Kuwait Journal of Computer Science
ISSN: 2984-7605
Vol 1 Issue 1 (2023)

Application of Artificial Neural Network for Internal Combustion Engines

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Submitted: 20/01/2023 **Revised**: 14/02/2023 **Accepted**: 05/03/2023

Abstract:

In this research, acoustic emission (AE) technology is used to detect faults in the valves in the internal combustion engine, where the cylinder head of a spark ignition engine was used as an experimental setup. The study was conducted on three types of valve damage ((clearance, half-notch, and notch) on valve leakage. The study proved that the acoustic emission technique is an effective method in detecting damage to valves in both the time and frequency domain. The neural network was trained based on time domain analysis using AE parametric features (, number, absolute AE power, maximum signal amplitude, and average signal level).

Keywords: Internal Combustion Engines , fault detection, Acoustic Emission, Artificial neural network.

Introduction:

The automotive industry is facing a difficult time, as the shift from internal combustion engines to modern electrical technologies requires huge investments, so the search for alternative fuels is a solution to improve operating standards. Therefore, IC engines will serve as a means of transportation during the coming years (1)

Diagnosing faults and monitoring the condition of the mechanical system are necessary to avoid faults. An internal combustion engine is a rotating machine that is operated in different conditions for different needs. The vibration signal of the engine presents the state of the engine by analyzing the vibration signal to detect faults. There are many techniques for analyzing the signal, such as the fast Fourier transform. (FFT) and other techniques have been developed such as the Short Fourier Transform (STFT), but the best of these techniques is the Wavelet Transform (WT). (3)

The wavelet transform technique was used to detect the faults in the internal combustion engine, where the continuous wave algorithm was used to find out the fault signal in the engine, as the results proved that the wavelet shunt technique is effective in detecting faults (4)

faults in the engine are detected by examining the deviation of the engine signals from their normal values. In this research, a fuzzy identifier was created to know the engine signals necessary to calculate the signals of deviation from the normal behavior of the engine so that we can know the errors in the engine. Experimental results were presented that show the effectiveness of the fuzzy identifier in the Detection of faults (5)

The audio signal emitted from the engine is used and analyzed using the wavelet packet to extract the features so that the neural network is formed from these features (6)

In this study, the visual dot pattern technique was used to determine the vibration signals to classify faults in the internal combustion engine and the drive axle shaft (7)

new nonlinear variable reconstruction algorithm and Binary Dispersion Plots (NLPCA) were used to isolate the fault, as this technique allows to diagnose of faults under different conditions, by isolating the abnormal behavior of the motor (8).

Artificial neural network (ANN) is an effective technique in predicting various operating variables of a combustion engine due to the complex behavior of internal combustion engine operations. Scientists have used the synthetic grid to predict power, torque, fuel consumption, air-to-fuel ratio, injection pressure, etc. As the neural network provides great accuracy while analyzing the performance of the internal combustion engine. (9)

Experimental test rig setup

- Test Rig and Measurement System

The experimental test consists of an aluminum cylinder head of a four-cylinder spark-ignition engine. Figure (1) shows four AE sensors on the cylinder head so that compressed air enters the combustion chamber through the spark plug hole so that the airflow is measured with an accuracy of 1 liter/minute

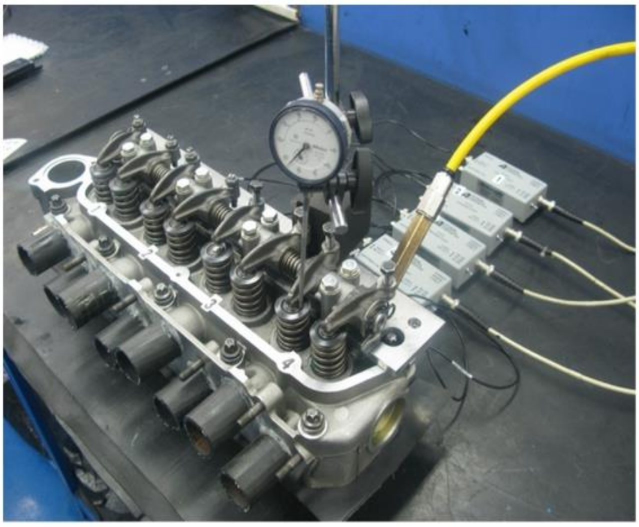
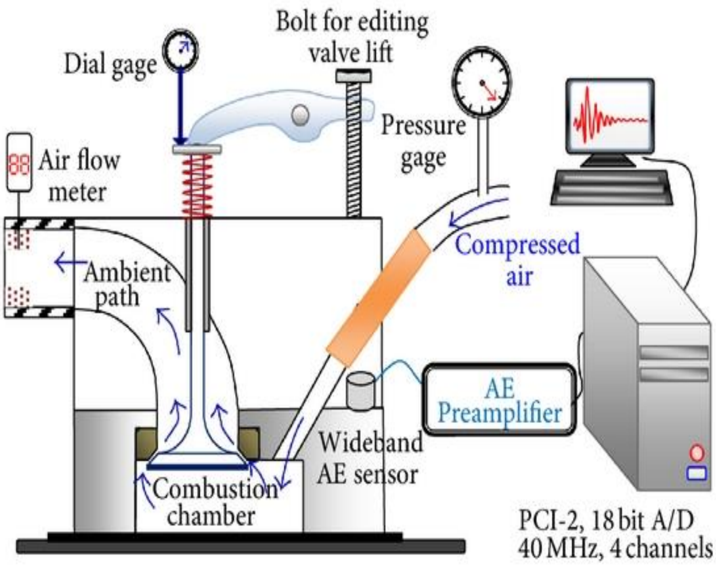


Figure (1) AE sensors on the cylinder head

- AE Data Acquisition System

AE signals were obtained by means of four sensors where the operating frequency filtered from 100 kHz to 1 MHz where the exposure sensors were attached to the cylinder head using thin layers of vacuum grease, where the signals were amplified using PAC 2/4/6 preamplifiers before being registered. The signals were digitized using a PAC PCI-2 (18-bit A/D, 40 MHz, 4 channels) to acquire the AE data. The raw data was acquired at a sampling rate of 2 MHz. As shown in Figure(2)



Figure(2) raw data was acquired at a sampling rate

- Simulated Valve Fault Types

Three types of valve defects were simulated by introducing compressed air from the spark plug hole and measuring the leakage that occurs due to the faulty valve. These defects were as follows:

1-Half-cracking valve, where a fracture (half crack) was made on the valve head, where the exhaust valve of cylinder number 1 and intake valve of cylinder number 2 was simulated using this method. The surface area removed from the valve head was 0.27 * 72.3 as shown in Figure (a).

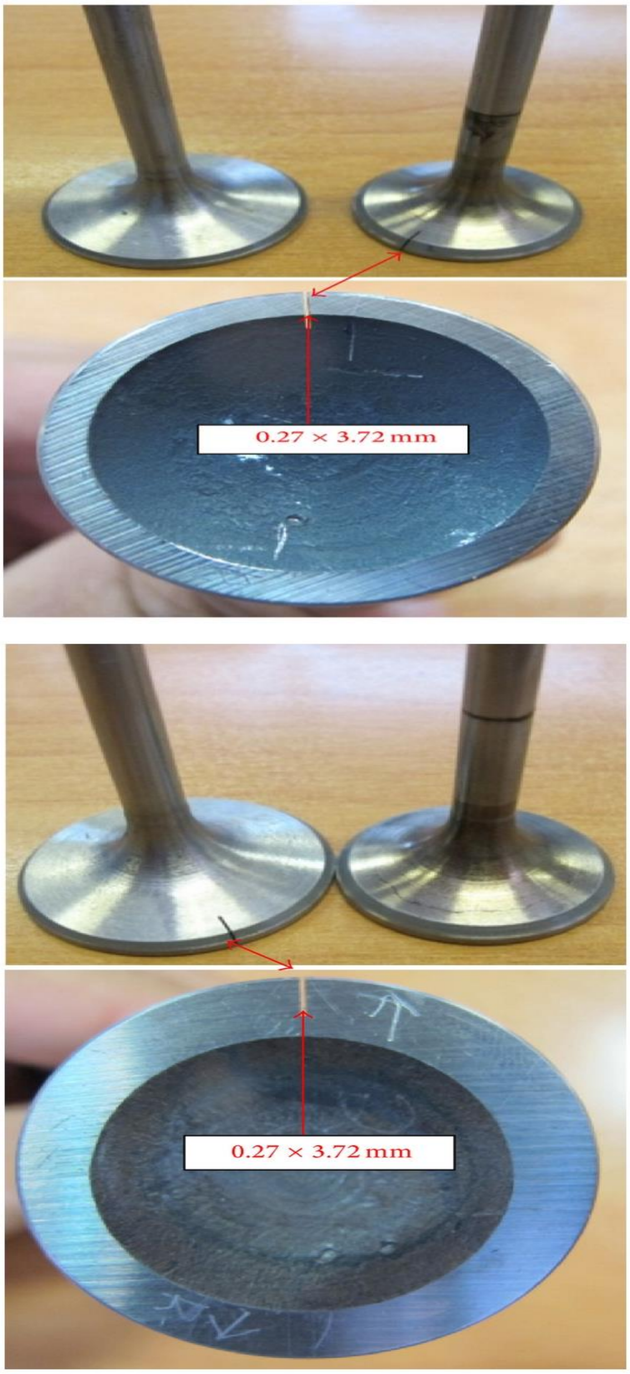


Figure a: Semicracked valves. Cylinder number 1 and cylinder nymber 2.

Kuwait Journal of Computer Science
ISSN: 2984-7605
Vol 1 Issue 1 (2023)

2-Notched Valve by removing a slight amount from the width face of the valve as shown in Figure (b)

Figure b: Notched exhaust valve of cylinder number b

3-Valve Clearance. This error was simulated by raising 0.1 mm to the exhaust valves. Figure c shows a healthy valve in the cylinder with no leakage at zero lift.

Figure c: Healthy valves of cylinder number c. Clearance fault was simulated by lift on valve

Results and Discussion:

Valve Leakage Results: The sedimentation rate increased with increasing pressure.

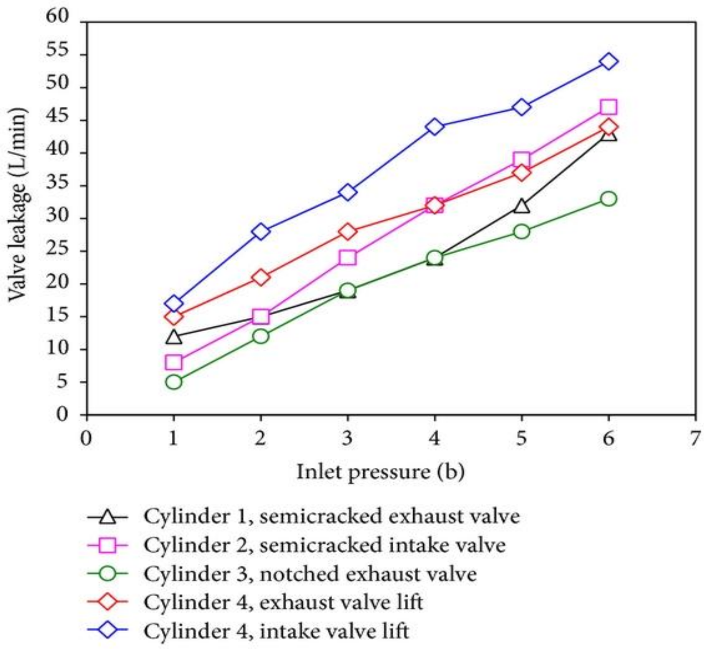


Figure 5: VL rate of all cylinders versus inlet pressurized air.

Time Domain Signal Analysis:

Figures 6, 7, 8, and 9 show the signal analysis in the time domain and the type of AE signal. Figure 10 shows the reference morphology of the valves with no leakage

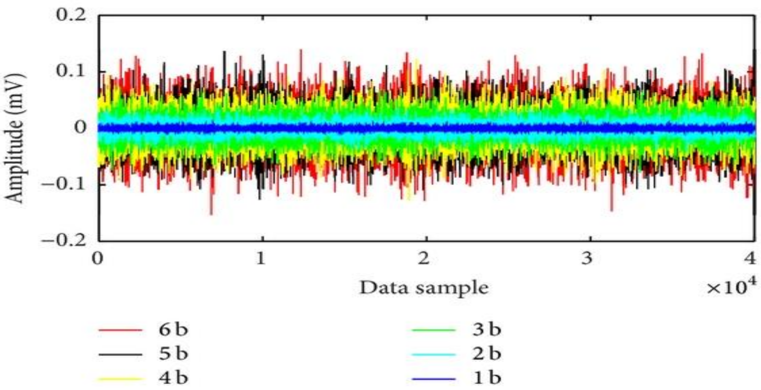


Figure 6: Raw AE signal due to VL through semicracked exhaust valve in cylinder 1

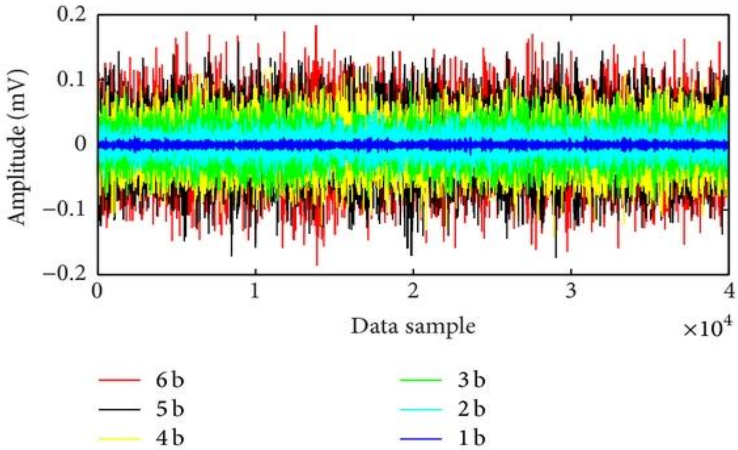


Figure 7: Raw AE signal due to VL through semicracked intake valve in cylinder 2.

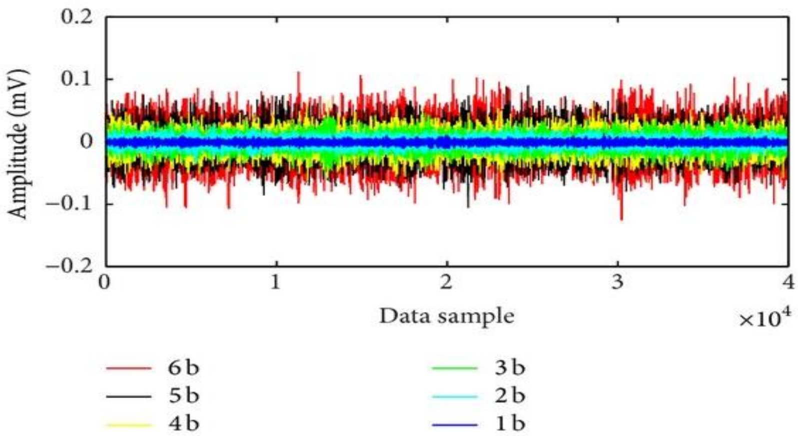


Figure 8: Raw AE signal due to VL through notched exhaust valve in cylinder 3.

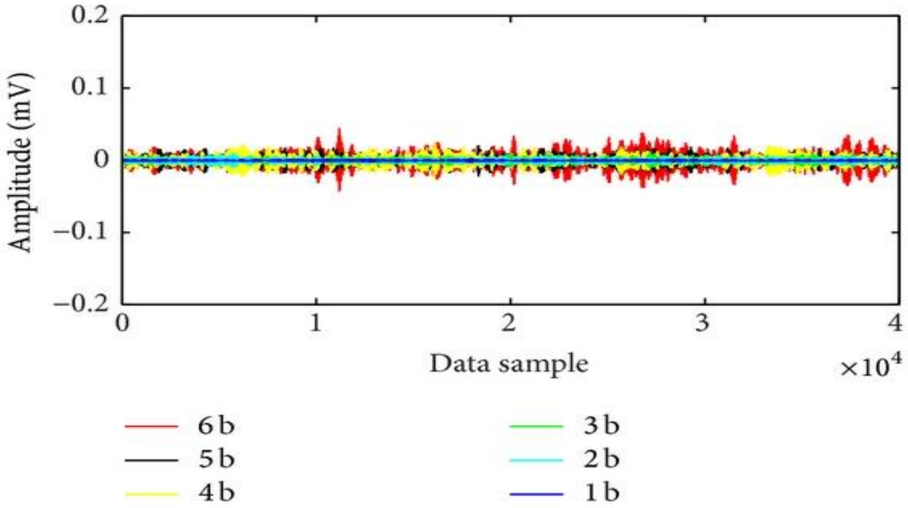


Figure9: Raw AE signal due to leakage through lifted valve in cylinder 4

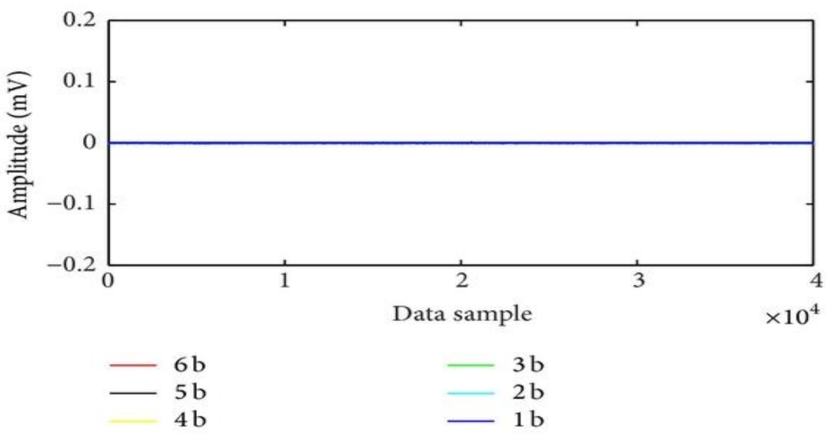


Figure 10: Raw AE signal relate to healthy valves with no leakage in cylinder 4.

In all previous cases, the AE signals were continuous and the signal increased with increasing pressure. Figures 6-8 show the results for the semi-slotted and notched valves in cylinders 1-3. It was noted that the AE signals were very similar in waveform and amplitude; Thus, it was not easy to distinguish between the signals due to different faults. But in Figure 9 the results for the valves raised in cylinder 4 indicated that the signals had only a slightly different wavelength. As for Figure 10, the results were for the valves that did not have any leakage

Frequency Domain Signal Analysis

An analysis of the AE signal in the time-frequency domain shows that Figures 11, 12, 13, and 14 show the power spectral density (PSD) of the signals shown in Figures 6-9.

Figure 15 shows the spectrum of healthy valves (without leaking) showing that there are some spots in the spectrum of defective valves, while there are none in healthy valves.

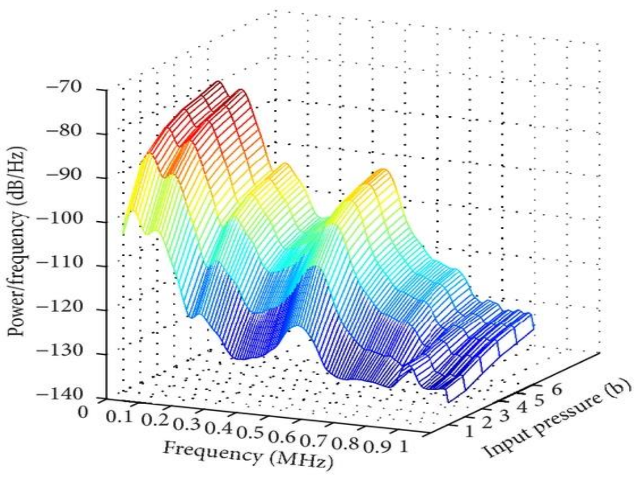


Figure 11: Power spectral density of raw AE signal due to VL through semicracked exhaust valve in cylinder 1 versus time at 1–6 bar by sensor number 1.

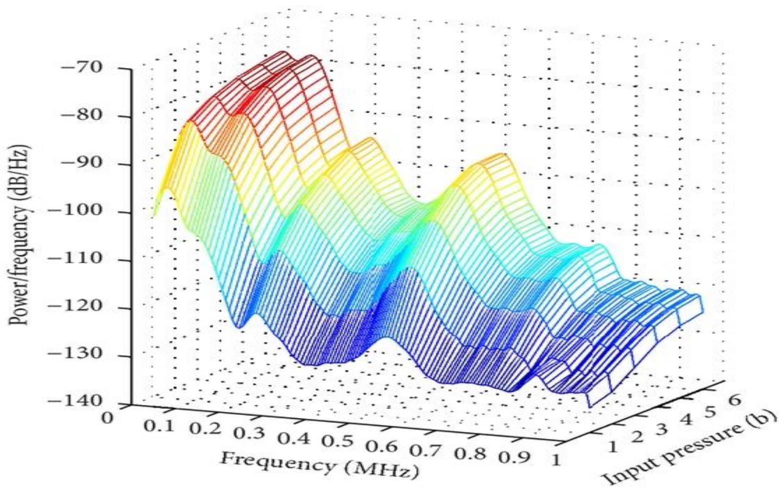


Figure 12: Power spectral density of raw AE signal due to VL through semicracked intake valve in cylinder 2.

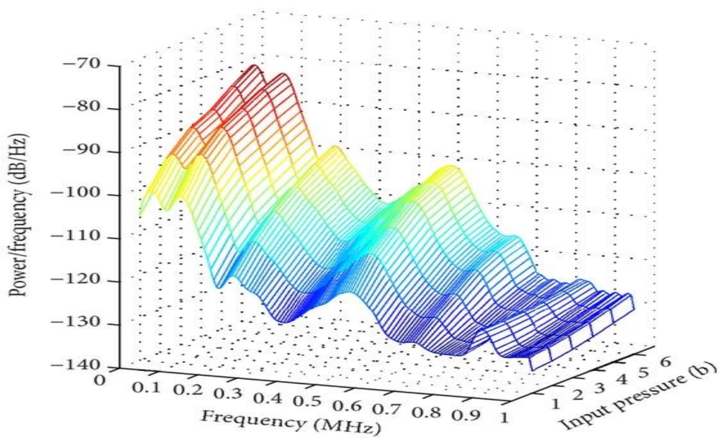


Figure 13: Power spectral density of raw AE signal due to VL through notched exhaust valve in cylinder 3.

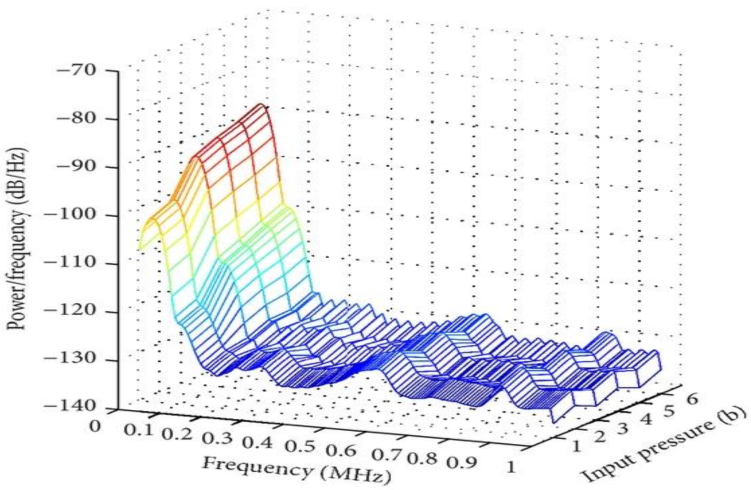


Figure 14: Power spectral density of raw AE signal due to VL through 0.1 mm lifted valve in cylinder 4.

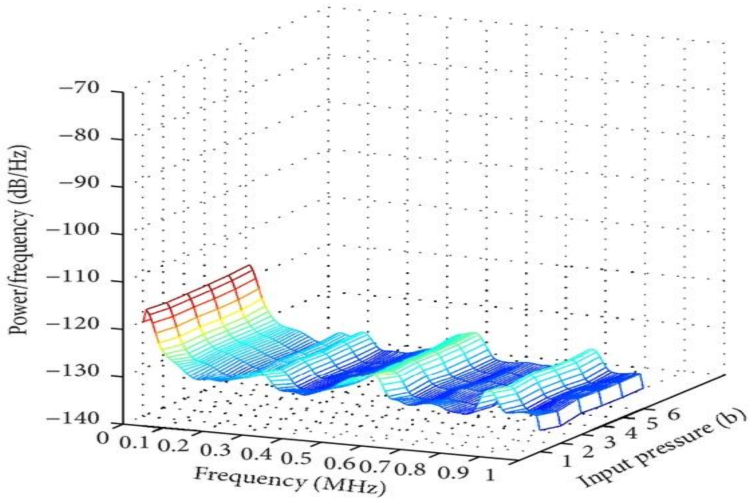


Figure 15: Power spectral density of raw AE signal for healthy valves with no leakage in cylinder 4.

Analysis in the time-frequency domain revealed the presence of defective and healthy valves. However, this method encountered difficulty in showing the different types of faults in the valves. Therefore, an artificial neural network (ANN) was used based on the AE parameters extracted from the raw AE signals for this stage. The parameters were the basic AE parameters: AErms, number, absolute AE power, maximum signal amplitude, and average signal level

An artificial neural network

The artificial neural network has the ability to identify the correlative patterns between the input data set and the corresponding target values. The artificial neural network has the ability to predict failures and make decisions. Figure 16 shows a model of an artificial neuron

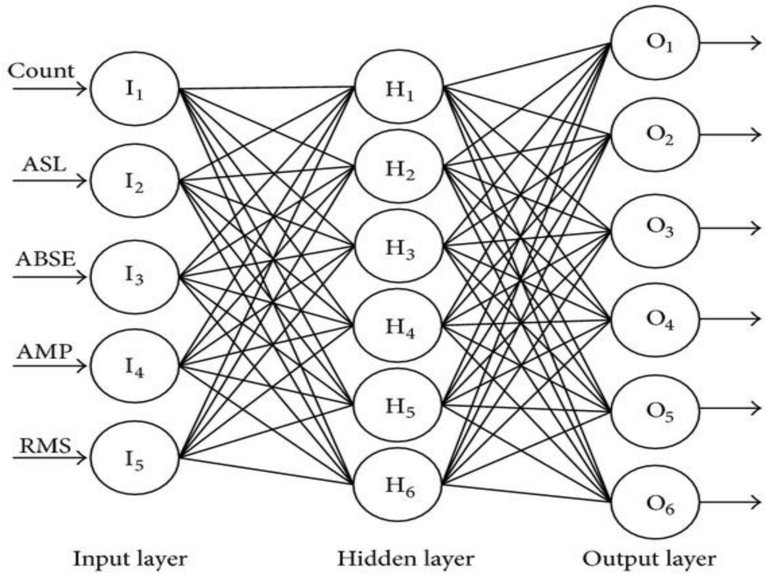


Figure 16: Artificial Neuron model.

ANN of five parameters (AErms, Number, Absolute AE Power, Maximum Signal Amplitude, Average Signal Level) was used to determine the fault type of the valve. The input layer consists of five points corresponding to the five input features. The hidden layer contains six nodes and the output layer contains six nodes, where the five nodes represent the type of valve failure and one node represents the health status of the valve. The output of each node is determined by the following sigmoid function:

$$\mathrm{F}(x) = \frac{1}{1 + e^{-x}}$$

backpropagation method was used to determine the weights

Where each group consists of 200 samples of data, and each sample consists of 40,000 data points, where the samples are divided into two groups, one for training and one for testing, as Table 1 shows the output

Table 1

Output condition meaning.

number of Node	type of fault valve
O_1	Cylinder 4, healthy valves, no leakage at zero valve lift
O_2	Cylinder 1, semicracked exhaust valve
O_3	Cylinder 2, semicracked intake valve
O_4	Cylinder 3, notched exhaust valve
O_5	Cylinder 4, valve clearance, exhaust valve lift
O_6	Cylinder 4, valve clearance, intake valve lift

Conclusion:

This study shows the use of the acoustic emission method to find out the faults that occur to the valves, where three types of faults (cracked valve, indented valve, and valve clearance) were simulated and used in the cylinder head of an internal combustion engine, where the time domain and frequency domain were used for signal analysis and fault detection, but it was found The time and frequency domain analysis reveals only the defective and healthy valve but does not reveal the type of defect in the valve, so the artificial neural network was used to detect the type of error that occurred to the valve, as it was trained using five AE parameters

(AErms, number, absolute AE energy, maximum signal amplitude, And the average level of the signal) to separate the fault, as the results showed a percentage (more than 92%) in identifying the types of faults in the valves.

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