
NMSE	0.219	0.213	0.262	0.045	0.199	0.127	0.071	0.050	0.014
r	0.888	0.891	0.876	0.980	0.898	0.938	0.966	0.975	0.994
Percent Correct	90.476	82.927	97.297	97.222	92.105	97.826	100.000	96.296	100.000

Table 4: Performance of two Hidden layer MLP L1 PE-25 & L2 PE-50- and Epochs-2000

Performance	Test Dataset			CV Dataset			Training Dataset		
	Sym (FF)	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*
MSE	0.013	0.024	0.020	0.005	0.020	0.025	0.003	0.004	0.002
NMSE	0.055	0.106	0.092	0.024	0.094	0.106	0.012	0.019	0.008
r	0.972	0.946	0.954	0.989	0.952	0.947	0.994	0.991	0.996
Percent Correct	95.238	100.000	97.297	97.222	97.368	97.826	100.000	100.000	100.000

Table 5: Optimal Parameters for one and two Hidden Layer MLP

One Hidden Layer MLP NN with Epochs - 4000			*Two Hidden Layer MLP NN with Epochs - 2000*		
Optimal Parameter	**Hidden Layer**	**Output Layer**	**Hidden Layer-1**	**Hidden Layer-2**	**Output Layer**
Processing Elements	**30**	**1**	**25**	**50**	**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**

Table 6: Performance of Support Vector Machine for Epochs -70

Performance	Test Dataset			CV Dataset			Training Dataset		
	Sym (FF)	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*	*Sym (FF)*	*Sym (SP)*	*Sym (Nor)*
MSE	0.066	0.070	0.067	0.073	0.081	0.096	0.025	0.023	0.023
NMSE	0.289	0.312	0.316	0.347	0.375	0.407	0.113	0.103	0.105
r	0.885	0.853	0.856	0.850	0.814	0.789	0.962	0.966	0.964
Percent Correct	95.238	90.244	89.189	88.889	86.842	86.957	100.000	100.000	98.701

8. Results

After detailed analysis of one hidden layer MLP NN, two hidden layer MLP NN and SVM, it is found that the ACA obtained for one hidden layer MLP NN for Test, CV and Training datasets are 90.23344 %, 95.71786 % and 98.76574 %, respectively. ACA obtained for two hidden layer MLP for Test, CV and Training datasets are 97.5118 %, 97.47224 % and 100 %, respectively and for SVM ACA for Test, CV and Training datasets are 91.55706 %, 87.56251 % and 99.5671 %, respectively. The minimum absolute error in 2 Hidden layer MLP is found to be nearly zero for training data sets. It is found that the ACA is Maximum for 1Hidden Layer MLP at PE equal to 30 and for 2HL MLP PE at L1-25, PE at L2-50.

It is also noticed that ACA for the SVM is 100 % for training datasets at epochs 70 but for test data sets and CV datasets ACA is found to be below 90 % as shown in Fig 9. The circle on the Fig 9 indicates the optimum value for ACA for three data sets. The performance of SVM is also shown in Table 6 which shows the MSE, NMSE, Correlation Factor - r, and Classification Accuracy in percentage.

It is found that the percentage ACA for 2Hidden Layer MLP NN is found to be the maximum for test data sets, CV datasets and for training datasets as compared to one HL MLP NN and SVM.

9. Conclusion

In this paper, a Fault Detection and Isolation technique in Four Stroke Automobile Engine Using Sound Signal has been proposed. It is suggested that, if the proposed FDI system attached to the newly manufactured vehicle then it will be very useful. It can detect the fault at an incipient stage. The two faults considered for detection are Air Filter Fault and Spark Plug fault. The experimentation has been carried out on Hero Honda Passion four stroke automobile engine using MLP NN and SVM. It is not a complete automatic fault detection system. But the main advantage of this system is its simplicity and compactness having a single sensor system. The system can be extended to any number of faults using single sensor but step by step analysis is required.

The comparative analysis of Artificial Neural Networks as shown in Table 4 and Table 5, depicts that the performance of two Hidden Layer MLP NN with Epochs – 2000, L1 PE - 25, L2 PE – 50 is found to be superior than One Hidden Layer MLP with Epochs – 4000 with PE-30 and SVM with Epochs -70. Therefore, 2 Hidden Layer MLP can be used as a reasonable classifier for fault detection in a four stroke automobile engine.

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