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ENGINE DIAGNOSIS BASED ON VIBRATION ANALYSIS USING DIFFERENT FUEL BLENDS

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Abstract

Fault diagnosis of an internal combustion engine is proposed herein by means of vibration analysis and a comparative analysis of normal operation and induced misfire scenarios. In order to validate previous works on misfire with pure gasoline, measurements also included tests performed with ethanol-gasoline fuel blends. According to results, changes in the fuel mix seem to have little impact on the performance and behaviour of the engine. And additionally, the particular frequency components that allowed differentiation between normal and faulty conditions were also present on all the fuel blends tested. Fast Fourier Transform was applied to obtain the frequency domain of the signal as a previous step to the subsequent identification process based on statistical characteristics extraction. A fuel blend classification method based on the analysis of the vibration signals of the engine was studied using envelope, Spike Energy and Peak Value techniques. Differentiation was possible with the extraction of the statistical features of the Peak Value spectrum of the longitudinal acceleration with a specific filter selection.

Keywords: engine diagnosis, vibration analysis, frequency analysis

1. INTRODUCTION

Given importance to predictive maintenance within the modern industry, many manufacturing plants rely heavily on internal combustion engines. Due to its relevance, approaches like condition monitoring have gained growing interest, whose main indicator, the cylinder pressure [7,11], reveals a great deal of information concerning the internal combustion process. However, it is an invasive and expensive procedure due to additional costs of sensors and engine modifications. In an attempt of finding more affordable options, the use of less specific type of sensors also has reported good performance in techniques such as angular speed measurement [5,20], oil analysis [13], surface temperature and exhaust emissions [14].

Most of the studies have focused on acceleration measurement [16,17] using sensors, such as accelerometers [12], acoustic sensors [2] and knock sensors [22], with satisfactory results and wide-spread deployments in condition monitoring of rotating machinery [15], including pumps [1], ball bearings [10] and gearboxes [19]. However, they have been found to present problems when using conventional analysis methods for assessment of particular conditions of internal combustion engines, since the measured signals are non-stationary.

The identification of diverse causes to engine block vibration from single point measuring in [22] was achieved based on short time Fourier transform on the signal, collected with a commercial knock sensor. A methodology for simple model of internal combustion engine is studied in [18]; the emphasis of the paper is placed on the use of the in-cylinder parameters (pressure and temperature) and inertial loads in the crank-slider mechanism to derive the loads that act on all the components of the crankslider mechanism as well as the theoretical output torque for a given geometrical structure and inertial properties. A determination of combustion parameters by means of neural networks reported in [20] was supported on angular velocity measuring. Both indicated and load torques were estimated in [4] using the variations in motor speed. An estimation of combustion pressure based on the processing of the vibration signal is presented in [11]. An assessment of the influence of the shape variations of the piston bowl on the combustion process was given in [21], for this purpose vibration data from the engine block was analysed.

Nevertheless, these researches did not take into account the influence of alcohol-gasoline blends of fuel on the vibration features. According to [3], results from studies with pure gasoline in faulty operations, such as a misfire, reported changes in the spectral composition of the vibratory signal of an engine and the presence of peaks different from the combustion frequency. To report on engine performance [9] used a chassis dynamometer, at different speeds and loads, with a vehicle operating on fuel blends consisting of gasoline and alcohol derivatives like ethanol and methanol (E5, E10, M5 and M10). Their results showed that alcohol-gasoline blends increased brake specific fuel consumption and delayed cylinder gas pressure. Attempts to identify fuel blends through vibration analysis have been made by [12], who used RMS values of filtered acceleration signals to identify pure gasoline from blends of ethanol or methanol, however, the percentage of the blends could not be identified.

The object of the present study was to assess the effects of using different blends of gasoline and ethanol as fuel on the spectral composition of the vibration signal of an engine, when operating under faulty conditions, in this case a simulated misfire. In order to provide a robust data base, supplementary sensors were employed. Based on the results from the present work, it could be stated that under misfire conditions pure gasoline and gasoline-ethanol blends (such as E8, E20 and E30) share the same characteristic frequencies and peaks. Exploration of particular frequency bands by means of extraction of some statistical features from the frequency domain of signals helped to simplify the comparative analysis between normal and faulty operations. Making use of said engine vibration database, additional processing of the signals was employed, namely envelope, Peak Value and Spike Energy, in order to identify the different fuel blends, thus allowing to perform the same spectrum comparison and the use of the statistical feature extraction. This article describes in details the experimental setup, test procedure and a comparative analysis of measurements under normal conditions, induced misfire and the different fuel blends.

2. EXPERIMENTAL SETUP

The experimental test bench for this study consisted of a two litre, four cylinders, spark ignited internal combustion engine from a truck, and mounted on a movable structure that allowed access to the components of the motor as well as better control of temperatures and leaks which in turn simplified condition monitoring.

Vibrations analysed herein correspond to three different measured accelerations. These accelerometers were installed on three different areas depicted in Figure 1 (the first one, with a sensitivity of 100mv/g, vertically positioned at the top of the engine, the second one, with a sensitivity of 10 mv/g, longitudinally positioned in respect to the crankshaft axis and mounted close to cylinder one, and the last one, with a sensitivity of 10 mv/g, mounted in the middle of cylinders two and three with a normal direction to the crankshaft axis).

Said locations and orientations were selected based on previous results from different authors. For fault detection purposes [3] found that transversal and longitudinal vibration signals, with sensors located on the engine block, provided good results, whereas [8] achieved good results using the vertical vibration signal from a sensor on the cylinder head. Looking for the effects of different injection parameters on vibration signal [6] obtained good results using both vertical and transversal vibrations, with sensors located on the cylinder head and engine block respectively. Considering these and several other authors results, the vertical, longitudinal and transversal vibration signals were measured.

Respective data acquisition resorted to two equipments mounted on a NI cDAQ 9174 four-slot chassis (NI 9232, 3 channel +/-30V analogue input module and a NI 9234, 4 channel +/-5V analogue input module).

The cost of accelerometers is around a third of the cost of a combustion pressure sensor, and they normally have a longer useful life since they can be located outside of the engine, which means they aren't exposed to the difficult conditions, of high pressures and temperatures, inside the combustion chamber.

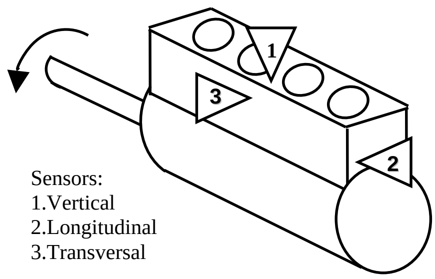

Fig. 1. Schematic location and orientation of the accelerometers on the engine

In order to determinate stable speeds of the engine for measurement and reliable conditions for the running periods of testing, preliminary test was run.

Since the test bench allowed easy access to the engine components, it was possible to test two different operational conditions with no load. 1) Normal: with four cylinders running and 2) Misfiring Piston: Induced misfire of a piston by dis-connecting the spark plug from cylinder four. The comparative analysis between normal and faulty operations of the engine was based on an experimental testing that focused on different variables of speed and fuel blend. Three fuels were used during the tests:

i) E8: Commercially available with eight percent ethanol with gasoline
ii) E20: Blend of gasoline with twenty percent ethanol
iii) E30: Blend of gasoline with thirty percent ethanol.

And the speed variables were 1500, 1700 and 2000 rpm. Both operational conditions with no load were tested with the speed and fuel blend variables aforementioned, three different measurements were taken each time with the eight measuring devices.

Due to technical specification of the data acquisition modules, sampling frequency was set at 51.2 kS/s/channel. Recording time for all the measurements was 2 seconds. This means that a total of 54 sets of measurements were registered, each with a length of 2 seconds, 3 sets at each speed tested, with each fuel blend and for each operating condition (normal and misfire). For the speeds tested, with the length of 2 seconds, more than 50 full combustion cycles were recorded in each data set.

The process of differentiation between normal and faulty conditions was based on data obtained from signals in time domain and frequency domain transformation of the signal, namely full spectrum of acceleration vibrations and subsequent focus on areas/zones of special interest due to the presence of excited frequencies. This study also resorted to the extraction of the following eight statistical features applied to all the data obtained from the aforementioned signals: Root mean square (RMS), Arithmetical mean, Kurtosis, Standard deviation, Skewness, Energy, Maximum value, Minimum value.

The classification of the signals according to the percentage of ethanol in the blend was studied using further processing of the data with envelope, Peak Value or Spike Energy techniques to generate another set of spectrums to compare and to apply the statistical features extraction.

3. RESULTS

Measuring started after installing the pressure sensor on the engine heated and maintaining a stable operation. Firstly, the normal condition was tested for the E8 fuel blend; three different measurements were taken for each one of the speeds selected. Afterwards, misfire is induced by disconnecting the spark plug of the fourth cylinder, and the measuring process is repeated for each speed. After completing the tests for E8, remaining fuel was removed from the tank before introducing the next fuel blend. The same measuring procedure described above was repeated until obtaining complete data from the remaining fuel blends (E20 and E30). Figure 2 shows an example of the measurements with the vertical accelerometer. As can be seen, visually the raw acceleration signals can't be differentiated, requiring different options like frequency analysis techniques to extract characteristics from them.

3.1. Fault detection

With assistance of the Fast Fourier Transform, signals in the frequency domain could be observed for comparative analysis, to identify differences in the frequency components of the signals from one operation condition to another and also to corroborate their presence when changing fuel blend.

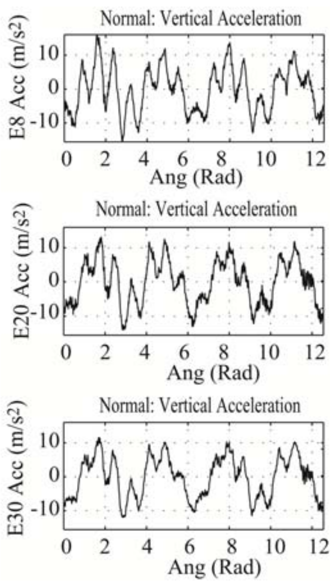

Fig. 2. Vertical acceleration, normal operating conditions on three fuels, second axis, spark detection

Vibrations in the transversal direction were the first to be compared, since they usually provide the most relevant data. Frequency domain signals for the three fuel blends under both normal and faulty conditions at 1500 rpm can be seen in Figure 3.

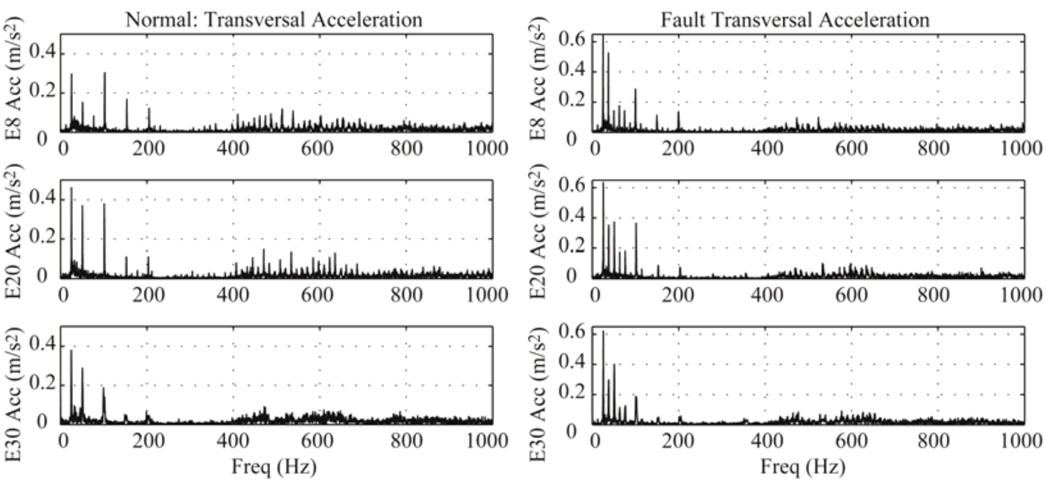

Fig. 3. Transversal acceleration, normal and fault operating conditions on three fuels, 1500 rpm

In the graphic, two tendencies are recurrent in both conditions for all the fuel blends. Firstly, from 400 to 700 Hz, several smaller peaks can be seen, which may be resonant responses from the supporting structure due to their repetitive presence in almost every measurement. And secondly, the prominence of three particular peaks is recurrent: namely at 25 Hz, 50 Hz, and 100 Hz. As expected for the motor used (four cylinder, four strokes), under normal conditions at 1500 rpm combustion frequency (CF) was reported at 50 Hz but oddly the peak at 25 Hz corresponding to revolution or speed frequency (RF) also appeared in CF peak is the only one expected to appear and the peak at 100 Hz may be considered its harmonic, hence the presence of RF peak should have stemmed from some unbalance and differences in the support of the mounting.

From faulty conditions, the two tendencies described above kept taking place, however a couple of new facts provided enough distinction between faulty and normal conditions. Firstly, RF peak at 25 Hz is reported to be the highest. And secondly, under faulty conditions there was a constant presence of another three peaks at 37.5 Hz, 62.5 Hz and 75 Hz. Such frequencies may also be considered as 0.5 CF, 0.75 CF, 1.25 CF and 1.5 CF respectively. It is worth of noting that these distinctive and discrepant tendencies of normal and faulty conditions took place with all fuel blends. Results with similar behaviours were obtained for tests run at 1700 rpm and 2000 rpm.

Neither the longitudinal nor the vertical acceleration measurements reveal any significant discrepancy between faulty and normal conditions. The results obtained with vertical accelerometers reported in Figure 4 are in accordance with [4]: On both operational modes, CF peaks took place very clearly and the only differentiating elements are minor increases of the small RF peaks for the instances of induced misfire. Just like in the previous measurements, all the tested fuel blends repeatedly shared tendencies.

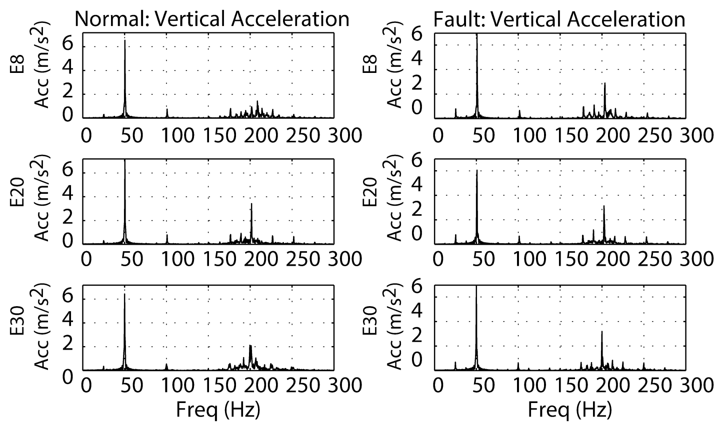

Fig. 4. Vertical acceleration, normal and fault operating conditions on three fuels, 1500 rpm

Since the first comparisons based on frequency domain transformations revealed that distinguishing elements between operating modes exhibited greater salience at frequencies under each one of the CF peaks, the analysis of statistical characteristics, extracted from the frequency spectrum, focused on such lower frequencies. The first band frequency selected for statistical characteristics extraction corresponded to the zone 0.6-0.9 CF. Analysing this frequency from transversal measurements, only one (minimum value) out of the eight statistical properties did not report discrepancies that allowed to differentiate between normal and faulty conditions.

The constant tendency of the seven differentiating properties was higher values under faulty conditions. Main values and Standard Deviations were the ones that provided a better distinction, i.e. a greater gap between values of the two conditions tested. Maximum values (Figure 5) serve as an example to illustrate the satisfactory distinction obtained by means of statistical characteristics extraction from transversal acceleration measurements at the aforementioned frequency band for all the speed and fuel blends variables of this study.

Further analysis on transversal acceleration at the wider frequency band 0 CF to 0.9 CF reported that 5 statistical characteristics (maximum value, RMS, mean value, standard deviation and energy) allowed clear distinction between conditions for the three fuel blends at 1500 and 1700 rpm, however differentiation didn't take place at all from measurements at 2000 rpm.

The remaining three characteristics (Kurtosis, Skewness, and Minimum value) exhibited inconsistency in their results, whether they didn't report differences whatsoever or only for isolated conditions.

Despite full spectrum readings of vertical vibrations reported an overall similarity unpromising for signs of differentiating elements between operational modes, the corresponding statistical characteristics surprisingly allowed some distinctions but with inconsistency. However, maximum value was the only statistical characteristic that showed a tendency for differentiation of normal and faulty conditions at the 0-0.9 CF frequency band from vertical vibrations. Such a tendency was constant for all the speed and fuel blends variables of the study as shown on Figure 6.

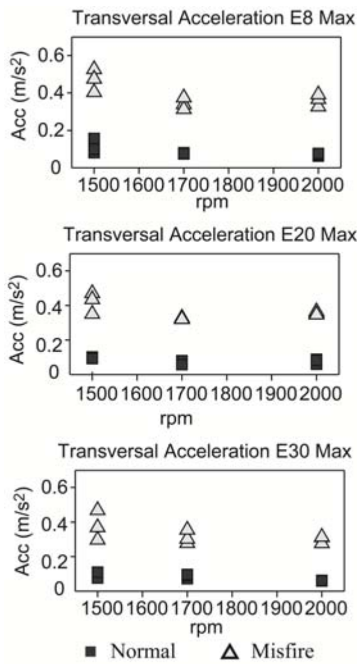

Fig. 5. Transversal acceleration, normal and fault operating conditions on three fuels, maximum value, 0.6-0.9 CF

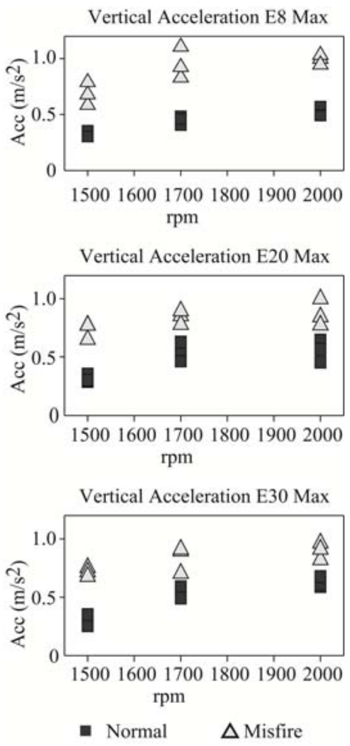

Fig. 6. Vertical acceleration, normal and fault operating conditions on three fuels, maximum value, 0-0.9 CF

A tendency can be seen where lower maximum values take place in normal conditions in comparison to those for conditions with induced misfire, although the differences found were not as clear as with the transversal acceleration. None of the other statistical characteristics provided results as reliable as those from maximum values to assist in the differentiation process between operation ones.

Yet again, longitudinal vibrations signal didn't yield any statistical characteristic capable of providing constant and reliable distinction between the operation modes tested herein.

Frequency domain analysis reported some excited frequencies during normal operation, most of them correspond to the combustion frequency (CF) and its harmonics, a foreseen fact due to typical characteristics of a spark ignited internal combustion engine. The equipment used herein was a four-cylinder engine, whose CF is known to be two times the revolution frequency (RF). The latter also appeared in the analysis. As opposed to literature reporting the largest magnitudes for CF peaks on normal conditions, normal conditions tested at 1500 rpm (Figure 3) revealed RF peaks to be the highest, which in turn can be explained with a test bench problem stemmed from unbalance of the pieces. Specially, the inertia added to the system by the dynamometer attached to the engine.

In parallel with the above analysis, the non-harmonic nature of readings from faulty conditions was confirmed with the presence of 0.75 CF, 1.25 CF and 1.5 CF peaks for all the speed and fuel blend variables of the study, such peaks never appeared on normal conditions measurements. That anharmonicity was also a foreseen fact due to one idle cylinder led to three combustions in a two cycle period.

This work extends the scope of previous studies by including different fuel mixes and thus more scenarios for assessment. Extra amount of oxygen provided by the addition of ethanol changes the characteristics of the combustion process particularly in respect to speed and power of the combustion. However, the same excited frequencies reported in literature with pure gasoline operations were also found in the three ethanol-gasoline blends tested herein, despite that the engine uses a carburettor that does not compensate for the conditions of the fuel.

3.2. Fuel blend detection

Considering the importance of internal combustion engines in the industry and the increasing use of ethanol-gasoline fuel blends, it is important to not only perform fault detection, but it is also of interest to identify the fuel blend being used. Industrial engines normally use carburettors and other relatively simple technology in order to provide reliable performance on tough conditions for long operation hours, making it important to recognise the fuel blend to perform adequate set up and maintenance of the engine components.

The first part of this test was to check the results from the fault detection analysis for differences in the signals from the different fuel blends.

A simple Fast Fourier Transform applied to all the signals did not reveal differences between the fuel blends in any of the recorded data from any of the accelerometers, an example of this can be seen in Figure 3 and Figure 4. Neither different frequency peaks nor differences in the amplitude of the spectrum components allowed classification, because they were inconsistent in the different rotational speeds and even in the different measurements performed at the same operating conditions.

The statistical features were also checked, reaching the same results as no differentiation was possible between the fuel blend signals, in any of the accelerometers, in any of the frequency bands tested.

In order to extract more information from the signals, further processing was required. The proposed method for fault detection was based on the Fast Fourier Transform of the signal and the identification of significant frequencies related to its operation (Like CF and RF). These frequencies are normally very low. But a look at the full spectrum of the signal reveals that there is a great component in higher frequencies above 3 kHz for all tested conditions, for the accelerometers located in the longitudinal and transversal directions. An example of the frequency spectrum up to 10 kHz for E30 at 2000 rpm is presented in Figure 7.

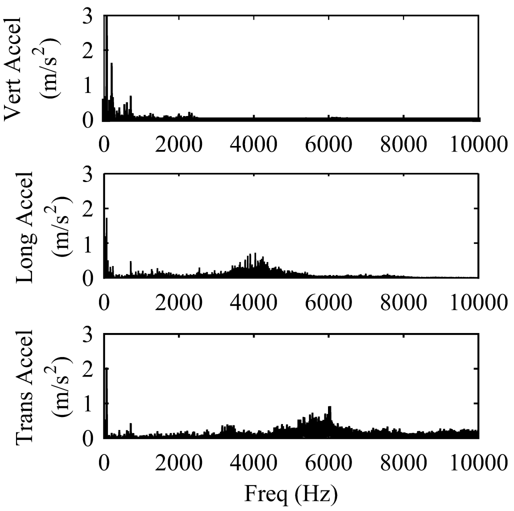

Fig. 7. Frequency spectrum, normal operating condition, E30, 2000 rpm

Given the acquisition frequency of the database, a maximum of 25,6 kHz could be studied, but no signal had significant content beyond 10 kHz.

To take advantage of this behaviour, three different techniques that operate on high frequencies were applied, namely: Envelope, Peak Value and Spike Energy. These techniques are normally used on ball bearing high frequency vibration analysis, looking for stress waves. We found some singular interest in them because they are specially used in high frequency features detection and we are presuming that pressure wave energy can be identified from high level spectrum frequencies, therefore we have tuned their characteristics to better suit the conditions of the collected signals, applying them to slightly lower frequency spectrums than usual. All these techniques operate first filtering the signal to eliminate lower frequencies, then they process it to generate a new signal, which, in the end is transformed to the frequency domain to produce a spectrum that can provide means for differentiation, in the same way as with the fault classification, that is, first a visual comparison and then a statistical feature extraction.

Different types of filters and frequency limits were selected for testing based on the behaviour of the full spectrum of the original signals (Figure 7), to make sure that the frequency bands with more content were studied, and making use of the fact that the filtering selection on these methods relies heavily on operator experience. Those filters were Butter type: high-pass filters at 1000, 3000 and 5000 Hz, and band-pass filters at 2000-5000, 3000-6000, 5000-7000 and 5000-10000 Hz.

Envelope analysis was the first to be tested, an example of the results at 1700 rpm for the band-pass filter at 5000-7000 Hz, from the longitudinal accelerometer are shown on Figure 8.

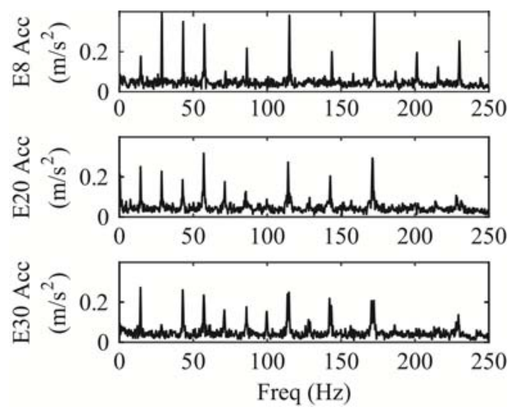

Fig. 8. Envelope spectrum, longitudinal acceleration, 1700 rpm, band-pass filter at 5000-7000 Hz

The results seen in Figure 8 show that the same frequency components are excited when using the different fuel blends on the envelope spectrum. The same happened on all the other rotational speeds and all the other accelerometers. Now considering the peaks magnitude, apparent differences can be seen, for example at 14 or 28 Hz, that can differentiate fuel blends, but this differences were not present at the other rotational speeds, or even when comparing the other measurements done at the same conditions. This kind of behaviour repeated with every filter type and filter limit tested. These results were further ratified with the statistical feature extraction, where no clear differentiation could be made, with inconsistent results that worked only on specific conditions, like only at one speed.

Next, Spike Energy was tested, an example of the results at 1500 rpm for the high-pass filter at 5000 Hz, from the vertical accelerometer are shown on Figure 9. In the Spike Energy spectrum, once again, the same frequency components were excited with all the fuel blends, and again, sporadic differences in magnitudes were present that did not appear at all speeds or when comparing the different measurements done at the same operating conditions. This kind of behaviour was present in the Spike Energy spectrum from all sensors in all filter types and filter frequency limits tested. And, once more, it could be verified with the results from the statistical feature extraction.

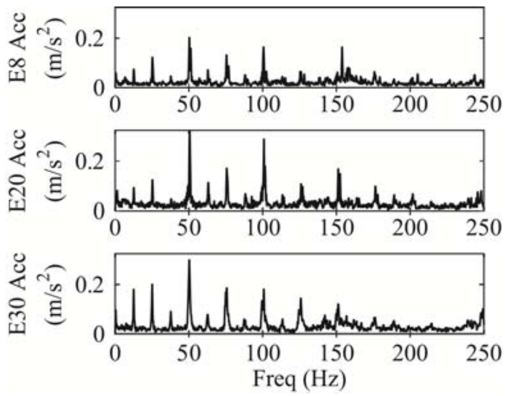

Fig. 9. Spike Energy spectrum, vertical acceleration, 1500 rpm, high-pass filter at 5000 Hz

Finally, Peak Value was applied to the signals and the spectrums were obtained. An example of the results at 2000 rpm for the band-pass filter at 5000-7000 Hz, from the longitudinal acceleration are presented on Figure 10.

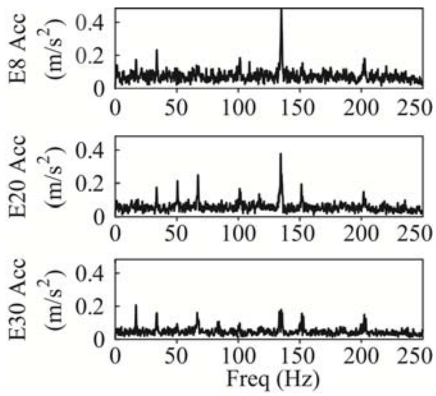

Fig. 10. Peak Value spectrum, longitudinal acceleration, 2000 rpm, band-pass filter at 5000-7000 Hz.

The results from the Peak Value analysis were mixed. Visual comparison of the spectrums revealed a behaviour similar to the ones from envelope and Spike Energy in that the same frequency components were excited in all the fuel blends. When inspecting the differences in magnitudes for the peaks, the transversal and vertical vibration signals provided results that behaved similarly to the ones from envelope and Spike Energy, in that they were inconsistent even after extracting the statistical features. On the other hand, longitudinal vibrations did show differences in magnitudes that were not easy to identify visually, but allowed, on certain filter conditions, to classify the signals from the different fuel blends with the statistical features extracted. The filters that worked were high-pass at 5000 Hz and band-pass at 5000-7000 Hz and 5000-10000 Hz, with the features RMS, energy and mean applied to the frequency spectrums of each of the data sets for each fuel blend and speed. An example of the results is presented on Figure 11.

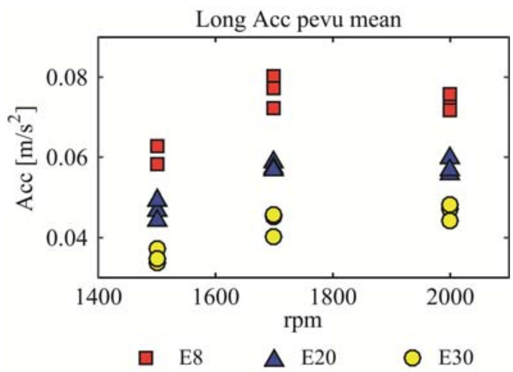

Fig. 11. Mean of the Peak Value, longitudinal acceleration, three fuels, band-pass filter at 5000-7000 Hz

As shown on Figure 11, the mean of the frequency spectrum for the Peak Value data, with a band-pass filter at 5000-7000 Hz, shows enough differentiation between fuel blend signals to allow classification of them. As can be seen, the mean characteristic was extracted from each of the spectrums from the Peak Value analysis for each of the 3 data sets taken for each setup. The means of the Peak Value spectrums for the lowest fuel blend (E8) is the highest, and the means lower with the increase in percentage of alcohol, reaching the lowest values with the highest blend tested (E30). The same behaviour was present in the three mentioned statistical features (RMS, mean and energy) extracted from the Peak Value spectrums of the longitudinal vibration signal, for the three mentioned filter types that worked (high-pass at 5000 Hz, band-pass at 5000-7000 Hz and 5000-10000 Hz), that means higher values for the lowest fuel blends. None of the other statistical features extracted provided consistent means for classification of the fuel blends.

Considering that the statistical features that provided differentiation were those of energy or related heavily to energy (RMS and mean) of the spectrum from the Peak Value analysis, the lower results for the higher fuel blends can be attributed to the differences in combustion speed and cyclic variability produced by the increase in ethanol percentage. A higher concentration of oxygen in the fuel mix, increased flame propagation speed and cyclic variability produce a vibration that excites the same frequencies, but overall on a lower magnitude (a more complete combustion). Since these differences in combustion are very subtle, it could be that the interaction with the engine block was better captured by the longitudinal accelerometer, due to its location in the 4-cylinder engine used in this study (farthest away from most cylinders, with a lot of material in-between), since the Peak Value technique is meant to analyse stress waves from the impacted metal. It would be interesting to further test this methodology on different engines with different configurations.

4. CONCLUSIONS

A time frequency transformation focused on finding frequency components able to differentiate normal from induced misfired condition of an internal-combustion, spark-ignited engine, was applied on three measured accelerations (vertical, transversal and longitudinal). Induced misfire was achieved by taking off spark plug number four. Besides the measurements at three different speeds, the study also expands the research scope by including three gasoline-ethanol fuel blends (E8, E20 and E30). Additional sensors were used for future investigations.

The results herein coincided with the literature, to the extent that the expected presence of three peaks (referred to as 0.75, 1.25, and 1.5 CF) in the transversal direction signal for the induced misfire condition, provided differentiation between the two operations tested herein, in all tested fuel blends.

Eight statistical characteristics were extracted from the signal in the time domain and on several frequency domain bands, aiming to simplify the differentiation process. 7 out of the eight statistical characteristics extracted from the spectrum of the transversal vibrations in the frequency band 0.6-0.9 CF, provided a clear distinction between operational conditions for all the variables tested.

In the case of vertical vibrations signals, the only statistical property that shows a tendency to differentiation between operational conditions for all the variables tested was the maximum value in the frequency band 0-0.9 CF, but it isn't as clear as the differences shown on transversal acceleration. Data from longitudinal vibrations only were able to provide isolated distinctions between conditions since inconsistency was reported throughout the variables of fuel blends and speed during the analysis.

A time frequency transformation focused on differentiating the signals from an engine operating on three different gasoline-ethanol fuel blends was performed. Normal FFT analysis of the signals provided no significant differences between blends, neither in excited frequency nor in the magnitude of the spectrum components, in any of the accelerations measured. Extraction of statistical features corroborated these results.

Further processing of the signals was carried out with three techniques that focus on high frequency analysis: Envelope, Spike Energy and Peak Value. Several types and limits of filters were selected to be used on said techniques based on the results of the full spectrum of the original signal.

Envelope and Spike Energy techniques didn't provide significant difference for the fuel blend classification neither in excited frequency components nor in the magnitude of the spectrum components, in any of the accelerometer signals, in any of the filter configurations tested. Extraction of statistical features corroborated these results.

Peak Value analysis of the signals didn't show characteristic frequencies to identify fuel blends in any of the accelerometers, in any of the filter configurations. However, differences in magnitude of the frequency spectrum were present, with some filters. Fuel blend classification was possible with the extraction of the statistical features mean, RMS and energy in the spectrum from the Peak Value of the longitudinal accelerometer, using the filters: high-pass at 5000 Hz, band-pass at 5000-7000 Hz and 5000-10000 Hz. Results that can be related to stress waves generated differently according to the combustion characteristics of the blend. No other signal or statistical feature provided satisfactory results.

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