Acoustic emissions in the valuation of the combustion chamber pressure of an engine

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Abstract. Internal combustion engines demand advanced monitoring methodologies to promote efficient operation; particularly, the combustion pressure plays a central role in the overall performance, which promotes the utilization of transducers that hinders. Therefore, the present study introduces an acoustic emission methodology that serves for indirect combustion pressure measurements. Accordingly, the compound methodology integrates the Hilbert transform and the complex cepstrum using neural networks to accomplish pressure signal reconstruction. Results demonstrated that the proposed methodology featured robust performance while estimating pressure signals as it mitigates the combined noise effect produced by variations in engine speed, engine load, and fuel type. Moreover, the reconstructed signal facilitated the determination of key performance parameters such as peak pressure, pressure timing, and effective mean pressure. Relative error amounted to less than 10%, which ratified the robustness of the indirect pressure measurements. In conclusion, acoustic signal techniques represent an adequate approach to estimate the combustion pressure at variable engine conditions.

1. Introduction
Internal combustion engines (ICE) features strong optimization potential in terms of fuel consumption and environmental pollution by adequate control of combustion operation [1]. Moreover, implementing control strategies in ICEs promotes techno-economic operation while alleviating the adverse effects of wear damage in engine components due to the presence of abrasive pollutants [2]. Therefore, the characterization of the combustion pressure in ICE becomes essential to achieve reliable and clean operation [3,4].

Particularly, combustion phenomena modeling requires the estimation of the combustion pressure throughout combustion stages, which ratifies the importance of this parameter. The latter is commonly measured directly by means of pressure transducers that are integrated into the chamber structure. The direct measurement technique serves for evaluating both engine designs and experimental test rigs. However, the main drawbacks of this technique center on the high acquisition cost and the required engine modifications for installation, which hinders its massive implementation in commercial applications [5]. Besides, space requirements for installation in compact engines become a concrete limitation of pressure transducers. In this sense, direct measurement implementation has not been extensively implemented for industrial and commercial applications [6].

Recently, two different proposals have emerged to measure the combustion pressure indirectly by means of reconstructed signals from alternative sensors. The first one focuses on vibration signals
examination from the engine block and crankshaft [7]. The second one uses polluting emissions for the indirect pressure measurement [8]. These methodologies have been employed to portray the combustion quality while elucidating different perspectives to enhance the overall performance of ICEs. Published research stated that accelerometers and acoustic emission (AE) sensors assist in determining malfunctioning operation in applications such as misfires, shock, and vibration issues in injectors and valves. Thus, this sensor overcomes a significant opportunity to displace pressure transducers that features several challenges for combustion pressure measurements [9]. Nevertheless, the implementation of AE sensors still requires the identification of a suitable installation within the engine block and further integration of the filtering process to minimize interference from external sources [10,11]. Therefore, integrating low-pass filtering techniques becomes essential in this type of measurement since it mitigates the generation of noise signals in time and frequency that limits the accurate prediction during combustion.

Specifically, the fundamentals of indirect measurement methodologies center on developing dynamic models that associate in-cylinder pressure and the signal response recorded by the sensor. Different studies have denoted the importance of a fully calibrated model to obtain reliable measurements. For instance, Trimby et al. [12] introduced a technique based on the implementation of neural networks to reconstruct the pressure signal from an accelerometer. In this study, a systematic correlation was established to relate engine block vibrations and crankshaft fluctuations. Results demonstrated that including crankshaft vibration signals facilitated adequate pressure measurements. On the other hand, Dunee et al. [13] applied a reconstruction approach using non-linear functions to consider the influence of system variables such as crankshaft angle, engine speed, and instant acceleration. Results stated that both the magnitude and timing of in-cylinder pressure could be obtained with a relative error of 6.5% and 2.7%, respectively.

So far, studies have reported that implementing accelerometers for pressure signal estimation can lead to inaccurate measurements due to the presence of noise that limits signal reconstruction. In terms of acoustic emissions, a strong correlation between signal and noise is achieved, which contributes to emulate in-cylinder pressure conditions. Nonetheless, most published research considers a limited operational range. Therefore, the scope of this investigation is to develop a compound methodology consisting of complex cepstrum analysis and a neural network for pressure signal reconstruction based on acoustic emissions. The novelty of the study relies on the characterization of system variables such as rotation speed, torque, and biodiesel percentage.

2. Methodology
Pressure signal reconstruction is performed based on acoustic signals derived from the engine body that comprises the crankshaft angle. Moreover, the acoustic emissions are processed via Hilbert transform to maintain a similar frequency that facilitates pressure reconstruction [14]. The acoustic signal processed can be classified into three components [15], as denoted in Equation (1).

\[ S(\theta) = R(\theta) + Z(\theta) + N(\theta), \]  \( \text{(1)} \)

where \( R(\theta) \) relates the repetitive behavior found on each cycle that is encountered by calculating the mean cyclical signals measured. \( Z(\theta) \) accounts for signal variations produced by modifications in engine speed and load condition. \( N(\theta) \) represents noise signal effects. Consequently, Equation (2) is employed for pressure signal reconstruction \( P(\theta) \) from the envelope of the acoustic signal \( A(\theta) \).

\[ A(\theta) = P(\theta) \cdot T(\theta), \]  \( \text{(2)} \)

where \( T(\theta) \) accounts for the transfer path. An equal spaced pseudo-frequency domain (Equation (3)) can be obtained by applying the Discrete Fourier Transform (DFT) as depicted in Equation (2).
\[ A(\omega) = P(\omega) \cdot T(\omega). \] (3)

The complex cepstrum method is utilized to solve Equation (3), which facilitates restoring the domain of the crankshaft angle, as depicted in Equation (4).

\[ A_{\text{ceps}}(\theta) = P_{\text{ceps}}(\theta) + T_{\text{ceps}}(\theta), \] (4)

where \( A_{\text{ceps}}(\theta) \), \( P_{\text{ceps}}(\theta) \), and \( T_{\text{ceps}}(\theta) \), are determined from Equation (5) to Equation (7).

\[ A_{\text{ceps}}(\theta) = f^{-1}[\log (A(\omega))], \] (5)

\[ P_{\text{ceps}}(\theta) = f^{-1}[\log (P(\omega))], \] (6)

\[ T_{\text{ceps}}(\theta) = f^{-1}[\log (T(\omega))]. \] (7)

From the transfer path, the pressure signal is reconstructed, taking into consideration different load levels and engine speed. Notice that the incidence of disturbance on the fluctuations on each cycle features a non-linear trend. Therefore, a neural network (NN) is implemented as it contributes to training pressure processing in a vast range of engine load, engine speed, and fuel types.

The training of the neural network is performed using the reconstructed pressure signal obtained in the transfer path; particularly, the study implements a feed-forward-type neural network in MATLAB® software environment. Note that the neural training is based on the Levenberg-Marquardt approach since it guarantees robustness and convergence [16]. Figure 1 displays the main characteristics of the reconstructed pressure signal procedure. The study uses a stationary single-cylinder diesel engine, whose technical characteristics are listed in Table 1.

![Procedure of reconstruction of the pressure signal](image)

**Figure 1.** Procedure of reconstruction of the pressure signal.

| Model     | Maximum power | Bore (mm) | Stroke (mm) | Displaced volume (cc) | Compression ratio | Injection system |
|-----------|---------------|-----------|-------------|-----------------------|-------------------|-----------------|
| SK-MDF300 | 4.6 hp at 3600 rpm | 78        | 62.57       | 299                   | 20:1              | Direct injection |

The diesel engine is the major component of the test rig, as illustrated in Figure 2. A dynamometer is responsible for controlling both engine speed and torque. The in-cylinder pressure is recorded using a piezoelectric sensor (KISTLER type 7063-A). Similarly, an acoustic piezoelectric sensor was employed to measure acoustic emissions (R15A). The angle sensor (Beck Arnley 180-0420) is installed for monitoring the crankshaft rotation. Lastly, data acquisition and recordings of each sensor were powered by LabVIEW® software.
Within the experiments, the operational range of the engine was set to three levels for engine speed (3000 rpm, 3400 rpm, and 3800 rpm) and engine torque (3 Nm, 4 Nm, and 5 Nm). Moreover, three different fuel blends are evaluated in the study, namely D100 (pure diesel), B5 (95% diesel+5% palm oil biodiesel) and B10 (90% diesel+10% palm oil biodiesel). Notice that every operational condition test records 200 consecutive cycles for further classification in the algorithm training and algorithm validation.

3. Results

Figure 3 displays a simultaneous comparison between the pressure signal, the original acoustic signal, and the envelope acoustic signal. According to the results, the noise associated with pressure and acoustic signals is reduced through the implementation of a bandpass filter at a frequency of 0.05 KHz-20 KHz and 40 KHz-85 KHz, respectively; based on Figure 3, it can be verified that the envelope of the acoustic signal features less disturbance, especially during the compression and expansion stage. Therefore, it can be stated that the best performance of pressure signal reconstruction occurs for the envelope of the acoustic signal, which is shown in detail in Figure 4.

According to Figure 4, the maximum error obtained between experimental measurements and the reconstructed signal processing reaches 33%, taking place during the final compression stage. The latter can be directly associated with external disturbances derived in each cycle, which are not counterbalanced by the average of the cycle. To tackle this issue, a training process via a neural network becomes essential within the analysis. The neural network-reconstructed signal features improved behavior when compared with the experimental measurements. In this specific case, the maximum error amount of less than 4%, demonstrating the effectiveness of this methodology.

The reliability of the pressure signal estimation is verified using the error of the reconstruction process as depicted in Equation (8).
\[ E_r = \frac{1}{n} \sum_{n=1}^{n} \frac{|P_e - P_r|}{P_e}, \]  

(8)

where \( P_e \) represents the value of the experimental pressure, \( P_r \) accounts for the reconstructed value, and \( n \) is the number of samples for each cycle. For the reconstruction error analysis, 5000 combustion cycles were selected. The error distribution is shown in Figure 5.

\[ E_c = \frac{P_{LPS} - P_{LRS}}{P_{LPS}} \times 100, \]  

(9)

where \( P_{LPS} \) and \( P_{LRS} \) represent the magnitude of the pressure parameter \( i \), obtained via experimental pressure signal and the reconstructed signal, respectively. The relative error is calculated and further compared with the probability density, as shown in Figure 6.
Based on Figure 6, the error in the peak pressure is concentrated in a zone below 8%. For the PPT parameter, a great part of the error is obtained below 2%. The IMEP parameter features the greatest error zone (25%), but it is consistent with the permissible range in this analysis.

4. Conclusions

This study reports on the implementation of an indirect in-cylinder pressure measurement technique that integrates complex cepstrum analysis and training via neural networks. The reconstruction of the pressure signal is evaluated based on acoustic emissions derived from the body of a diesel engine.

Results demonstrated that the complex cepstrum analysis contributed to the consolidation of a transfer path, which further facilitates data training using a feedforward neural network. Moreover, the estimation of the reconstruction error showed that 90% of the signal features an error lower than 10%. Besides, the evaluation of the peak pressure and peak pressure timing demonstrated that the error does not exceed 8% when implementing the reconstructed pressure signal. The maximum error was achieved for the indicated mean effective pressure (＜25%). In conclusion, the study elucidated the robustness of indirect acoustic signal envelope as a suitable alternative to accurately determine pressure signal while minimizing engine intrusion or modification.

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