IC Engine Fault diagnosis Using ROC

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Abstract

Advanced methods of supervision fault detection and fault diagnosis become increasingly important for many technical processes, for the improvement of reliability, safety and efficiency. This especially important for safety related processes in aircraft, trains, automobiles, power plants and chemical plants. The classical approaches are limited for checking of some measurable output variables and does not provide a deeper insight and usually do not allow a fault diagnosis. The proposed system has model-based approach for fault diagnosis of IC engine using audio signals from engine. The audio signals are captured from the engine using microphone and are processed using MATLAB to find characteristics parameters of the signals. Artificial Neural Network is used to identify the fault in IC engine, the Receiver operating characteristic (ROC) analysis is used to obtain the most appropriate transfer function for the ANN and it also provides the most comprehensive description of diagnostic accuracy which is used to diagnose the faults in IC Engine.

Keywords: *IC Engine, Fault detection, Artificial Neural Network, Digital Signal Processing and ROC*

1. Introduction

With the development of AI techniques knowledge-based diagnosis systems for automobile engine repair are becoming more important for 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. Therefore, repair consultant systems are needed to aid maintenance engineers.

So the techniques employing Vibration and acoustic emission signals are often used for fault diagnosis in automobile systems, since they carry dynamic information from the mechanical elements. These signals normally consist of a combination of the fundamental frequency with a narrow band frequency and the harmonics. Most of these are related to the revolutions of the rotating system since the energy of acoustic and vibration signal is increased when mechanical element is damaged or worn out. This paper discusses the faults due to Piston.

The methodology suggested is for the detection of incipient faults in four stroke IC Engine using audio signals, Digital Signal Processing and Artificial Neural Network. Determination of fault at an early stage and repairing them before it leads to larger fault is important, because it reduces the other damages, repairing cost and also reduces down time of the engine.

In the proposed system for fault diagnosis of four stroke IC engine, classifiers are used based on a receiver operating characteristics (ROC) graph. Which is a technique for visualizing, organizing and selecting classifiers based on their performance, ROC graphs have been used in signal detection theory to depict the tradeoff between hit rates and false alarm rates of classifiers (Egan,1975; Swets et al., 2000). ROC analysis has been extended for use in visualizing and analyzing the behavior of diagnostic systems (Swets, 1988).

2. System Architecture

It is a natural process that because of wear and tear the faults are develops in an automobile systems and there may be a possibility of more than one fault as the engine runs for longer duration. It is important that the fault must be detected in an early stage. If the fault is simple then the faulty component can be detected and replaced easily. But if the fault is critical like “Piston Fault” then it will be difficult to diagnose and repair in short duration. Therefore, the propose system consider the “Piston Fault” for fault detection. The working of the system is shown in the block diagram of Fig.1

2.1 Piston

A piston is a component of reciprocating engines, reciprocating pumps, gas compressors and pneumatic cylinders, among other similar mechanisms. It is the moving component that is contained by a cylinder and is made gas-tight by piston rings. In an engine, its purpose is to transfer force from expanding gas in the cylinder to the crankshaft via a piston rod and/or connecting rod. In a pump, the function is reversed and force is transferred from the crankshaft to the piston for the purpose of compressing or ejecting the fluid in the cylinder. In some engines, the piston also acts as a valve by covering and uncovering ports in the cylinder wall.

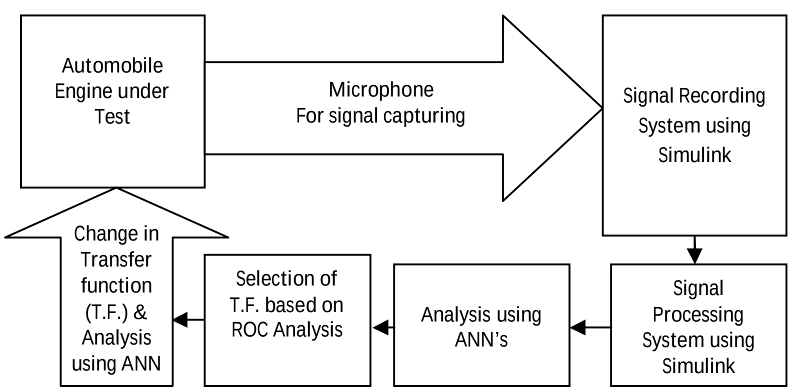


Fig.1: Block Diagram of the system

The piston of an internal combustion engine is acted upon by the pressure of the expanding combustion gases in the combustion chamber space at the top of the cylinder. This force then acts downwards through the connecting rod and onto the crankshaft. The connecting rod is attached to the piston by a swiveling gudgeon pin.

Normal piston: the normal working piston shows Brown to greyish-tan colour and slight electrode wear, correct heat range for engine and operating conditions. When new spark plugs are installed, replace with plugs of the same heat range.

Damaged or inappropriate Piston: The piston damage may arise due to following reasons

i. Removable of material from by melting piston crown and ring zone.
ii. Hole in piston crown.
iii. Piston fracture due to mechanical contact between piston and cylinder head.
iv. Erosion on piston top land and piston crown.
v. Piston fracture in piston pin boss.

The damaged or warn piston cause loss of power during acceleration which results in. Poor engine performance and a loss in fuel economy are qualities of a worn or spoiled spark plug. The main cause of damaging the piston is because of rough materials that accumulate on the piston may melt to bridge the gap when the engine is suddenly put under a heavy load.

a) Normal Piston

b) Inappropriate Piston or damaged piston Ring

Fig. 2: Normal and Faulty of Inappropriate piston of 4 stroke IC Engine

2.2 Audio signal recording and processing

The audio signals from the IC engine are captured by using simple carbon microphone placed in front of the engine head. The signals are recorded at sampling frequency of 11025 Hz in Simulink by creating a simulink model and are normalize, processed to find signal parameters like energy, mean, standard deviation, maximum, minimum and variance.

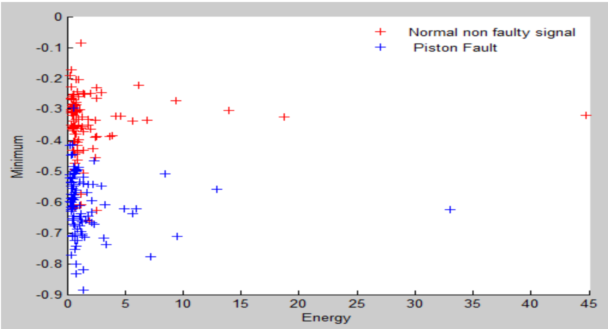


Fig.3A. Scatter plot - Minimum Vs Energy

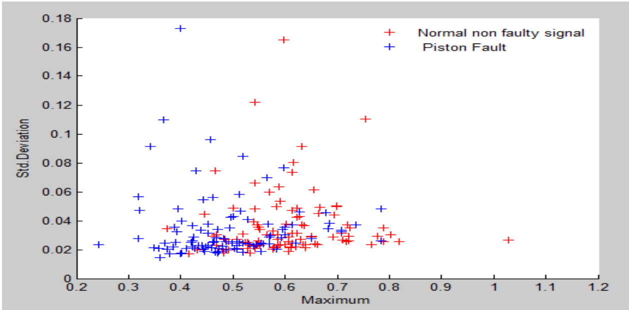


Fig.3B. Scatter plot -Std. Deviation Vs Maximum

Fig.3: Scatter plot between parameters of Normal Non-faulty and Faulty Signal

2.3 Artificial Neural Network

Fig. 3 shows the scatter plot for extracted parameters of normal non-faulty and faulty signal. In most of the cases, some parameters are overlapped and but some parameters are slightly separated. In Fig. 3b the parameters are found to be overlapped but in case of fig.3a the parameters are slightly separated, but decision boundaries are not separable and linear classification is not possible. Since like a real nervous system, the artificial neural network is Parallel organization that permits solutions to problems where multiple constraints can be satisfied simultaneously with implicit rules rather than explicit. Therefore artificial neural networks have been employed to separate the fault. The performance of each network can be observed on the basis of classification accuracy.

In proposed system the performance of MLP, MNN, SOFM, PCA, JEN, RBF and SVM are tested for fault detection in an automobile engine. The best one found from the several types of neural networks is *Multi Layer Perceptron (MLP)*. MLP are a useful technique for data classification. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value" (i.e. the class labels) and several attributes" (i.e. the features or observed variables). The goal of MLP is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

Selection of classifier transfer function is based on Receiver operating characteristic (ROC) analysis, which provides the most comprehensive description of diagnostic accuracy available to date, because it estimates and reports all of the combinations of sensitivity and specificity that a diagnostic test is able to provide. This paper explains the conceptual foundations of conventional ROC analysis.

3. Experimental Setup

The average classification accuracy (ACA) of all types of neural networks for piston Fault is shown in the table1. Each ANN is simulated and the number of PE and Epoch are increased successively for better performance and optimum number of nodes and PE are evaluated. Out of ten neural networks, the SOFM, MLP and SVM are giving the best performance, therefore for the classification and identification of the faults in four stroke IC engine, The Multilayer Perceptron is developed to classify the given data into faulty and non faulty.

Table 1: The average classification accuracy of all types of neural networks for Piston fault

ANN	HL	PE	ACA
MLP	One	59	96.12
MNN	One	53	93.89
SOFM	One	50	94.68
PCA	One	50	92.19
JEN	One	50	91.29
RBF	One	50	87.80
SVM	Epochs- 600		95.75

Fig.4: Experimental Setup with audio signal capturing system

Fig. 4.Shows the Experimental Setup with four stroke IC engine, Audio signal capturing and recording system. It is single sensor system, which is placed in front of engine head so that, it will capture the audio signals from the engine. Audio signal carry valuable information about the engine behavior and status of engine. The engine used is a four stroke, single cylinder IC engine of Hero Honda Splendor the detail specification is as in table 2. The sensor specifications are given as in table 3:

Table 2: Specification of Hero Honda Splendor

Displacement:	97.50 ccm (5.95 cubic inches)
Engine type:	Single cylinder, four-stroke
Power:	7.37 HP (5.4 kW)) @ 8000 RPM
Torque:	7.95 Nm (0.8 kgf-m or 5.9 ft.lbs) @ 5000 RPM
Compression:	8.8:1
Fuel system:	Carburetor
Fuel control:	OHC
Ignition:	CDI
Gearbox:	4-speed
Transmission type, final drive:	Chain
Clutch:	Wet. multiplate
Driveline:	4 speed constant mesh

Table 3: Specification of Sensor

Frequency ranger:	50-16KHZ ,
Impedance	Low
Sensitivity	-60dB+/-3dB
Cable length	180cm
3.5mm Plug Microphone Size	26X15X12mm
Weight	30g

To capture the signals from the IC engine, initially the engine was started in healthy condition and audio signals are recorded at different speed i.e. 1000rpm to 5000rpm with 1000rpm interval. Then the normal Piston is replaced by piston having damaged piston ring (inappropriate piston) and again signals were recorded at same speed and gear positions. The simulink model was used to record the sound signals captured by carbon microphone from the engine is shown in fig. 5.

These audio signals are processed using Simulink in MATLAB to find the parameters as minimum value, maximum value, mean value, energy, standard deviation and variance. The Simulink model for parameter extraction is shown in Fig. 6.

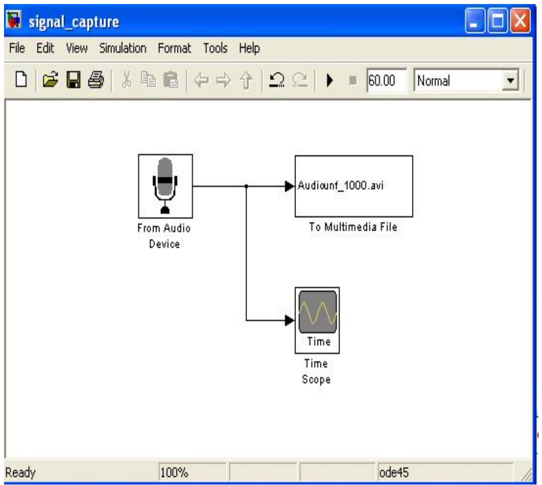


Fig. 6: Model for parameter calculation

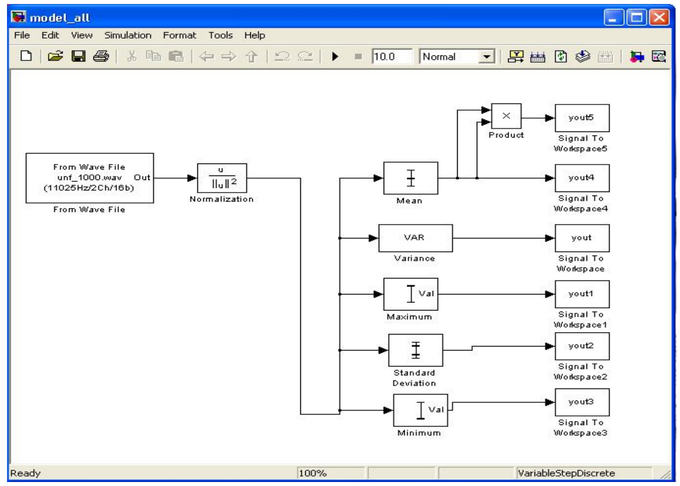


Fig.5: Simulink Model for Signal Recording

4. Results

The recorded audio signals are normalized and plotted as shown in fig.7. Faulty (Red) and Non Faulty (Green) Audio Signals.

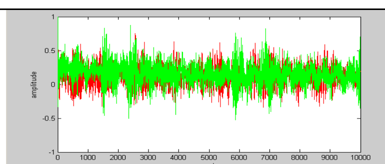
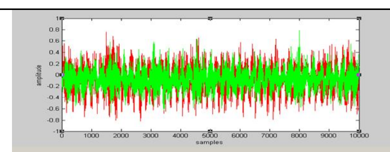
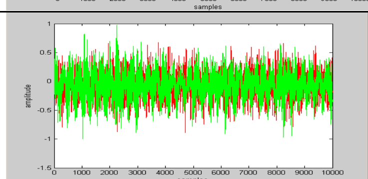
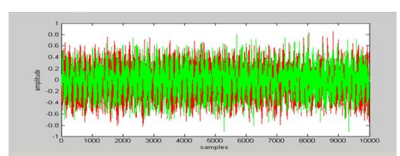
A		Signal plot at 1000 rpm	C		Signal plot at 3000 rpm
B		Signal plot at 2000 rpm	D		Signal plot at 4000 rpm

Fig 7: Signal plots at different RPMs as Faulty (Red) and Non Faulty (Green) Audio Signals

It is observed from the plots that

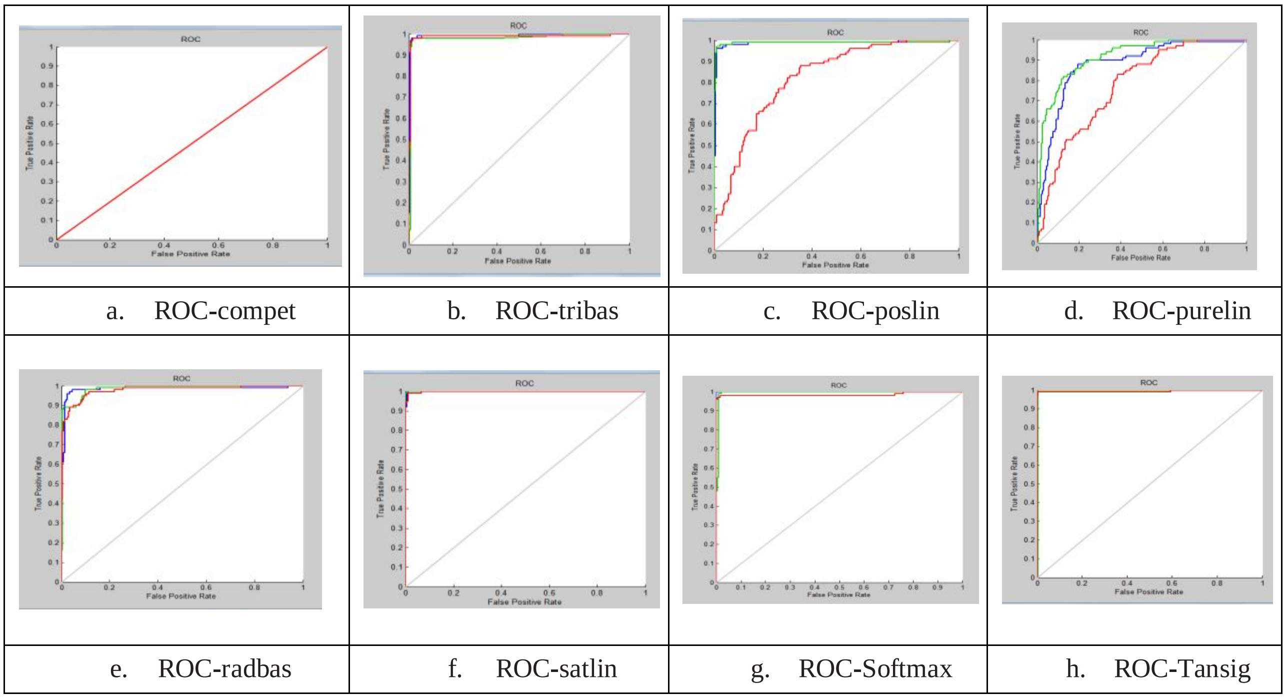
i. The amplitudes of the signal for Faulty piston are smaller than that signals for Non Faulty piston.

ii. There is no linear separation between faulty and normal signals.

iii. The mean value of faulty signal is shifted down as compared to the mean value of non faulty signal.

iv. The maximum and minimum values of non faulty and faulty signal are different.

Receiver operating characteristic (ROC) analysis provides the most comprehensive description of diagnostic accuracy, because it estimates and reports all of the combinations of sensitivity and specificity that a diagnostic test is able to provide. The piston fault in four stroke IC Engine is identified by using MLP with different transfer functions as, compet, hardlims, poslin, purelin, radbas, satlin, softmax, tansig, tribas and ROCs are plot as shown in fig.8.



a. ROC-compet | b. ROC-tribas | c. ROC-poslin | d. ROC-purelin

e. ROC-radbas | f. ROC-satlin | g. ROC-Softmax | h. ROC-Tansig

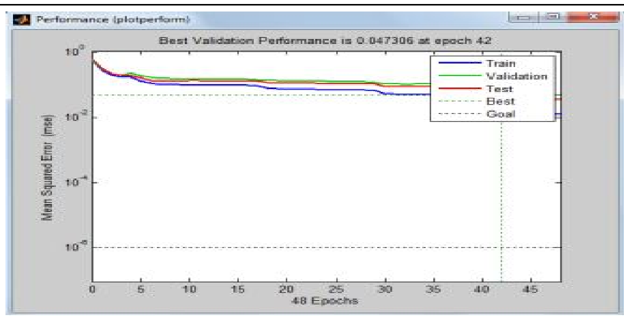
Fig.8: Receiver Operating Characteristics for different transfer functions

The area under the ROC curve (AUC) is a common metric that can be used to compare different tests (indicator variables). An AUC is a measure of test accuracy. ROC curve describe two-dimensional visualization of ROC curve set of classifiers performance. For the reason of comparing two sets of classifiers it is sometimes suitable to reduce ROC performance to a single scalar value representing expected performance. Consequently the value of AUC will always satisfies the following inequalities $0 \leq AUC \leq 1$. It is clear that if the AUC is close to 1 (area of unit square) AUC indicates very good diagnostic test. On the other hand as the random guessing produces the diagonal line between the points [0; 0] and [1; 1], which has an area of 0.5, reasonable tests should have $0.5 \leq AUC \leq 1$.

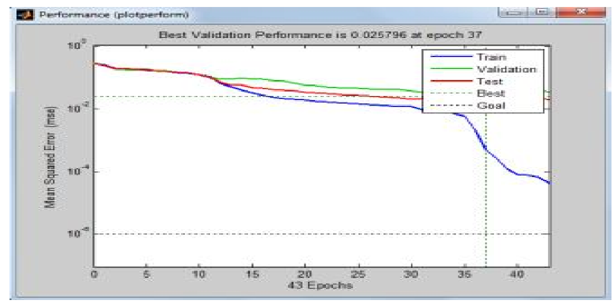
The AUC has an important statistical property, the AUC of a classifier is equivalent to the probability that the classifier will evaluate randomly chosen positive instance higher than a randomly chosen negative instance. Figure shows the ROC's for different transfer functions.

It is observed from ROCs of 'compet' that it is random guessing produces the diagonal line between the points [0; 0] and [1; 1], which has an area of 0.5. The diagonal line y = x represents the strategy of randomly guessing a class. For example, if a classifier randomly guesses the positive class half the time, it can be expected to get half the positives and half the negatives correct; this yields the point (0.5, 0.5) in ROC space.

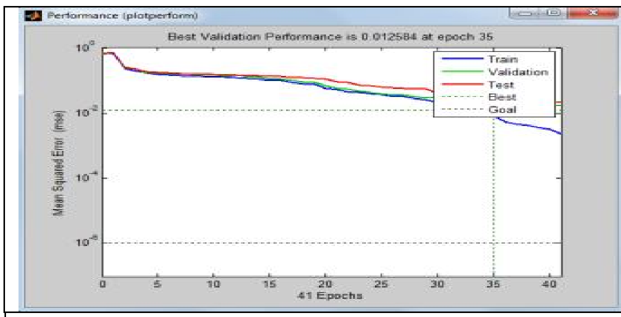
Poslin, purelin and radbas has ROCs whose area $0.5 \leq AUC \leq 0.8$.which shows about 80% positives are correctly classified among all the positives, where as in case of satlin, Softmax, Sansig and tribas the AUC is nearly 1. The performances of MLP network with transfer function satlin, Softmax, tansig, are plotted as in fig.9.



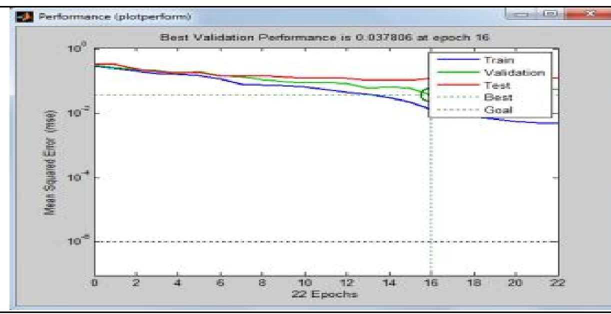
A. Best validation performance-Satlin



B. Best validation performance- Softmax



C. Best validation performance-Tansig



D. Best validation performance-Tribas

Fig.9: The performances of MLP network with transfer function satlin, Softmax, tansig

From fig.8 it is found that the best validation performance for tansig is 0.012584 at 35 epoch, for softmax is 0.025796 at 37 epoch, for satlin it is 0.047306 at 42 epoch and for tribas it is 0.037806 at 16 epoch, so from the above result it is observed that the performance of 'satlin' transfer function is better than the tansig and softmax. So, fault in four stroke IC engine can be identified most accurately by use of MLP with satlin transfer function. Fig.10 shows output of system in command window that Engine has Piston fault when a signal for piston fault is given to a system as unknown signal.

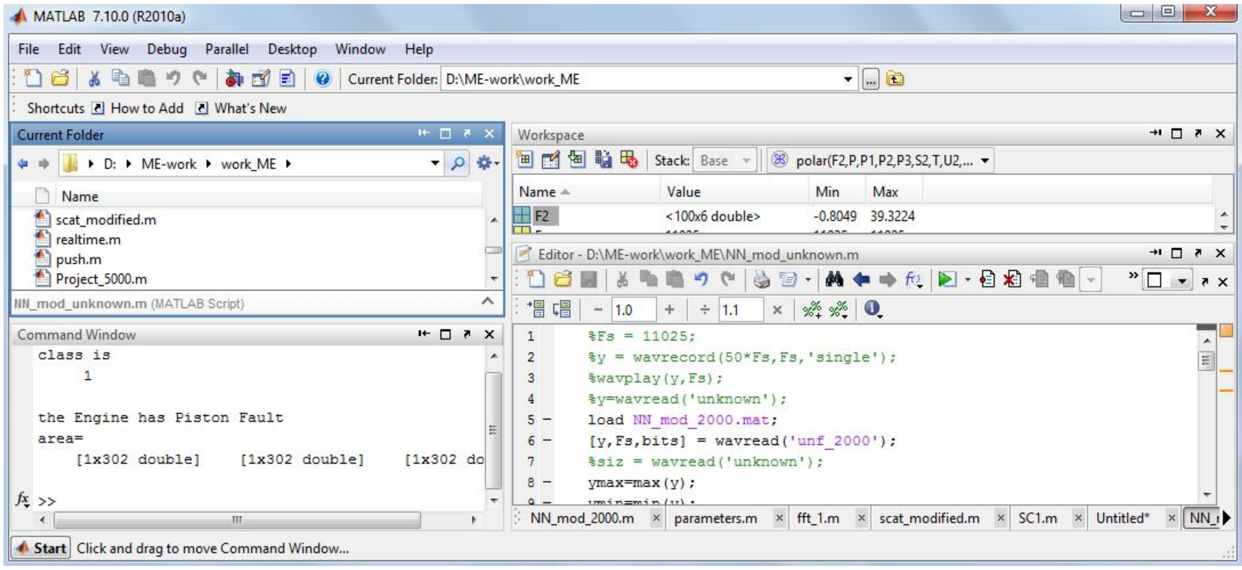


Figure 10: Output of system in command window

5. Conclusion

From comparative study of ROC and Performance of all types of neural network transfer function for the identification of piston fault in four stroke IC engine It depicts that out of eight transfer functions satlin, softmax and tansig gives better performance, it is also observed that performance of satlin is found to be the best amongst all eight transfer function and therefore it is proposed that salin can be preeminent transfer function for MLP to detect piston fault in a four strokes IC engine.

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