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DIAGNOSTICS AND CLASSIFICATION OF FAULTS IN DIESEL ENGINE COMPONENTS USING TIME-FREQUENCY APPROACH AND MACHINE

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Annotation

Diagnosing engine component faults is a challenging task for every researcher due to the complexity of engine operation. Developed faults in engine components subsequently reduce their performance and lead to increased maintenance costs. Therefore, it is necessary to implement an effective condition monitoring method to diagnose faults in engine components. Therefore, this work presents potential fault diagnosis techniques for detecting and diagnosing scuffing defects occurring in diesel engine components. Condition monitoring techniques such as vibration and acoustic emission analysis were used to obtain signals associated with faults. These signals were analyzed in time domain, frequency domain and time-frequency domain using signal processing techniques viz. fast Fourier transform (FFT) and short time Fourier transform (STFT). Statistical feature parameters were also extracted from the received signals to diagnose fault severity. Additionally, artificial neural network (ANN) models have been developed to predict and classify scuffing defects occurring in engine components. The results showed that FFT and STFT methods provided better diagnostic information. The developed neural network models effectively classified scoring defects on engine components with 100% accuracy.

Keywords: Diesel engine, vibration, acoustics, fast fourier transform, short time fourier transform, artificial neural network.

Introduction

The piston, piston rings and cylinder liners are the most important components of a diesel engine. Under operating conditions, failure of the above engine components leads to an increase in the overhaul period and can cause financial disaster [1]. Scuffing is the most common wear condition in a diesel engine and is caused by abrasive forces between engine components. When scuffing defects occur on the cylinder liner and piston, they are called liner/piston scuffing defects. In addition, these faults impair the mechanical performance of other engine components, resulting in vibration and noise from the engine structure [2,3]. Therefore, in recent years, researchers have been working to develop effective condition monitoring systems for predicting faults in internal combustion engines (ICEs).

Condition monitoring and fault diagnosis using signal processing techniques and machine learning algorithms have attracted the attention of researchers due to their ability to provide better diagnostic information. Various signal processing techniques, e.g. Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), etc. play a key role in fault diagnosis of machine components. In addition, numerous machine learning algorithms viz. artificial neural network (ANN), support vector machine (SVM), decision tree, etc. are widely used to predict and classify various faults occurring in machine components [4].

In work, experimental studies were carried out on the diagnosis of internal combustion engine piston scuffing. The vibration signals were collected under healthy and faulty engine operating conditions and analyzed using signal processing techniques viz. FFT and CVT. The results showed that the piston scuffing fault greatly increased engine vibrations, which were diagnosed using frequency spectra obtained by FFT and CWT methods [5]. Moosavian et al. investigated the effect of a simulated piston scratch defect on internal combustion engine vibration. The resulting vibration signals were processed using STFT and CWT methods . The results showed that the scraper fault significantly increased the engine vibration and excited the frequency band in the region of 3–4.7 kHz [6].

Alisaray et al. used vibration signature analysis to study combustion and detonation phenomena occurring in internal combustion engines. Experiments were carried out using various biodiesel mixtures. The vibration signals were analyzed using the time-frequency representation (TFR) method. The results showed that malfunctions in the injection and valve units lead to abnormal combustion and an increase in the detonation phenomenon, thereby causing high-frequency oscillations in the range of 7-25 kHz. Alisarai et al. conducted experimental studies to study the vibration characteristics of a diesel engine using biodiesel blends [7]. The authors monitored engine vibrations before and after engine maintenance. The results showed that vibrations in the engine were mainly caused by the piston stroke. These vibrations were significantly reduced by 12% after engine servicing. In addition, the authors concluded that biodiesel blends make a significant contribution to minimizing engine vibration. Alisaray et al investigated the effects of ethanol addition on diesel engine combustion, performance, knocking and vibration. Vibration signals were analyzed using FFT and STFT methods . The results showed high-frequency bands in the case of pure diesel fuel, indicating severe vibration and shock to the engine structure [8]. These vibration levels were reduced when the engine was run with different fuel mixture combinations. Adding more than 6% ethanol to diesel fuel increased engine power and torque, while ethanol concentrations greater than 8% increased ignition delay, which caused cylinder pressure fluctuations, leading to detonation. Selebi et al. conducted experimental studies to study the vibration and acoustic characteristics of a diesel engine running on various biodiesel blends. The authors developed a linear regression (LR) and ANN model to predict vibration and sound pressure levels (SPL) of a diesel engine. The results showed that vibration and engine noise were significantly reduced due to biodiesel blends. The addition of natural gas to the intake manifold improved the vibroacoustic characteristics of the engine compared to biodiesel mixtures. In addition, the ANN model showed higher classification and prediction accuracy than the LR model [9].

Jena and Panigrahi developed a fault diagnosis methodology to identify the piston bore fault of a commercial vehicle using noise signature analysis. Acoustic signals were obtained under healthy and faulty engine conditions and analyzed using FFT and CWT methods . Moreover, the faults were classified using machine learning algorithms viz. SVM and ANN. The results showed that the time-limit integration (TMI) of the CWT method showed a failure-related frequency of 16.25 Hz in the frequency spectra. Fault classification using the ANN method showed an average prediction accuracy of 99.9 and 98.1%, while the SVM method showed approximately 100% prediction accuracy. Hosseini et al. developed an ANN model to predict vibration, emissions and performance parameters of a diesel engine. The engine ran on biodiesel mixtures with varying concentrations of alumina as an additive [10]. The results showed that the ANN model with two hidden layers having 25–25 neurons each showed better prediction accuracy of approximately 0.9999, 0.9995 and 0.9994 for training, testing and validation respectively. Xu et al analyzed various data-driven models viz. evidentiary reasoning (ER), ANN and belief rule based inference (BRB) to predict the wear mechanism occurring in a marine diesel engine. Data-driven models have been combined to overcome the shortcomings of predicting inaccurate faults in a diesel engine. The results showed that the pooled diagnostic model was more reliable and accurate than the individual data-driven model. Wu et al. studied engine faults using discrete wavelet transform (DWT) and ANN methods. Acoustic signals were obtained under various engine operating conditions. These signals were analyzed in the time and time-frequency domains using the CWT method , however due to the longest computation time, these signals were further analyzed using the DWT method [11]. In addition, acoustic characteristics were extracted from the audio signals and considered for fault classification using ANN algorithm. The results showed that DWT and ANN methods were able to accurately detect and classify ICE faults . Jafari et al. In work, experimental studies were carried out on the diagnosis of valve malfunctions of internal combustion engines using the method of acoustic emission analysis. Acoustic emission signals were obtained from an engine running with three different valve faults viz. gap, notch and halfcrack [12]. These signals were analyzed in the time and frequency domain using the power spectral density (PSD) method. Parametric features were extracted from the acoustic emission signals to develop the ANN model. The results showed that time-frequency analysis makes it possible to distinguish between healthy and faulty internal combustion engine valves. In addition, the developed ANN model sufficiently classified valve faults and their types with an accuracy of more than 92% [13].

Shatnavi et al. proposed a fault detection method for diagnosing ICE faults using an extended neural network (ENN) algorithm. The engine was operated under five different operating conditions, such as no fault, single cylinder misfire, intake air leak, mass flow sensor failure, and CAM sensor failure . Acoustic emission method was used to obtain fault signals from the engine. Various parametric characteristics were obtained from the acoustic signals using the wavelet packet decomposition (WPD) method. ANN and ENS models were developed and analyzed for efficient fault classification. The results showed promising and superior classification using the ENN model compared to the traditional ANN technique [14]. Ahmed et al. studied numerous ANN algorithms viz. backpropagation (BP), quasi-Newton (QN), Levenberg-Marquardt (LM), variable structure smooth filter (SVSF) and extended Kalman filter (EKF) for diagnosing and classifying faults occurring in ICE . Vibration signals were obtained from an engine running with seven different faults viz. missing bearing (MB), chain tensioner (CT), chain sprocket (CS), piston knock (PC), broken lash adjuster (CLA), loose lash adjuster (LA), and CC malfunction . Among the studied algorithms, the SVSF method showed a higher classification accuracy of more than 97% for detecting and classifying the above faults. Ayati et al. investigated the fuel injection fault in a diesel train engine using vibration characteristics analysis. The vibration signals were obtained from the engine and analyzed using signal processing techniques viz. FFT and Wavelet Packet Transform (WPT) [15]. These methods have been used to obtain uncorrelated characteristics of vibration signals. Several classification methods such as SVM , Multilayer Perceptron (MLP), Local Linear Model (LOLIMOT) and K -Nearest Neighbor (KNN) have been considered to classify faults occurring in the fuel injection unit. The results showed that FFT-based features were classified more accurately compared to WPT- based features using the KNN method , which had a classification accuracy of up to 99.7%. Hou et al. developed an ANN model to diagnose faults occurring in a marine diesel engine using MLP and genetic algorithm (GA) methods [16]. To train the neural network model, ten different faults that occurred in a marine diesel engine were considered. The input parameters were first optimized using the GA algorithm , and then considered to improve the performance of the MLP algorithm . The results showed that the GA - based MLP method showed effective fault classification with an accuracy of more than 95%.

Ravikumar et al. conducted experimental studies on engine gearbox fault diagnosis using vibration signature, signal processing and machine learning techniques [17]. Gear faults with 50% and 100% tooth failure were considered to extract the vibration signals associated with the faults. The obtained signals were analyzed using signal processing techniques viz. spectrum, cepstrum, STFT and CWT . The J 48 decision tree algorithm was used to classify faults occurring in the engine gearbox. The results showed that signal processing techniques provided better diagnostic information about faults, while the J 48 algorithm classified faults with an accuracy of about 85.1%. Shibley et al. [18] proposed a fault diagnosis model to detect faults occurring in internal combustion engines using empirical mode decomposition (EMD) and ANN techniques. Vibration signals were recorded under conditions of normal and faulty engine operation. These signals were analyzed using EMD and decomposed into various intrinsic mode functions (IMFs) and cumulative mode functions (CMFs). Useful statistical features such as crest factor, shape factor, etc. were extracted from CMF and considered as input for fault classification using ANN method. The results showed that the EMDANN- based classification method achieved a fault classification accuracy of approximately 96%. Wernekar et al conducted experimental studies on fault diagnosis of ICE designed gearboxes using machine learning techniques. Four gear failures with tooth failure rates of approximately 25, 50, 75 and 100% were considered for analysis. Vibration signals were obtained from an engine running with various faulty gears. Numerous statistical feature parameters such as mean, standard deviation, etc. were extracted from vibration signals and considered for fault classification using J 48 decision tree and ANN algorithms [18]. The decision tree algorithm provided important statistical characteristics parameters that were considered for fault classification using the ANN algorithm. Based on these features, the ANN method classified gear faults with a prediction accuracy of about 85.5%. Ramteke et al investigated liner scuffing in a diesel engine using vibration and acoustic emission analysis techniques. Vibroacoustic signals were recorded in normal and faulty engine operating modes. These signals were analyzed using FFT and statistical feature analysis techniques. Numerous fault-related features were extracted from vibration and acoustic signals. The results showed that the shank scuffing defect significantly excited numerous frequency components that were considered for diagnosing the shank scuffing defect. In addition, the severity of the fault was determined using statistical parametric analysis [19,20].

The above literature review describes that numerous works have been conducted on fault diagnosis of engine components using signal processing techniques and machine learning algorithms. However, to the best of the authors' knowledge, very few research works have been observed on diagnosing seizures occurring on engine components using machine learning techniques. Therefore, in this work, scuffing defects occurring on diesel engine components are considered and evaluated using signal processing tools viz. FFT and STPF. Parameters of statistical features, viz. Mean, standard deviation, skewness and kurtosis are extracted from vibration and acoustic signals to determine the severity of faults encountered and their impact on engine vibration and noise emissions. In addition, neural network models are developed to predict and classify scuffing errors using the MLP feedforward and feedback neural network algorithm.

Methodology

Engine vibration and acoustic emission theory

Vibrations from engines are largely due to the reciprocating and rotating motion of engine components and the combustion phenomenon occurring in the combustion chamber. Inertial forces arising from the movement of engine components, fluctuations in combustion pressure in the cylinders and the occurrence of thermal stresses in the combustion chamber cause engine vibrations [21]. Additionally, scuffing occurring on engine components results in severe engine vibrations caused by the abrasive action of engine components in the presence of wear particles. The formation of wear particles is the result of a two- or three-component wear mechanism occurring in the piston-cylinder assembly [22].

The noise produced by a diesel engine is due to numerous excitation sources, which can be divided into two main types: combustion and mechanical. The noise emitted by the combustion chamber is due to the fluctuation of pressure waves generated during the combustion process. Mechanical noise occurs due to the excitation and shock forces caused by the movement of engine components, particularly the piston, connecting rod and crankshaft. In addition, the main contribution to noise emission is the piston impact phenomenon caused by the clearance between the cylinder liner and the piston due to scuffing. The noise emitted by the engine due to these sources is represented by equation (1) which is measured using a microphone [23],

$$W = \ . C. \_ S. \_ \sigma \mathrm{rad}.(\bar{V})2 \qquad (1)$$

where W denotes the sound pressure level. 휌 and 휎 rad represent specific gravity and radiation efficiency. C and S denote the sound speed and radiation area, while $\bar{V}$ indicates the spatial average of the vibration speed.

Fast Fourier Transform (FFT)

Engine components perform several actions among themselves, such as rolling and sliding, which provides dynamic information about their state. This information is associated with certain frequency characteristics that deteriorate when faults occur in engine components, which can be extracted using condition monitoring techniques such as vibration and acoustic emission analysis. The extracted signals are represented in the time domain, which often does not provide useful diagnostic information about faults occurring in engine components. Therefore, these signals need to be analyzed in the frequency domain using signal processing techniques viz. FFT, STFT , CWT , etc. The FFT of time domain data x (t) can be obtained using equation (2) [24].

$$F(\omega) = \int_{-\infty}^{+\infty} x(t).e^{-j\omega t}\,\mathrm{d}t \qquad (2)$$

where F indicates the FFT of signal x (t).

Short Time Fourier Transform (STFT)

STFT method is a slight improvement over the FFT method . In the FFT method, information in the time domain is lost when the signals are converted to the frequency domain. However, this information can be stored using the STFT method . This method can be applied to both stationary and non-stationary signals. The time domain signals are split into small windows of equal length using a windowing function, and then an FFT technique is applied to obtain the time-frequency spectrum. In this analysis, the Hanning window function is considered to provide time-frequency information. Time domain analysis of STFT signals x (t) is calculated using equation (3) [17, 22],

$$\mathrm{STFT}(\tau, \omega) = \int_{-\infty}^{+\infty} x(t).W^{*}(t-\tau).e^{-j\omega t}\mathrm{d}t \qquad (3)$$

Statistical parameters of the object

Statistical characteristics parameters such as mean, standard deviation, root mean square (RMS) are used to determine the difference between one vibration signal and another. More advanced options for statistical functions viz. skewness and kurtosis can be applied to signals that are both stationary and non-stationary. In this paper, the mean and standard deviation of the signals determine the difference between the healthy and faulty states of the engine. The values of these signs will be higher for signals received during faulty engine operating modes. Under different load conditions, the behavior of the signals changes, and therefore the parameters of the features. In general, the changes in signals obtained under different engine operating conditions can be easily distinguished using these parameters. More advanced options for statistical functions viz. skewness and kurtosis are most widely used for condition monitoring through vibration and acoustic emission analysis. In general, the skewness value determines whether the signal is positive or negative, while the kurtosis value determines whether the signal is impulsive or not. However, this paper has addressed the importance of these feature parameters in fault assessment. These function parameters are extracted from vibration and acoustic signals to diagnose the severity of faults occurring in engine components. Moreover , these features are considered as inputs to the ANN algorithm for classifying multiple faults. Brief description statistical parameters considered _ V given study , given below [1, 19]:

The mean is the sum of all samples divided by the total number of samples, which can be calculated using the equation (4).

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

The power or energy content of signals can be predicted by calculating the standard deviation of the signals, which is given by the equation. (5),

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{5}$$

The degree of asymmetry in the statistical distribution of vibration and acoustic data relative to their average value is denoted by asymmetry and is calculated using equation (6),

$$x_{\text{Skewness}} = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^3}{(N-1)\sigma^3} \tag{6}$$

The severity of a fault can be described using the kurtosis parameter, which measures the sharpness or flatness of the signals. Its low value indicates the normal condition of the component, while its high value indicates a serious fault has occurred in the components. It can be calculated using equation (7),

$$x_{\text{Kurtosis}} = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^4}{(N-1)\sigma^4} \tag{7}$$

Artificial neural network (ANN)

In engineering fields, data-driven ANN models are most widely used for fault diagnosis and classification. The neural network model works the same way the human brain works. It is the most powerful tool that deals with unsuitable knowledge and gives the best prediction of the system. It stores information for a longer period of time and uses this information for effective decision making. The accuracy of the model is improved with an efficient training process by optimizing the weights from the output to the input layer, which is called ANN training [8]. In addition, it consists of interconnected neurons that are assigned weights to calculate outputs, mathematically this is represented by equations. (8) and (9) respectively [7].

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \quad (8)$$

$$y_k = \phi(u_k + b_k) \quad (9)$$

Table 1 The technical specification of the experimental setup

Engine	Kirloskar
Cooling system	Water cooled
Rated Power	3.5 kW @ 1500 RPM
Compression ratio	12 to 18:1
Cylinder diameter	85 mm
No. of cylinder	1
No.of strokes	4
Stroke length	110 mm
Fuel	H.S Diesel
Connecting rod length	234 mm
Dynamometer arm length	185 mm

where uk and yk are the outputs of each neuron. x1, x2,.... xm denote the inputs, and wk1, wk2,.... wkm denote the weights assigned to each neuron. Swish represents the activation function, whereas b k specifies the offset that is used to increase or decrease the net input of the activation function.

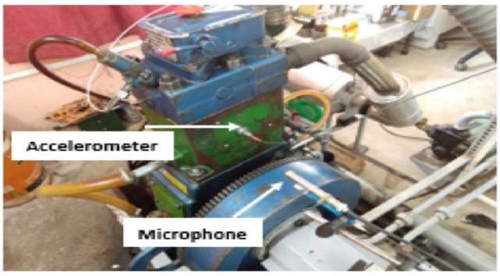
Experiment details

Experimental setup and procedure

A single-cylinder, four-stroke diesel engine is used to conduct fault-related experiments. The engine operates at a constant speed of 1500 rpm and has a variable load from 0 to 12 kg. An eddy current dynamometer coupled to the motor has the ability to provide different load conditions using a load cell. Engine technical characteristics are given in table. 1. The actual and schematic view of the experimental setup is shown in Fig.1a and b.

A KS78.100 single-axis accelerometer sensor is installed on the engine cylinder block to record vibration signals along the longitudinal axis from healthy and faulty engine operating modes. Vibration signals are acquired at a sampling rate of 20 kHz. Acoustic signals are obtained using an ICP microphone sensor MP 201, which is located next to the engine in accordance with the conditions of the near-field acoustic analysis [19]. Acoustic signals are captured at a sampling rate of 40 kHz. The received vibration and acoustic signals are processed by the DEWE 43 A data acquisition system and stored in a personal computer for further analysis.

(a)



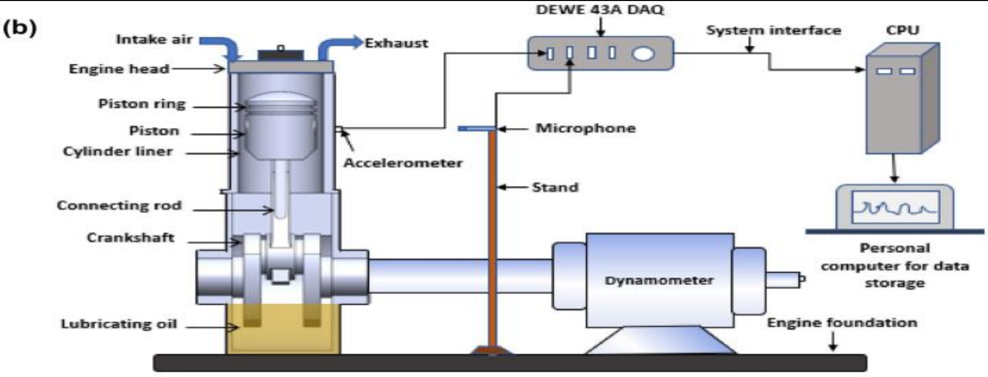
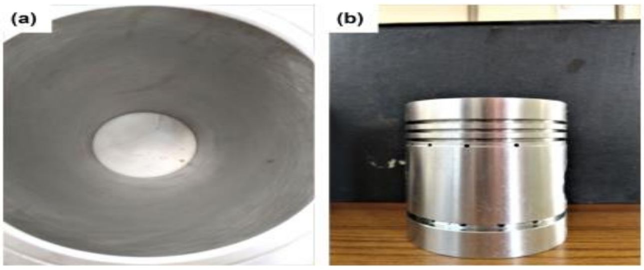


Fig. 2 The photographic view
of **a** healthy liner and **b** piston



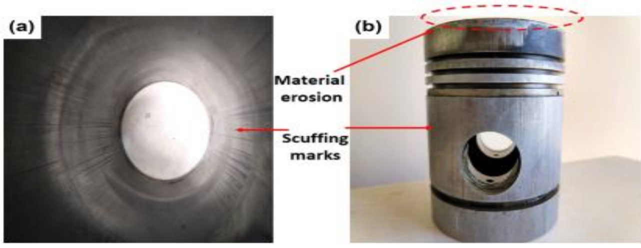


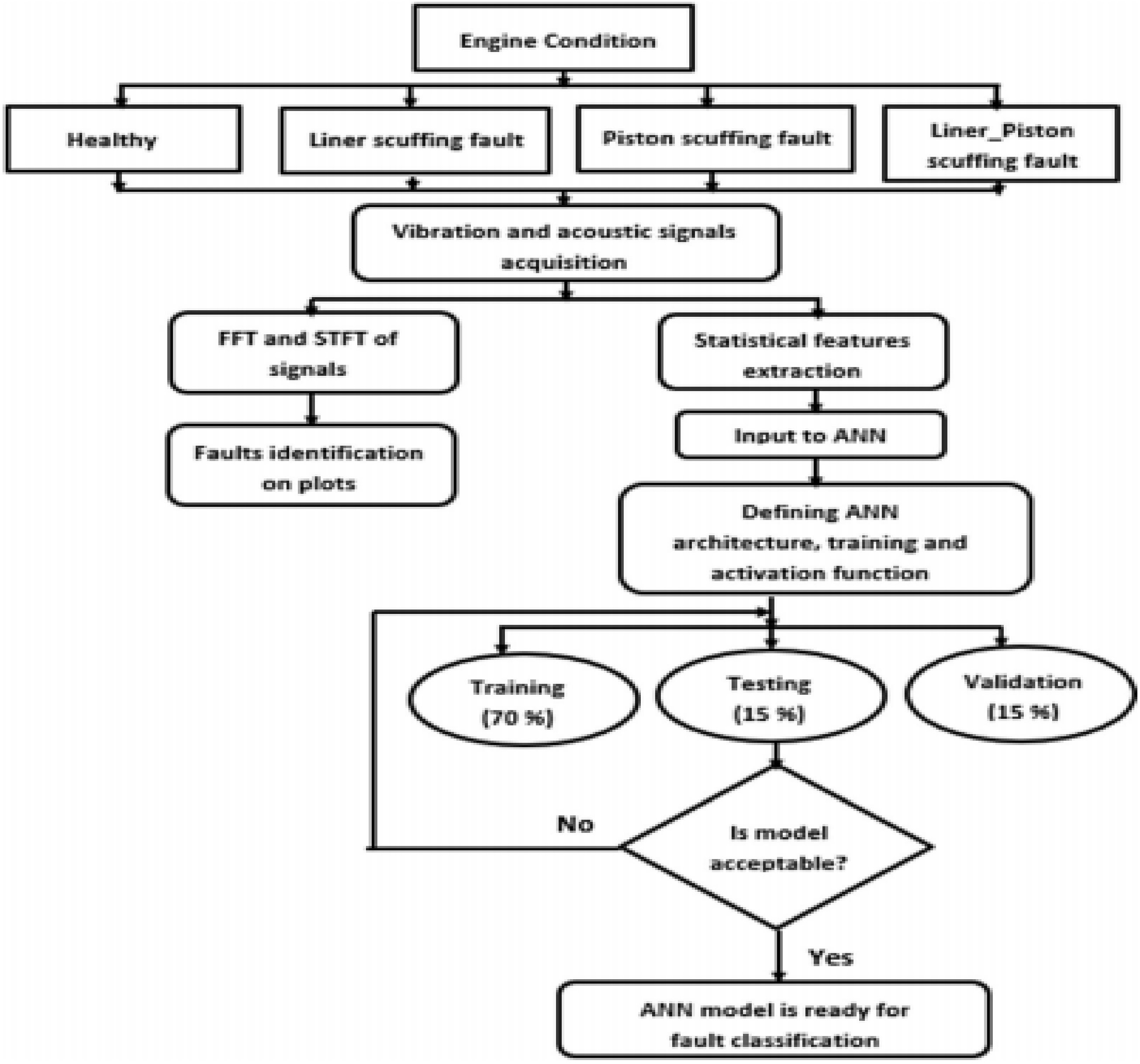
Fig. 3 The photographic view
of **a** faulty liner and **b** piston

Fault detection experiments were carried out under four different operating conditions: in the first stage, the diesel engine was used with a good liner, piston and piston rings, which were allowed to run for 10 hours to meet the engine run-in wear conditions. Next, the used engine oil was replaced with fresh oil. A photographic view of a healthy sleeve and piston is shown in Fig. 2a and b. This condition of the engine was found to be in good condition. At the second, third and fourth stages, the engine operated with scoring marks on the liners (the piston and rings were healthy), scoring marks on the pistons (the liner and rings were healthy), and scoring defects on the liners and pistons (only the rings were healthy). The conditions for conducting experiments from stages 2 to 4 were considered unsatisfactory. A photograph of a faulty liner and piston is shown in Fig. 3a and b. It is observed that the liner and piston have scratches on the inner and outer periphery, indicating a component failure. The depth of wear grooves on the inner periphery of the liner surface at top dead center (TDC), middle and bottom dead center (BDC) was measured using a Mitutoyo bore gauge , the data of which is given in Table 2. The piston was measured using a Mitutoyo 2000 mm caliper and a Contech high-precision scale . These measurements were carried out to determine the diameter and weight loss of the scuffed piston, the results are shown in Table 3. Vibration and acoustic signals were obtained from the engine operating under full load conditions at each stage of the experiment. A flow diagram illustrating the experimental procedure implemented in this study is presented in Fig. 4.

Results and Discussions

FFT and STFT analyzes vibrations And acoustics signals

Vibration and acoustic signals received from the engine in the time domain are presented in Fig. 5 a – d . It can be interpreted that the liner, piston and sleeve_piston scuffing defects seriously affected the engine vibrations and their acoustic characteristics. These signals were converted into a time-frequency signal using FFT and STFT techniques to extract fault-related frequency components with which the engine oscillates and emits noise emissions.



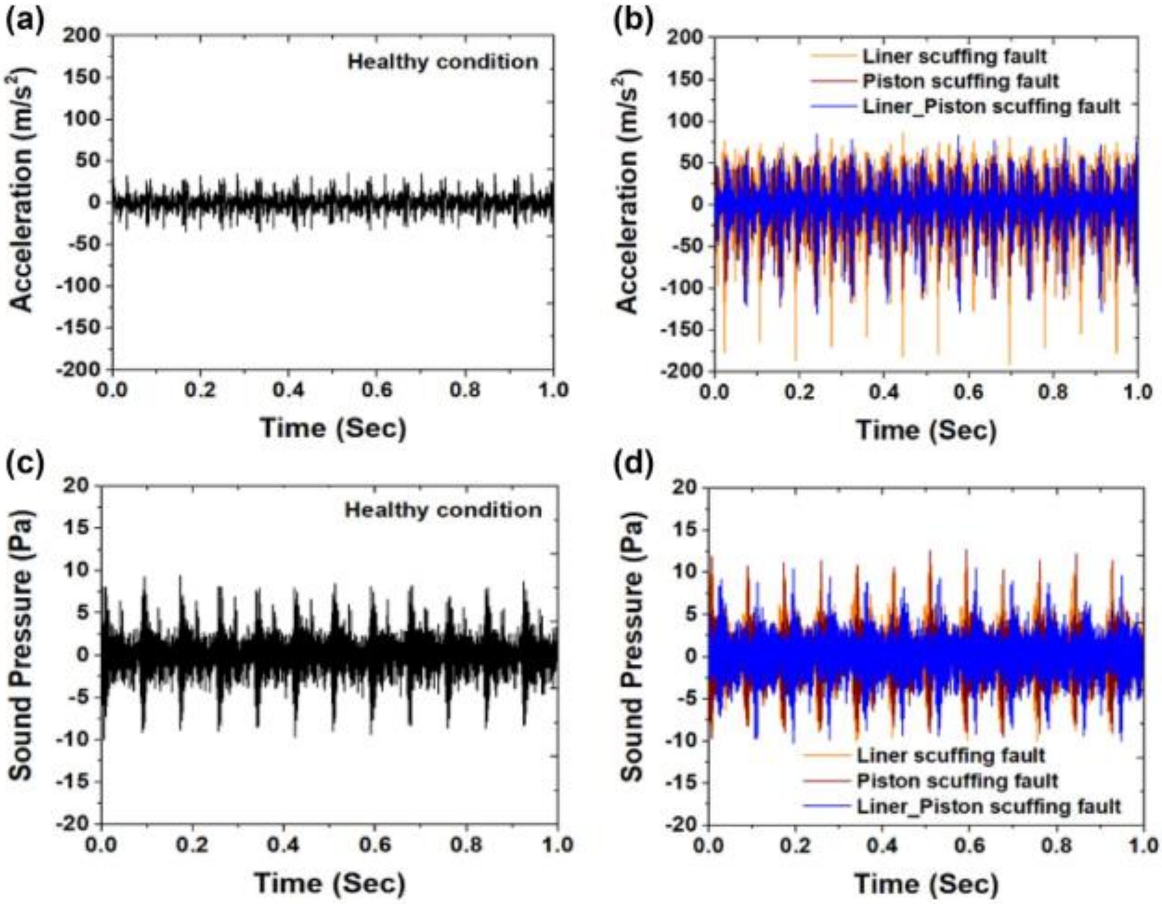
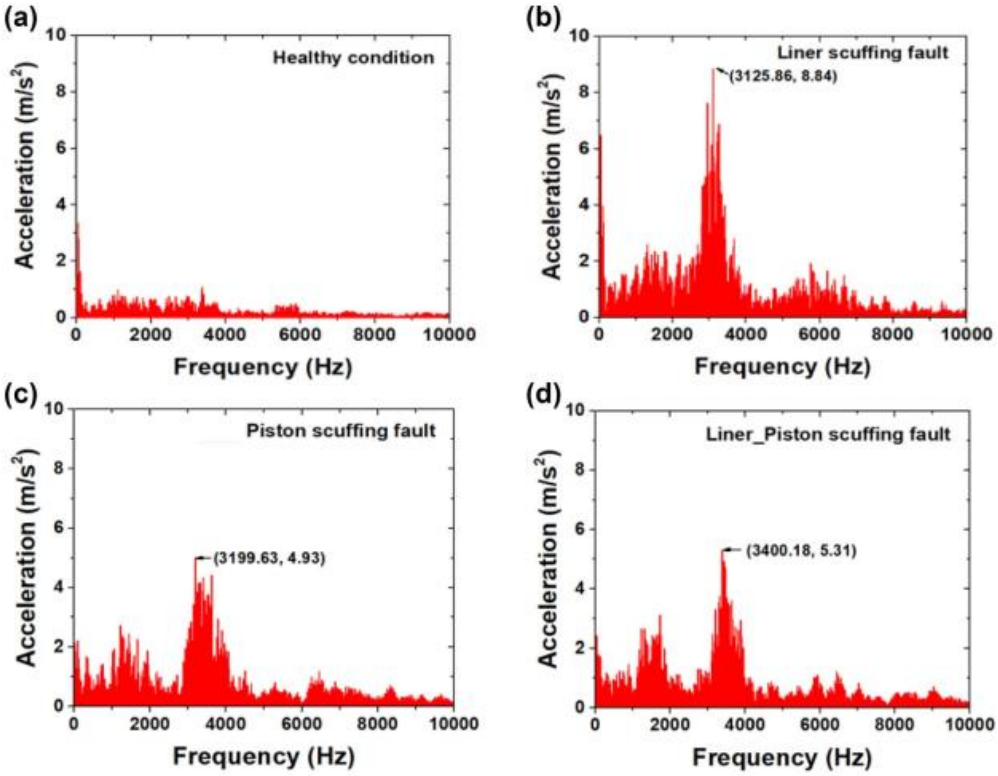


Fig. 5 Time domain (a), b vibration and c , d acoustic waveform obtained under healthy and faulty engine conditions

FFT spectra of vibration signals obtained under various operating conditions are presented in Fig. 6a–d. It is noted that the scuffing defects of the liner, piston and sleeve_piston significantly excite frequency components in the range of 0–7 kHz. In Fig. Figure 6a shows the absence of frequency components associated with failure when the engine is in good operating condition. However, the predominant frequency components associated with liner, piston, and liner_piston scuffing defects were observed at frequencies of 3.125, 3.199, and 3.4 kHz, as shown in Fig. 6 b – d respectively. Maximum engine vibrations were observed when the liner was scuffed with a maximum acceleration amplitude of 8.84 m/s2 at a frequency of 3.125 kHz, as shown in Fig. 6b. In addition, the FFT spectra of acoustic signals obtained under conditions of normal and faulty engine operation are shown in Fig. 7a–d. It was noted that the acoustic characteristics of the engine were significantly affected by faults that arose in the engine components, which excited the frequency band 0–2.5 kHz in all operating modes. The dominant frequency components associated with each fault were observed at frequencies of 1.028, 0.663, and 0.7 kHz. In addition, the liner scuffing defect significantly increased the acoustic emission of the engine with a maximum sound pressure amplitude of 1.57 Pa at a frequency of 1.028 kHz, as shown in Fig. 7(b).

A more detailed representation of the frequency ranges can be seen in the graphs produced by STFT analysis . Rice. 8 a – d and 9 a – d illustrate the time-frequency representation of vibration and acoustic signals obtained under different engine operating conditions. From Fig. 8b–d it can be seen that the value of the excited frequency band increased in the region of 0–7 kHz for all faulty engine operating modes. In this case, the maximum intensity value of more than 20 dB was observed when the shank was scuffed. In addition, the intensity of the color band was increased in case of liner, piston, and liner_piston scuffing defects, indicating the severity of the excited frequency band. According to Fig. 9a–d, faulty engine elements excited the acoustic frequency band 0–2.5 kHz at all engine operating modes. The acoustic characteristics of the engine were severely affected, mainly due to a defect in liner scuffing, the maximum intensity of which exceeded 10 dB. The vibrations and acoustic emissions of a diesel engine are mainly related to the reciprocating and rotating motion of the engine.

components and combustion phenomenon. Due to scuffing on engine parts, the mechanical performance of many machine elements deteriorates, which leads to engine vibrations and noise emissions [23-25].



Statistical analysis of object parameters

Useful statistical performance parameters extracted from vibration and acoustic signals under different loading conditions are calculated using Eqs. (6–9) and are presented in Fig. 10a–d and 11a–d, respectively. These performance parameters are extracted to predict the severity of faults encountered and their impact on engine vibration and noise levels. Figures 10 a – d and 11 a – d show a significant increase in the mean, standard deviation, skewness, and kurtosis values for the case of liner, piston, and liner_piston scuffing defects, which showed that the energy intensity and sharpness of the received signals increased dramatically. due to scoring on engine components. In addition, higher energy intensity of vibration and acoustic signals was observed in the case of liner scuffing. The uneven behavior of the feature parameters in all operating modes was due to the apparent influence of high-frequency amplitudes of the recorded signals.

Simulation of ANN based on vibration and acoustic signals

In this work, neural network models are developed using Matlab 2018 b version . A multilayer perceptron (MLP) neural network with feedforward feedback and backpropagation is used to develop ANN models , which consist of inputs, hidden layers, and outputs. To train the neural network, the Levenberg-Marquardt backpropagation learning algorithm (trainlm) is used. This algorithm is the fastest for calculating neural network weights. The logarithmic sigmoid (logsig) and hyperbolic tangential sigmoid (tansig) transfer functions are considered as the activation function to determine the output at each node, which is shown in the equations. (10) and (11) respectively [11].

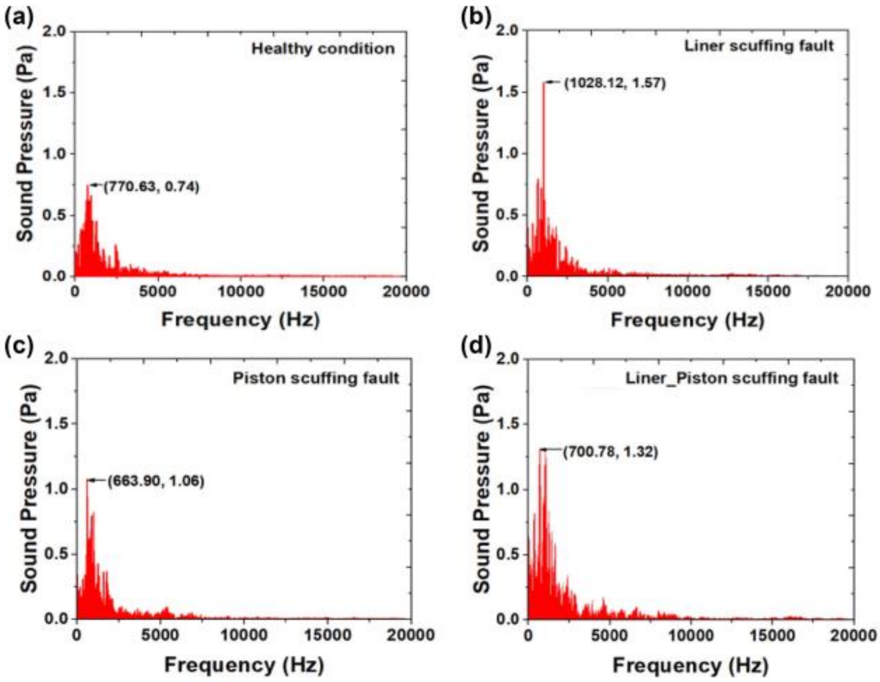


Fig. 7 FFT spectra of acoustic signals obtained with a working and faulty engine.

$$\text{logsig} = \frac{1}{1+e^{-x}} \tag{10}$$

$$\text{logsig} = \frac{1}{1+e^{-x}} \tag{11}$$

where x is the input data

Vibration and acoustic signals obtained from a healthy and faulty engine operating with liner, piston, and liner_piston scuffing defects were considered to develop ANN models for classifying these defects. Each data set considered 15,000 samples, and each set was divided into 20 bins of 750 samples each. Parameters of statistical features, viz. the mean, standard deviation, skewness, and kurtosis were calculated for every 20 bins and considered as input to the ANN. Each dataset contains 80 samples of vibration and acoustic signals. Out of 80 samples, 70% of the data was considered for training, 15% of the remaining data was considered for testing and 15% for validation. All input parameters were normalized to 0 and 1 using Eq. (12). Additionally, the performance of the neural network was determined using the least mean square error (MSE) criterion, which is calculated using Eq. (13). To determine the optimal architecture of the neural network, the network was trained with different numbers of hidden layers and neurons by trial and error.

$$I_{\text{norm}} = \frac{I - I_{\text{min}}}{I_{\text{max}} - I_{\text{min}}} \tag{12}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2 \tag{13}$$

where I and I norm - basic and normalized input data, Imax and Imin — the maximum and minimum value from the input data, respectively. Ti and Oi are the target and predicted yield, respectively, while n is the number of samples tested.

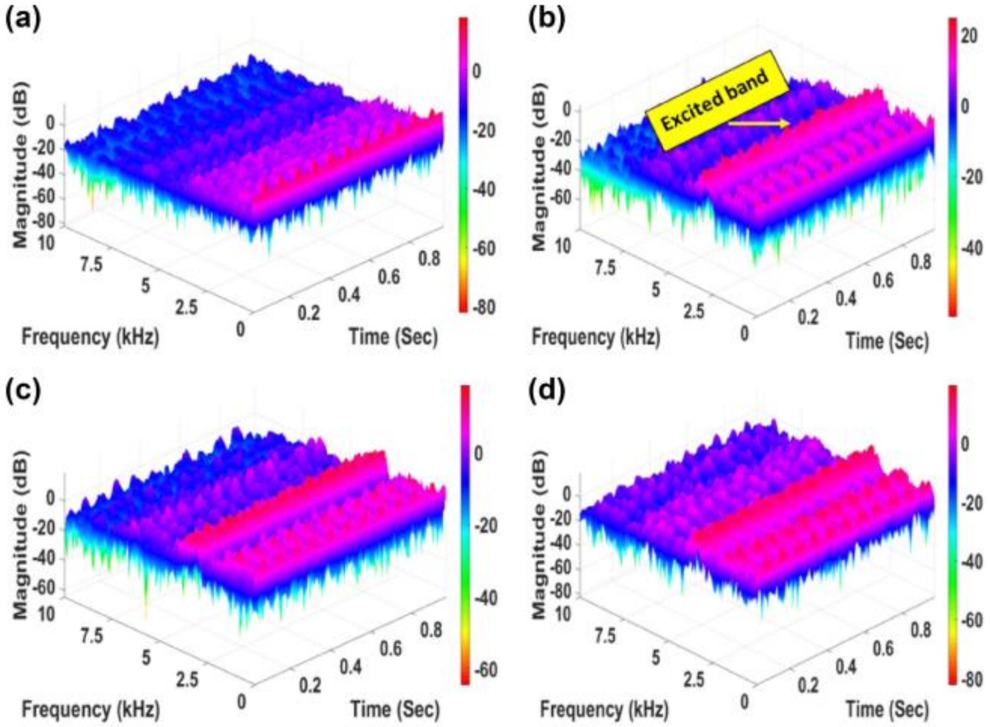


Fig 8. Time-frequency representation of vibration signals obtained from an engine running in normal condition, b Liner scuffing fault, c Piston scuffing fault and d Liner_piston scuffing fault

The results of different neural network architectures are presented in Table 4. A total of 28 experiments were evaluated for each case to determine the optimal neural network architecture. The network was tested with single, double, triple and four hidden layers with different numbers of neurons. A combination of activation functions logsig and tansig was used to calculate the output for the hidden layers, and the transfer function logsig was considered for the output layer. The optimal neural network was observed with trial numbers 23 and 28, having an architecture of 4-4-5-4-5-4 and 4-7-8-5-4-4, respectively. The MSE values for the optimal network architectures were 1.34 e -10 and 6.32 e -11, respectively. The performance of the developed neural network models is presented in Fig. 12a and b. The best test results were obtained when the minimum gradient was achieved. The developed neural network architectures for vibration and acoustic signals are shown in Fig. 13 and 14 respectively. The results showed that the developed ANN models effectively classified faults occurring in engine components with a classification accuracy of 100%. The resulting target vectors for experiments numbered 23 and 28 are shown in Table 5.

Summary and Conclusions

The main objective of this study was to diagnose and classify liner, piston and liner_piston scuffing defects occurring on engine components using time-frequency and machine learning methods. Fault experiments were carried out on a single-cylinder four-stroke diesel engine. Signal processing techniques such as FFT and STFT have been implemented for signal post-processing. Statistical characteristics were also extracted from the received signals to diagnose the severity of faults. An MLP feedforward and feedback neural network was used to develop ANN models. Experimental studies resulted in the following conclusions.

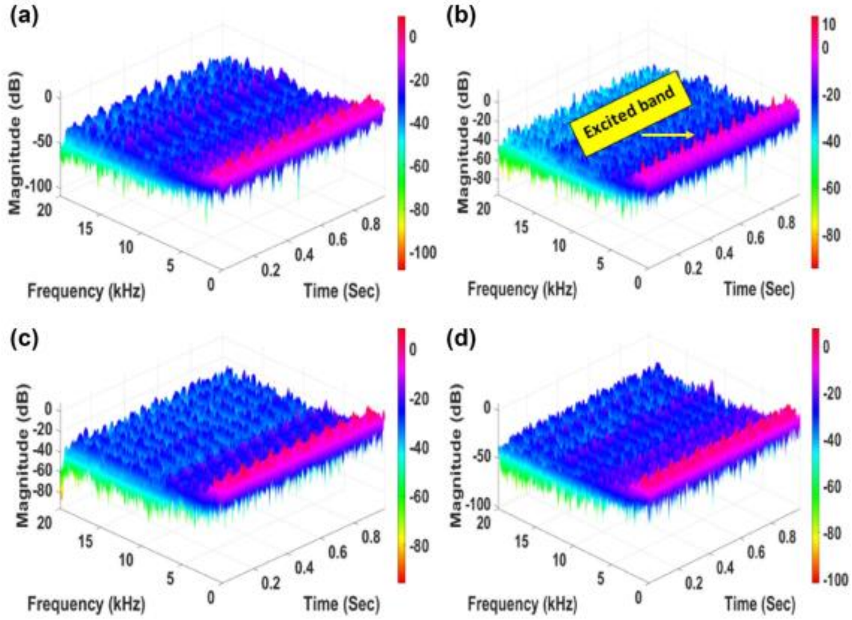


Fig. 9 Time-frequency representation of acoustic signals received from an engine operating in the Healthy state, b Liner scuffing defect, c Piston scuffing defect and d Liner_porston scuffing defect

1. Scoring on engine components caused a significant change in the time domain waveform under both normal and faulty engine conditions.
2. Faults occurring in the engine components excited the 0-7 kHz frequency band in the FFT spectra, while the most dominant frequency component was observed in the case of liner scuffing at a frequency of 3.125 kHz with a maximum acceleration of 8.84 m/s^2. The scuffing significantly increased the acoustic emission of the engine, and the maximum noise emissions were observed due to the scuffing of the liner with a sound pressure amplitude of 1.57 Pa at a frequency of 1.028 kHz.
STFT analysis provided better diagnostic information. The maximum excited band magnitude was observed due to the shank scuffing defect, indicating the severity of the defect.
4. An increase in the statistical characteristics of vibration and acoustic signals was observed for all engine operating modes. In addition, the sleeve scuffing defect resulted in higher energy content in the received signals.
5. ANN models developed using machine learning techniques have shown that statistical characteristics based on vibration and acoustic signals can be used to predict and classify numerous faults occurring in engine components. It is postulated that the frequency range and acceleration amplitude obtained by signal processing techniques for each fault condition can be used as a reference for predicting scuffing occurring on other engine components operating under different experimental conditions. The intensity of the acceleration amplitude and the frequency range may change due to extremely serious malfunctions of engine components. These methods are more effective in extracting fault diagnostic information from vibration and acoustic signals. Additionally, classification models developed using the acquired signals can be implemented in the

automotive industry to predict faults occurring in other engine components such as piston rings, bearings, intake exhaust valves, etc.

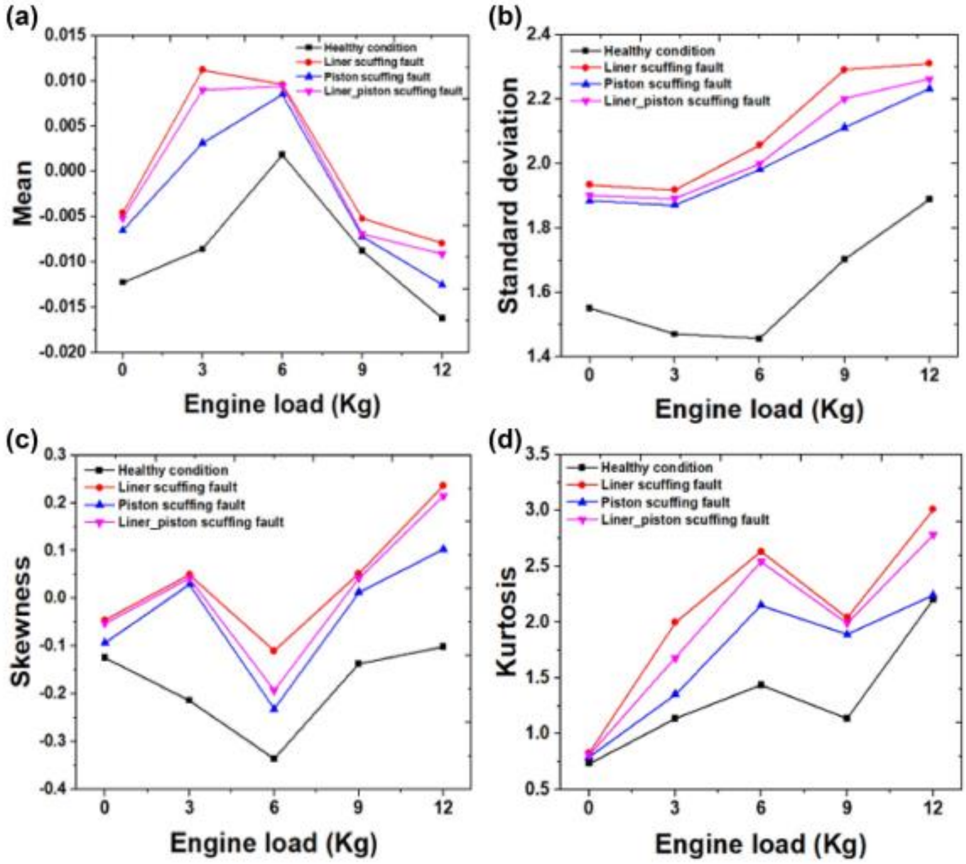


Fig. 11. Statistical characteristics of engine acoustic signals with a working and faulty engine.

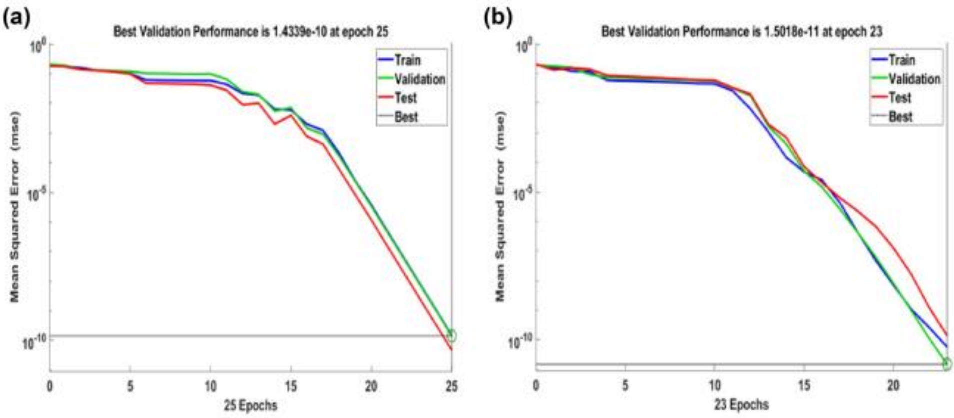


Fig. 12. Performance of a neural network for vibration and b acoustic signals based on ANN

Fig.13 Multilayer perceptron neural network model using vibration signals

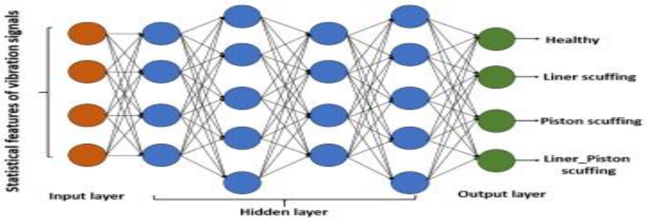


Fig.14 Multilayer perceptron neural network model using acoustic signals

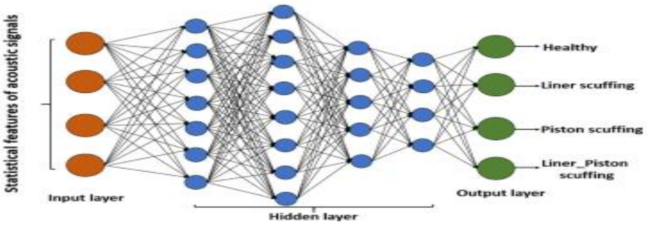


Table 4. Overview of various architectures rated as providing optimal network performance.

Trial No	Architecture	Activation function	Centering epoch		Centering mean squared error		Centering accuracy (%)	
			Vibration	Acoustic	Vibration	Acoustic	Vibration	Acoustic
1	4-4-4	logsig	31	10	0.0063	0.0629	98.8	75
2	4-5-4	logsig	24	18	8.83e−11	2.10e−05	100	100
3	4-6-4	logsig	18	20	2.92e−11	1.69e−08	100	100
4	4-7-4	logsig	9	119	0.1207	1.63e−09	75	100
5	4-8-4	logsig	42	23	4.75e−07	2.13e−07	100	100
6	4-9-4	logsig	30	30	4.27e−05	1.90e−10	100	100
7	4-10-4	logsig	21	8	5.90e−03	9.84e−02	100	75
8	4-4-4-4	logsig,logsig	19	25	4.51e−02	3.18e−08	92.5	92.5
9	4-4-5-4	logsig,logsig	10	13	1.10e−01	0.0707	73.8	75
10	4-5-4-4	logsig,logsig	9	24	8.00e−02	2.30e−10	75	100
11	4-5-5-4	logsig,logsig	25	220	7.94e−07	4.91e−08	100	100
12	4-5-6-4	logsig,logsig	43	21	2.38e−06	8.90e−11	100	100
13	4-6-5-4	logsig,logsig	8	45	9.38e−02	2.46e−10	73.8	100
14	4-6-6-4	logsig,logsig	44	49	4.85e−09	5.62e−08	100	100
15	4-4-4-4-4	logsig,logsig,logsig	22	29	2.01e−10	1.27e−10	100	100
16	4-4-5-4-4	logsig,logsig,logsig	34	25	6.59e−10	1.78e−10	100	100
17	4-5-4-5-4	logsig,logsig,logsig	26	49	3.68e−10	5.20e−03	100	100
18	4-5-5-5-4	logsig,logsig,logsig	22	37	1.24e−08	8.65e−10	100	100
19	4-6-5-6-4	logsig,logsig,logsig	31	25	3.89e−10	1.90e−08	100	100
20	4-6-6-6-4	logsig,logsig,logsig	33	37	2.24e−07	1.31e−09	100	100
21	4-7-6-7-4	logsig,logsig,logsig	33	37	1.09e−07	2.96e−10	100	100
22	4-4-4-4-4-4	logsig,logsig,logsig,tansig	13	40	6.48e−02	8.32e−08	75	75
23	4-4-5-4-5-4	logsig,logsig,logsig,tansig	25	48	1.34e−10	3.64e−08	100	100
24	4-5-4-5-4-4	logsig,logsig,logsig,tansig	26	23	5.15e-10	7.70e-03	100	96.3
25	4-6-5-4-6-4	logsig,logsig,logsig,tansig	23	18	6.19e-0	1.55e-09	100	100
26	4-7-5-4-3-4	logsig,logsig,logsig,tansig	15	39	1.75e-09	6.36e-02	75	100
27	4-8-5-3-6-4	logsig,logsig,logsig,tansig	24	54	9.04e-10	2.30e-09	100	100
28	4-7-8-5-4-4	logsig,logsig,logsig,tansig	31	23	9.74e-04	6.32e-11	100	100

Table 5 Typical target results for test no. 23 and 28

Engine condition	Target vectors			
Healthy	1	0	0	0
Liner scuffing fault	0	1	0	0
Piston scuffing fault	0	0	1	0
Liner_piston scuffing fault	0	0	0	1

Declaration

Conflict of interest on behalf of all authors, the corresponding author declares that there is no conflict of interest.

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