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Application of neural and bayesian networks in diesel engines under the flaw detection method

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Abstract. The identification of premature faults in Internal Combustion Engines has become determinant to guarantee suitable operation. Therefore, this study focuses on the implementation of fault diagnostic methodology by using advanced algorithms such as Back Propagation neural networks and Bayesian networks. Results indicated that the proposed methodology serves as a robust tool to identify different fault conditions in a wide operational spectrum with an reliability of nearly 73%. Moreover, the Backpropagation network diagnostic methodology presented an reliability of 18%, which is 3% higher than Bayesian networks. Overall, the implemented methodology counterbalanced interference conditions and noise signals while providing versatility to operate for different types of engines. In conclusion, this study can be extrapolated to different fields of physics to assist in identifying flaws in experimental test benches.

1. Introduction

Internal combustion engines represent a primary mover in energy applications, which set intensified pressure on maintaining high-quality standards on maintenance methodologies to promote efficient operation [1]. Nonetheless, there are significant limitations that like ahead the development of diagnostic techniques due to the complexity of the engine's components that inhibit the accurate identification of fault conditions. Nowadays, the fault diagnostics field commonly establishes three main categories: numerical model-based, experimental, and signal-based [2–5].

The model-based category mainly considers the overall patterns of the dynamic system to accurately define fault conditions. The latter has been previously addressed in published research. For instance, Xu, *et al.* [6] implemented a diagnostic model-based methodology to identify common fault conditions diesel engines for marine applications. In the same vein, Zhong, *et al.* [7] proposed a multiple coupled sparse Bayesian model to prematurely detect critical fault conditions in spark-ignited engines. Bi, *et al.* [8] addressed a combined methodology that integrates an enhanced variational mode and a bispectrum model to prevent valve clearance fault. Nevertheless, the proposed model is limited in terms of feasible applications due to the implementation of empirical assumptions. On the other hand, the experimental-based methodology disregards the utilization of mathematical models, which promotes simplicity and reliability in complex systems.

Wei, *et al.* [9] introduced a machine-learning algorithm to identify fault conditions in turbocharged diesel engines for marine applications. Likewise, Xu, *et al.* [10] used a machine learning approach for the identification of wear and tear fault conditions in internal combustion engines (ICEs). Lazakis, *et al.* [11] developed a monitoring methodology to characterize the engine performance engine via training support networks in vector machines. The signal-based approach has been widely implemented for fault diagnostics in ICEs. For example, Liu, *et al.* [12] examined the instantaneous pressure signal using



spectral analysis for fault diagnostics. Similarly, Tao, *et al.* [13] introduced a diagnostic methodology that centered on the time-frequency examination of vibration signals. Although, the main patterns of the signal processing presented occasional variations for the same fault condition.

From a global perspective, the selected approach for fault diagnostics should guarantee the minimization of signal interference during signal acquisition, signal noise reduction, and reduce error propagation [14]. Support vector machines [15,16], statistical methods [17,18], and computational fluid dynamics (CFD) simulations [19,20] have demonstrated reliable performance and accurate predictions for fault diagnostics. These last two methods are highlighted for learning progress under incomplete information conditions [21,22]. Besides, these methods assist in the classification of complex patterns while providing the mapping of multidimensional functions. Nevertheless, there still exist significant limitations such as the limited fault identification, diagnostics precision, and applicability to reliable operating conditions.

Therefore, the scope of this investigation is to introduce a fault detection methodology for ICEs applications while integrating advanced algorithms. Specifically, the study addressed rule-based and neural training approaches such as back propagation neural networks (BPNN) and Bayesian networks (BN). The detection of different types of fault conditions under a wide operational range of rotation speeds and torque conditions emerges as a remarkable factor in this research that contributes to closing the knowledge gap immersed in fault diagnostics methodologies.

2. Methodology

Figure 1 Shows the method used in diagnosing engine faults.

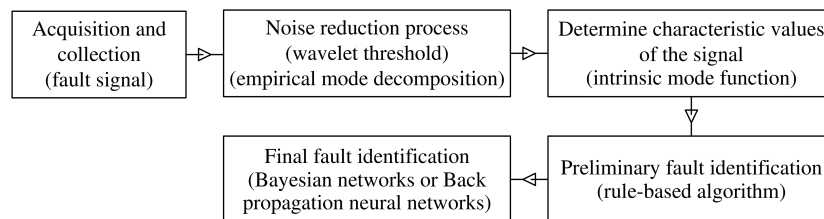


Figure 1. Fault diagnosis process.

The process starts with data acquisition and collection of the fault signal by means of vibration sensors. Next, signal noise is minimized by implementing a wavelet threshold method and the integration of an empirical mode decomposition (EEMD) method. The fundamental formulation of the noise removal method using the wavelet threshold is depicted in Equation (1).

$$Z(n) = S(n) + X(n), \quad (1)$$

where $X(n)$ represents the noise sequence signal, and $S(n)$ accounts for the useful part of the signal. Taking into account that $X(n)$ relate a random Gaussian distribution, Equation (1) can be expressed in Equation (2).

$$WT_z(a, b) = WT_s(a, b) + WT_x(a, b), \quad (2)$$

where W accounts for the wavelet transform matrix. Consequently, the intrinsic mode function (IMF) is included to describe the signal values. Also, preliminarily, an identification of the failure is made through an algorithm supported in rules. Finally, the training of the neural networks of posterior propagation or BN was carried out. The evaluation of the experiment was carried out on a test bench, as shown in Figure 2. The stationary single-cylinder diesel engine was evaluated and its elements are listed in Table 1.

An accelerometer (Endevco 7240C) was used to measure the vibration signal. This accelerometer was installed on the cylinder head of the exhaust cylinder and another was installed on the intake valve. An angle sensor (Beck Arnley 180-0420) was used to measure the rotational speed of the motor shaft. Five types of failures were evaluated for the motor study, this is shown in Table 2.

Table 1. Engine specification.

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

Table 2. Types of engine faults.

Fault	Details
Clearance in exhaust valve	A distance of 1 mm is set between the transmission and the valve
Intake valve clearance	A distance of 0.3 mm is set between the transmission and the valve
Intake valve spring wear	A material cut is made on the spring
Oil leakage	Slow oil leakage caused by bolt misalignment
Wear at the base of the intake valve	Valve seal misalignment

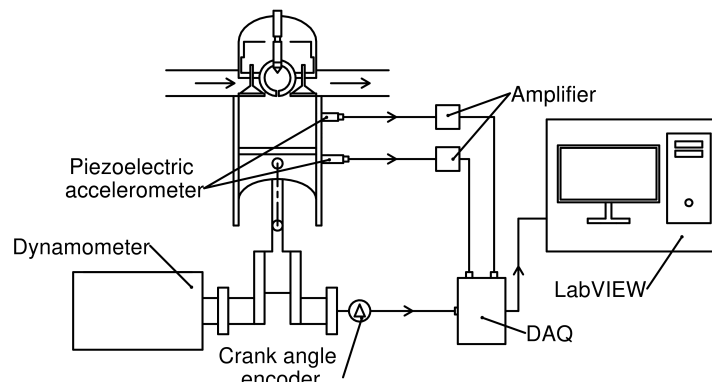


Figure 2. Engine test bench.

3. Results

3.1. Reliability analysis of the fault diagnosis method

As for the BN method, the BPDN method were evaluated at various rotational speeds and showed great efficiency in the diagnosis. This variation was made by changing the engine speed in three phases, using the reference condition that was used in the training of the model (3100 rpm, 3400 rpm and 3700 rpm). The intervals of these phases were 35 rpm, 70 rpm and 105 rpm. The results Figure 3 shows the results.

According to Figure 3, the reliability of the fault diagnostics resembles in all three cases when comparing the method based on BN and BPNN. The maximum precision occurred for training speeds, which decreases when examining speeds apart from 3100 rpm, 3400 rpm, and 3700 rpm. This behavior can be attributed to the fluctuations in signal characteristics derived from speed variations.

The implemented method displays improved performance when operating across the training speeds. Overall, speed increments of 35 rpm, 70 rpm, and 105 rpm featured a reliability of 91.2%, 85.4%, and 80.45%, respectively. Nevertheless, while examining differences of 35, 70, and 105 rpm below the training speed, the reliability dropped to 90.6%, 80.78%, and 68.45%, respectively. Consequently, both BN and BPNN methodologies feature a reliability of nearly 85% and 87%.

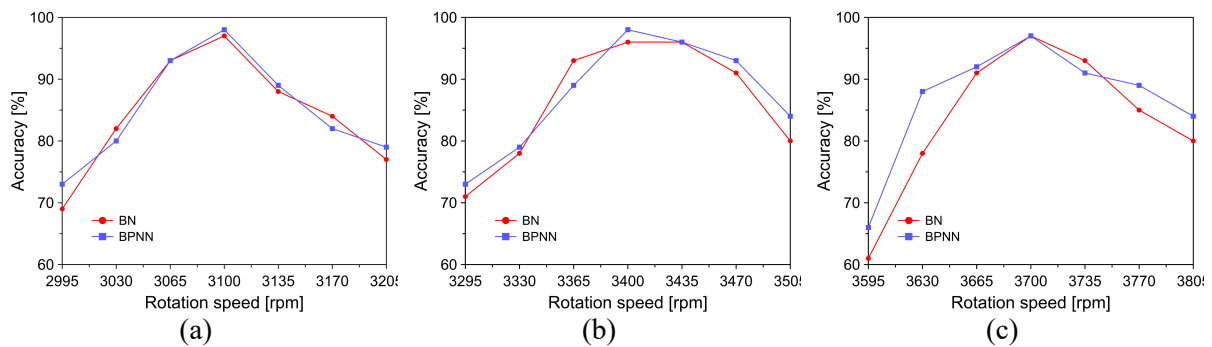


Figure 3. Reliability of fault diagnosis for training speeds of (a) 3100 rpm, (b) 3400 rpm, and (c) 3700 rpm.

3.2. Analysis of the influence of noise signals

There is an imminent possibility of fault conditions in sensors used in engine applications, directly affecting data acquisition and signal processing. As a consequence, fault identification is significantly affected by the propagation of errors. Therefore, diagnostic methodologies play a predominant role in minimizing the error induced by noise conditions. The incidence of noise is analyzed using a Gaussian white source that is simulated in a range of 3 dB to 9 dB, this simulation is added to the fault signal prior to the noise elimination process. In this way, a speed range between 3400 rpm and 3505 rpm was determined as a case study for the evaluation of noise, as evidenced in Figure 4.

Based on Figure 4, the BPNN approach overcomes the greatest reduction in precision at a speed condition of 3435 rpm. Precisely, the reliability of the model dropped by 1.48%, 2.62%, and 4.78% when implementing the BN approach. In contrast, the BPNN features reductions of 2.34%, 4.28%, and 5.82%, respectively.

Overall, it was not identified a progressing drop in the reliability of the proposed method when operating at speeds higher than the training speed (3400 rpm). This pattern is a direct consequence of the uncertainty derived within signal acquisition and processing, which results from engine motion variation. Thus, the influence of noise cannot be clearly determining for a specific engine speed. Specifically, the signal noise reduces the reliability between 0.28% – 4.62% and 0.22% – 5.78% when implementing BN and BPNN, respectively.

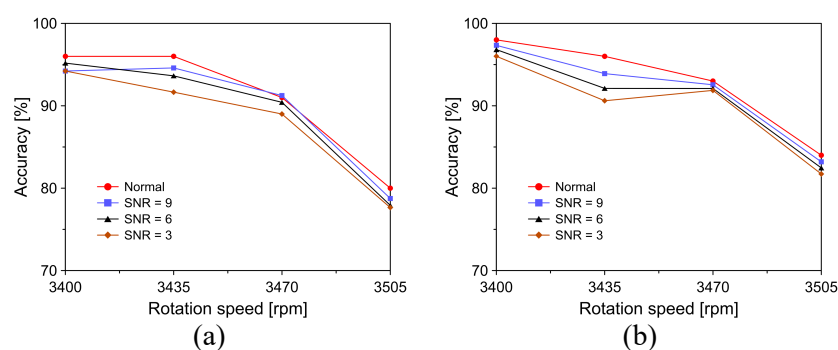


Figure 4. Reliability of noise fault diagnosis prior to the elimination process for (a) BN and (b) BPNN.

Consequently, Figure 5 displays the impact of noise signal presence after the denoising process. Based on the results of Figure 5(a) for BN and Figure 5(b) for BPNN, a greater reduction in diagnostic reliability compared to Figure 4 can be identified. Moreover, a reduction in reliability between 0.7% – 6.9% and 0.3% – 6.7% was observed when using BN and BPNN, respectively.

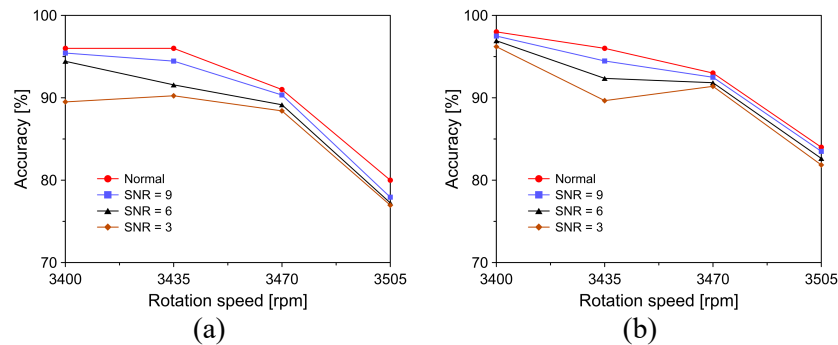


Figure 5. Reliability of fault diagnosis with the presence of noise after the elimination process for (a) BN and (b) BPNN.

3.3. Analysis of the interference signals and the effect they generate

There are more factors that have an effect on the fault signal. One of these is the external interference that is generated by the blows of the elements of the engine body. To analyze the effects of these interferences, the impact of these on the reliability of the diagnosis is evaluated. These results are shown in Figure 6.

Figure 6(a) for BN and Figure 6(b) for BPNN showed that the reliability trend is not entirely intuitive. Consequently, external interferences produced a significant minimization in the reliability of fault diagnoses. When comparing BN and BPNN, it can be seen that the BPNN shows a high level of tolerance to external interferences, this tolerance can be continuously or intermittently. On the other hand, the reliability of the BPNN is 21.23% and 16.89% higher when it is altered by continuous and intermittent interference, compared to the precisions obtained via BN. Of the cases analyzed, a greater reduction of 46.23% and 36.23% was obtained in the reliability of the diagnostic performance by BN for continuous and intermittent interferences. Regarding the BPNN, the reliability decreased to 34.23% and 26.12%, respectively.

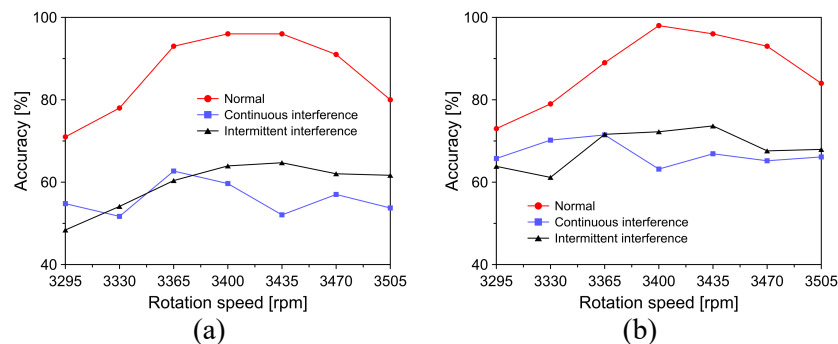


Figure 6. Reliability of fault diagnosis with the presence of interference for (a) BN and (b) BPNN.

4. Conclusions

This investigation addresses a fault diagnostics method for engine applications while integrating advanced algorithms of rule-based and BN or BPNN. The key aspects of the proposal rely on the capability to detect fault conditions in a wide range of engine speed conditions while using limited training data.

Results demonstrated the predominant reliability of the fault diagnosis method when implementing BN and BPNN that amounted to nearly 72.5% and 76.8% for engine speeds of more than 100 rpm across the training speed. Overall, implementing BN and BPNN featured similar precision conditions. Nevertheless, this condition varies when the fault signal is altered by noise fluctuations (interference). Moreover, using the BPNN method led to accuracies of 17.79% higher when compared to the BN.

Besides, implementing the BPNN approach increases the reliability by up to 3% after the denoising process. Overall, the proposed method can be alternated to examine different fault conditions and different types of engines by adjusting the BN and BPNN approach. In conclusion, this research can be beneficial for the development of diagnostic tools using BPNN and BN in which mathematical concepts are fundamental to solve complex problems with a great impact from a practical and investigative viewpoint.

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