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Nouby M Ghazaly
South Valley University

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AHMED F. MOFLEH, AHMED N. SHMROUKH & NOUBY M. GHAZALY

Faculty, Department of Mechanical Engineering, South Valley University, Qena, Egypt

ABSTRACT

Internal combustion (IC) engines have been used in many transportation and manufacturing applications. Therefore, early detection of malfunctions in engines is the most significant issue to help to avoid causalities and further damage. The present research analysis is aimed to detect the faults of the spark ignition engines using acoustic signals. Initially, the fault detection with the aid of digital computers and an automated diagnosis based on a system using the artificial neural network (ANN) is proposed. The acoustic signal are picked up from the engine as features to feed the network at four speeds 1000, 2000, 3000, and 4000 rpm. Then, acoustic signals from the spark-ignition engine with four strokes four cylinders have the misfire with one spark plug and two misfire fault simulated and are tested with the proposed network. Finally, the ANN system evaluated and classified the faults of the spark-ignition engine. It is found that the results are proved an excellent potential for using acoustic signal from the engine with ANN.

KEYWORDS: Spark Ignition Engines; Fault Detection; Acoustic Signal; Artificial Neural Network

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Original Article

1. INTRODUCTION

Degradation of the IC engine faulty adjustment may conduct to reduce the mechanical efficiency, decrease of the power, related to the reduction of thermal efficiency and filling coefficient, growth in the emission of toxic compounds in the exhaust fumes, and potential damage to the engine parts. Early fault detection of the IC engine can be mainly prevented damage of the engine from further causalities. Typically, the IC engine has been emitted the sound waves which are considered as pressure waves that are transmitted through the media. This media may be water, solid, or air. Once dealing with sound transmitted through the air its meaning acoustics and the speed of the sound relies on the compressibility in the air. The acoustic signals emitted from the internal combustion engines have significant roles in the output information relating to the operating parameters and healthy conditions of the engine. Unfortunately, this information is complex and has much background on the sound wave and demands more techniques to make its benefits [1:2].

The sound wave amplitude ranges according to the loudness of sound with different frequencies which acts as the pitch of the sound wave. Since the engine fault has a unique acoustic signal and distinguishable with sound recognition techniques, many researchers used acoustic signal as an effective method for fault detections. Marwan Madain et al. [3] used sound emission techniques on fault detection, isolation, and recovery for the IC engines. The engine noise was experimentally applied as a fault diagnosis approach in condition monitoring for a misfire inside the IC engine by Wail Adaileh [4]. On the basis of the analysis of the area of vibroacoustic signals which can be considered to diagnose the IC engines both on the test bench and under operating conditions. Ahmed and Elaraby [5] introduced an automatic approach of the engine diagnostics based on acoustic signal. A comparison between the vibrations and acoustic emission energy was conducted with reference values to decide whether the state of the engine was faulty or not. Fog et al. [6] described the diagnosis of the condition of exhaust valves for the two-stroke marine diesel engine. Three monitoring measurements were evaluated vibration, structural stress waves, and acoustic signal. They reported that acoustic emission has an important advantage over the other techniques.

Due to acoustic signals which are generated through the IC engines are non-stationary, the frequency domain or the time-frequency domain have been utilized as feature extraction techniques. In the frequency domain, Yadav and Kalra [7] proposed the spectrogram of the acoustic signal. Nine statistical features namely; kurtosis, shape factor, crest factor, mean, median, and the variance of spectrogram for classification through ANN-based classifiers were conducted. In the time-frequency domain, Yen and Lin [8] used feature extraction techniques from vibration information based on wavelet packet transform (WPT). The wavelet coefficients were used as the features of the vibration information and considered for classification by ANN-based classifier. Also, Wu and Liu [9] and Nouby et al. [10] used different levels of wavelet packet decomposition with several types of mother wavelets to find many types of feature spaces to use in the train ANN-based classifier.

Digital signal processing and artificial intelligence were conducted for fault detections of the four-stroke diesel engine through acoustic signals by Shankar Dandare and Dudul [11]. A single neural network was conducted to induce an intelligent diagnosis based on time-frequency distributions. The results reported that the faults in the diesel valve assemblies can be accurately classified by the intelligent diagnosis. Also, Multi-Layer Perception Neural Network (MLPNN) was used along with wavelets as distinguishable property to classify faults of the IC engine by Mehrdad Nouri et al. [12].

Throughout the past few decades, several researchers have been analyzed the fault detection of the IC engine and many research papers had been published [13-19]. Nevertheless, most of these papers con centered on the analysis of the IC engine through vibration signals, and few researchers have been focused on detecting the faults of the IC engine using the acoustic signals. Subsequently, the faults detections of the spark-ignition engine as well as diesel engines have received much research attention. In this study, the engine fault detection and classification technique using acoustic signal is conducted. The ANN approach is considered for detecting several faults of the spark-ignition engines which lead to a lack of power and pollutes the surrounding environment. The acoustic signal are picked up from the engine as features to feed the network at different speeds namely; 1000, 2000, 3000, and 4000 rpm for healthy conditions and faulty cases.

2. METHODOLOGY

In this section, the spark-ignition engine experimental setup and procedures is described in two subsections. The first data setup introduces how data is measured and collected by the instrumentations as preprocessing and preparation before feeding into the network. The second subsection is explained the neural network setup and preparation for calculations and processing.

2.1 Data Setup

The internal combustion engine that is used as shown in Figure 1 is a spark-ignition internal combustion engine four-stroke with four cylinders which has specifications as presented in Table 1.The operation running for four different speeds is selected at 1000, 2000, 3000 and 4000 rpm three conditions namely; healthy, one cylinder misfire (fault 1) and two-cylinder misfire (fault 2) conditions for experimental analysis. Acoustic data are acquired by Bruel & Kjaer Hand-Held Analyzer 2250-S, microphone sensor and 1 / 3 octave to obtain the frequency domain of the signal against sound pressure level (SPL).

The signals are measured with microphone and feed to the analyzer which transducers the signal and pressure waves of the sound to millivolts. The operation engine speed is measure by digital tachometer for all cases. The signal is converted into digital format with some capacitors and electronic components in data acquisition. The collected signals are stored and with the help of FFT algorithm the signal is transformed from the time domain to frequency domain. By applying Octave band filter, the signal is monitored with decibels which indicates the SPL in the vertical axis and frequency range in the human audible range (20 to 20 kHz) in flat response (z- freq. weighting) and the overall A-weighting and C- weighting. After that, the data is stored and fed into the neural network system. Finally, the ANN system is used to evaluate the acoustic data and the classifier is applied to classify faults of engine that is done as one-cylinder misfire and two-cylinder misfire. The fault detection algorithm of the spark ignition engine is represented, as shown in Figure 2.

Figure 1: Experimental Platform for Engine Fault Detection.

Table 1: Engine Specifications

Engine Type	2.0 DOHC L-4
Bore	86 mm
Stroke	86 mm
Displacement	1998CC
Compression ratio	9.6:1
Maximum power	98KW(131hp) at 5400 rpm
Maximum Torque	18.8Kg.m at 4600 rpm
Ignition Type	Direct Ignition system
Ignition Sequence	1-3-4-2

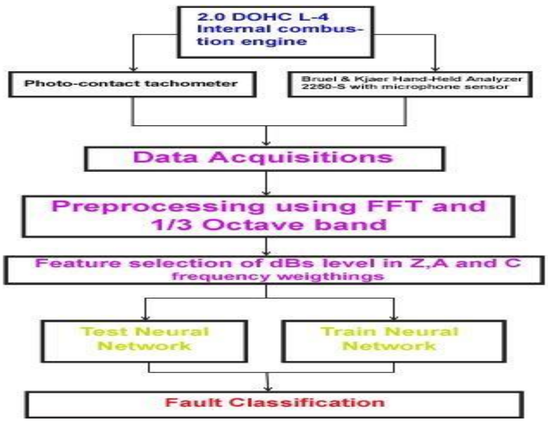


Figure 2: Fault-Detection Algorithm.

2.2 Neural Network Setup

The ANN is a technique in Artificial Intelligence (AI) areas such as Machine Learning (ML), Fuzzy Logic (FL), or Genetic Algorithm (GA). The ANN mimics the human brain and modeling its behavior and processes in learning. Supervised learning is the intelligence to learn from examples, this method used in this study as targeted labels which represent the outputs are fault free, one-cylinder misfire and two-cylinder misfire. Multi-layer perceptron feed-forward with back propagation neural network (MLPBNN) is a type of networks consists mainly of three main layers; input layer, hidden layer and output layer each layer comprises of single or multiple processing units called neurons (like neuron cell), input layer is selected I this study to have 35 neurons which are levels of sound (Z-Weighting) at frequencies in dB (12.5 Hz, 16 Hz, 20 Hz, 25 Hz,31.5 Hz, 40 Hz, 50 Hz, 63 Hz, 80 Hz, 100 Hz, 125 Hz, 160 Hz, 200 Hz, 250 Hz, 315 Hz, 400 Hz, 500 Hz, 630 Hz, 800 Hz, 1 kHz, 1.25 kHz, 1.6 kHz, 2 kHz, 2.5 kHz, 3.15 kHz, 4 kHz, 5 kHz, 6.3 kHz, 8 kHz, 10 kHz, 12.5 kHz, 16 kHz, 20 kHz) which means 33 input neurons and the other two input cells are the SPL overall at A-weighting frequency and C-weighting which produces total 35 inputs to the network system. The hidden layer which is disengaged from environment interaction unlike input and output neurons in human cells performs the main calculation the number of hidden neurons chosen to be 26 as 2/3 times input layer size plus output layer size [20-22]. The output layer contains three neurons that represent three labels fault free, one-cylinder misfire and two-cylinder misfire faults. Layers were connected with weights (like synapses in an organic neural system). Instances are 20 samples or observation for every three labels with 35 different inputs which make the total data set size 2100 sample where 75% is used in training and the remaining in network testing. A typical block diagram of the model of network structure is summarized, as shown in Figure 3. Back propagation algorithms used to modify network weights which initialized randomly according to loss function (error).The algorithm is selected in this study is Gradient Descent (GD) with Mean Square Error (MSE) performance as this algorithm fast with high recognition rate in such engine faults. Figure 4 illustrates the network setup in MALAB the number of each layer represents the number of neurons the function visualized in the hidden layer is a hyperbolic tangent as activation function after summations and w symbolize the weights and b for biases as network parameters function at output layer is soft max function.

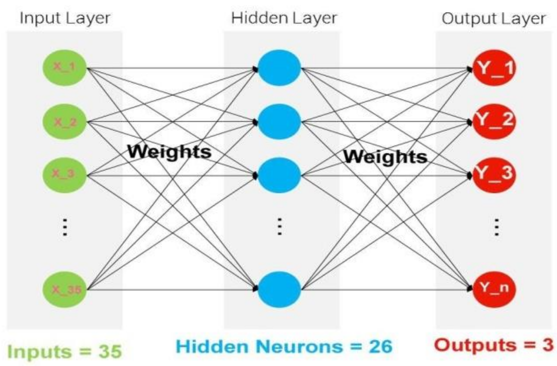


Figure 3: Structure of the ANN Architecture Used for Fault Classification.

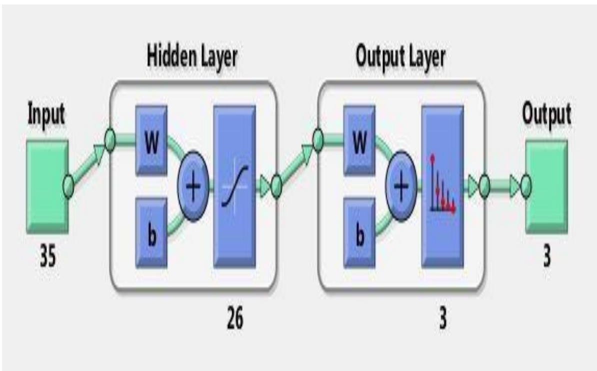


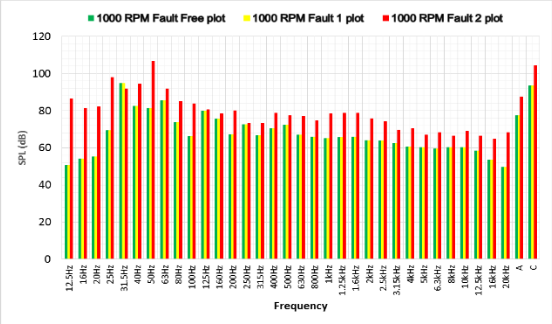
Figure 4: ANN Setup Used In Fault Classification.

3. RESULTS AND DISCUSSIONS

The experimental results under different running speeds of the IC engine are illustrated as bar charts plot and test confusion matrix to test network performance and classification. Class 1 is considered fault free and class 2 is considered one cylinder misfire as fault 1 where class 3 reserved for two cylinder misfire fault as fault 2 or B.Figure 5 illustrates the plot for each speed with three classification cases(fault free, fault 1, and fault 2)at 1000, 2000, 3000, and 4000 rpm. The horizontal axis represents frequencies where one can consider it as the sound source at audible human ear range with Z-Weighting, A, and C as the equivalent value where the vertical axis represents sound pressure level (SPL) in decibels (dB). At speed 1000 rpm the fault 2 level is higher than the level at fault 1 and fault-free, as shown in Figure 5a. It is found that the level for fault-free is maximum at 31.5 Hz with SPL equal to 94.5 dB (z) as well as fault 1 that is very clear that speed close to idling emits a noise that prevents discerning fault free from fault 1 classes but at fault, degree increases the signal's amplitude clearly distinguishable as it was maximum at 50 Hz with 106 dB (z) for fault 2 class (B). The plot shows the maximum level of 99.7 dB (z) at 63 Hz for fault-free and for fault 1 and 2 was 105.8 and 106.3 dB (z) at 50 Hz respectively which are closed. As engine speed increased (C) sound levels were clearly distinguishable as it far from noise at idling and emission of acoustics could be discerned.

Figure 6 illustrates the confusion matrix for different running conditions the classes 1, 2 and 3 are fault-free, fault 1 and fault 2 respectively. The horizontal categorizes which labeled as target classes are true classes where vertical categorizes is labeled as output classes for predicting classes from the network. There are fifteen samples are selected randomly from the data set for testing the network. Green squares are true class (i) and the network predicted it as the class (i) the red squares are true class (i) but the network doesn't predict it as the class (i). Numbers in green and red squares represent how many data correctly predicted by network and how many wrongly predicted respectively. The below percentages for each squares are represent as the percent of that number with respect to the total number of test samples which are 15.

The final result in confusion matrices are the percentages at the far right bottom square which the green percentage represents the recognition rate (accuracy) of network and error rate in the red ones. As shown in Figure 6 (A),there are 3 observations is selected from fault free and the predicted fault free and 12 observations are fault 3 but 6 predicted as fault 3 and 6 predicted wrongly as fault 2 which gives final recognition rate of 0.6 with error of 0.33. In Figure 6 (B), there are 3 observations is selected from fault free and the predicted fault free and 12 observations is selected from fault 3 and 7 of them is predicted correctly which gave the final recognition rate of 66 %. The maximum recognition rate of the network with the minimum error rate is shown in Figure 6 (C), the higher speed 3000 rpm where 73.3 % and the error rate of 26.7 %. It came synchronized with the results of the plot in Figure 5 which is shown the higher discretion ability at the higher speed above idling conditions as it came far from noise in the signal which may mask or decisive the system for fault detection. Figure 6(D) shows the case of 4000 rpm the discerning of the network is obvious as the recognition rate is 80 % with the error rate of 20 % only.



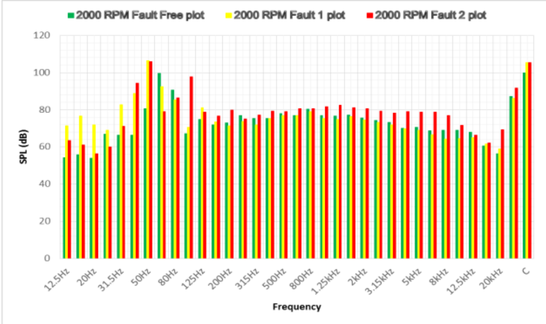
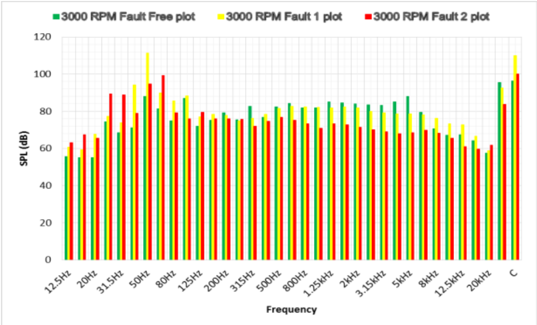


Figure 5: (A) Bars Plots at 1000 Rpm, (B) Bars Plots at 2000 Rpm.



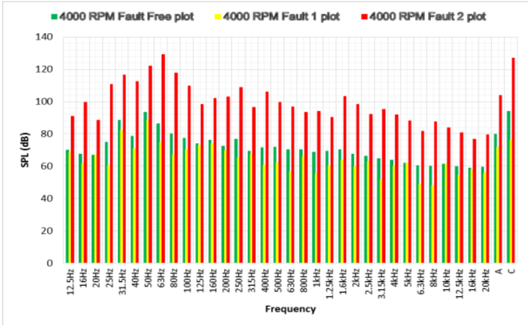
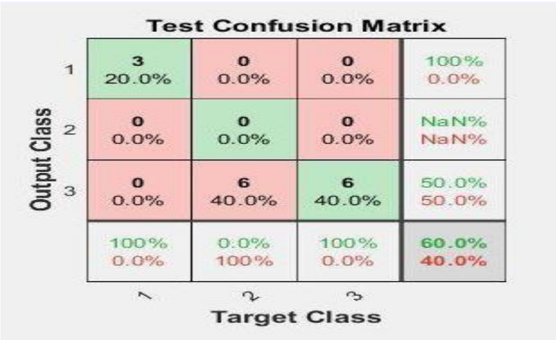


Figure 5: (C) Bars Plots at 3000 Rpm, (D) Bars Plots at 4000 Rpm.



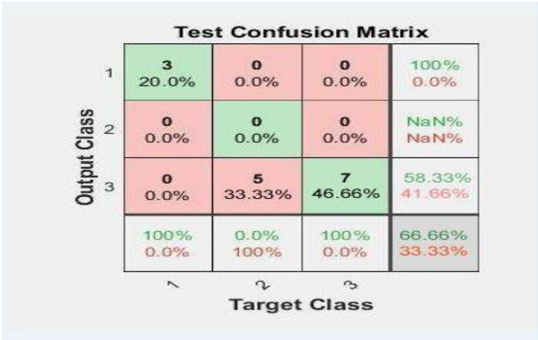
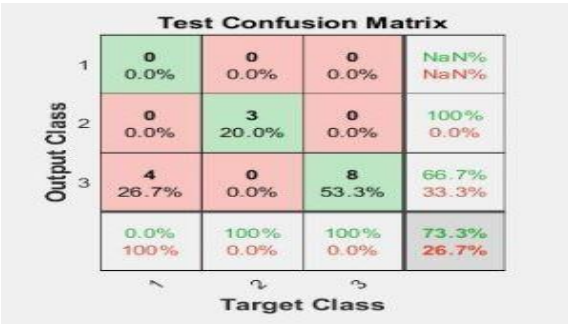


Figure 6: (A) 1000 Rpm, (B) 2000 Rpm.

Figure 6: Confusion Matrices for Each Speed.



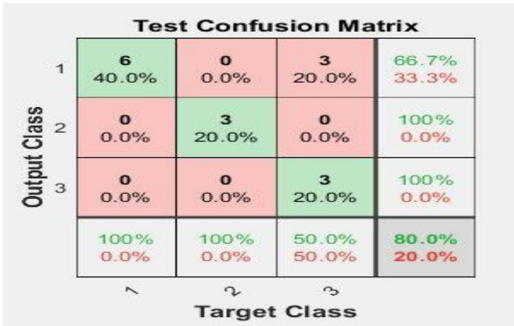


Figure 6: (C) 3000 Rpm, (D) 4000 Rpm

Figure 6: Confusion Matrices for Each Speed.

4. CONCLUSIONS

The proposed technique for automated fault detection and classification for the spark ignition engine is conducted. Acoustic signal for four-cylinder four-stroke spark ignition engine is acquired and analyzed to feed Multi-layer feed-forward neural network with back propagation algorithm. Every proposed fault emits its dynamic properties as acoustic signature. After that, it is export to the neural networks to use in fault detection, isolation, recovery, and diagnosis. It is found that the acoustic signal with ANN gives high potential in fault detection in the IC engine. Also, it is recommended to make the network model at a higher speed to give high accuracy and minimize loss (error).

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