Engine knock detection: an eigenpressure approach

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Abstract: In this work a knock detection approach based on in-cylinder pressure principal component analysis is proposed. The introduction of a set of basis functions called eigenpressures - used to describe the principal components of the pressure traces - allows for an easy and effective separation between the typical "bell shape" component of pressure profiles and the knock-induced pressure oscillations, making possible the classification of knocking and not knocking cycles. The proposed approach is compared to a standard knock detection method based on the in-cylinder pressure trace band-pass filtering and to a pure data-driven algorithm. The method shows the best knock classification performances and proves to be advantageous thanks to the low number of easily tunable parameters and their ease of calibration/interpretation.

Keywords: Engine knock, Engine control, Principal Component Analysis, Classification

1. INTRODUCTION

In the spark ignited engine technology, knocking phenomenon is recognized as an undesirable event caused by unburnt gasoline/air mixture self-ignition (Heywood et al. (1988)), and is capable of causing serious engine damages. In the pursue of higher performances and efficiency, production engines underwent to a significant increase of their compression ratio which, unfortunately, leads also to higher end-gas temperatures and pressures, increasing susceptibility to knock (Hudson et al. (2001)). In this context, fuel octane number and spark ignition control come to hand in order to mitigate the knocking behavior: closed-loop strategies have been developed in order to counteract to knock events and operating conditions modification, see *e.g.* Kiencke and Nielsen (2005); Jones et al. (2009).

In order to develop a closed-loop control strategy, detection of abnormal combustion and knock intensity is a crucial aspect. According to Zhen et al. (2012), knock detection can be achieved by means of different methodologies based on the analysis of in-cylinder pressure, engine block vibration, ionization current (Kinoshita et al. (2000)), exhaust gas temperature (Abu-Qudais (1996)) and heat transfer (Worret et al. (2002)). Above all these methods, those based on the investigation of (a) pressure and (b) vibrations are the most common and well-known. The former approach (a) generally relies on band-pass filtering of in-cylinder pressure profiles in order to extract the high frequency signature typical of knocking events, as shown by Millo and Ferraro (1998); Puzinauskas (1992)). Based on these filtered signals, knock indicators such as per-cycle energy, Maximum Amplitude of Pressure Oscillations ($MAPO$) or Logarithmic Knock Intensity (LKI) (Hudson et al. (2001)) may be adopted. The latter approach (b) is based on the idea that end-gas self-ignitions cause vibrations of the engine block which can be studied by means of accelerometers, as proposed by Millo and Ferraro (1998); Pipitone and D'Acquisto (2003). After band-pass filtering the vibration measurements, knock indicators such as root mean square of filtered signals or maximum oscillations amplitude may be computed. Generally, this is a relatively low-cost approach, practical for mass-production vehicles. For both the aforementioned methods, engine cycles are classified as knocking or not knocking depending on whether the computed indicators are exceeding some thresholds or not.

In this paper, a knock detection technique based on in-cylinder pressure Principal Component Analysis (PCA) is proposed. The main idea is the description of pressure profiles by means of a restricted set of eigenvectors - called eigenpressures - computed relying on PCA over experimental pressure data. This allows for a clear separation between the typical "bell shape" component of pressure traces and the knock-induced pressure oscillations, making detection of knocking cycles easier. One of the major advantages of this methodology is the low number of tuning parameters which can be easily adjusted without the need of a complex pressure traces spectral analysis. Moreover, the proposed approach is prone to an easier interpretation and prediction of the knock detection perfor-

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mances. The paper focuses not only on the computation of knock indicators but also on thresholds selection (decision hyperplanes) by means of logistic regression: this allows for a performance-oriented calibration of the algorithm parameters which, to the best of the authors' knowledge, is not discussed in the available scientific literature. To assess the performance of the presented approach, a comparison with a standard pressure based detection method and with a pure data-driven technique is proposed considering pressure data acquired from an in-line six cylinders marine engine. Eventually, this method shows also to be easily implementable and suitable for real-time applications.

The paper is organized as follows. Section 2 recalls a standard knock detection technique based on band-pass filtering of pressure traces. Then, Section 3 introduces the novel knock detection method based on eigenpressures analysis and Section 4 discusses a pure data-driven approach. In Section 5, a comparison between the three detection methodologies is advanced. Finally, in Section 6 the contributions of this work are summarized.

2. STANDARD KNOCK DETECTION

Self-ignition of unburnt air/fuel mixture causes pressure waves inside the cylinder, absent when self-ignition does not occur. The availability of an in-cylinder pressure sensor gives a direct sight of knock occurrence and eases its detection. Indeed, to objectively assess the knock occurrence of a combustion cycle a common procedure is to extract the oscillation from the pressure traces, to evaluate its relevance and to assign a knock/no-knock label, see *e.g.* Millo and Ferraro (1998). A key feature which makes such approach effective is that pressure oscillations show a dominant frequency, which can be related to geometrical parameters of the engine and of the mixture composition. Thus, by properly filtering the cycle pressure trace it is possible to extract the oscillations and evaluate their relevance: the index which is commonly employed for this task is the so called $MAPO$. The actual implementation of

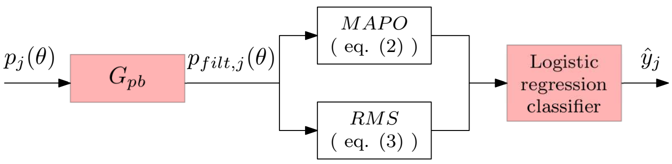

Fig. 1. Block diagram of the standard knock detection algorithm.

the previously discussed method is depicted in the block diagram of Figure 1. The signal $p_{filt,j}(\theta)$ (where θ refers to the engine crank angle and j to the cycle count) is obtained band-pass filtering the measured pressure traces $p_j(\theta)$. For the sake of simplicity the band-pass filter is defined as follows:

$$G_{bp}(s) = \frac{(2\pi f_{osc} \cdot s)^n}{(s^2 + 2\pi f_{osc} \cdot s + (2\pi f_{osc})^2)^n} \tag{1}$$

with $2 \cdot n$ poles located at $2\pi f_{osc}$ [rad/s] and n zeros in the origin. For the actual implementation, the filter is discretized using a sampling time of $T_s = \Delta_\theta / \omega$ where Δ_θ is the crank-angle sampling resolution of the pressure trace and ω the engine speed (expressed in [°/s]). Figure 2 shows an example of a knocking pressure trace and its corresponding filtered version, as function of the crank angle (the top-dead-centre - TDC - is explicitly marked).

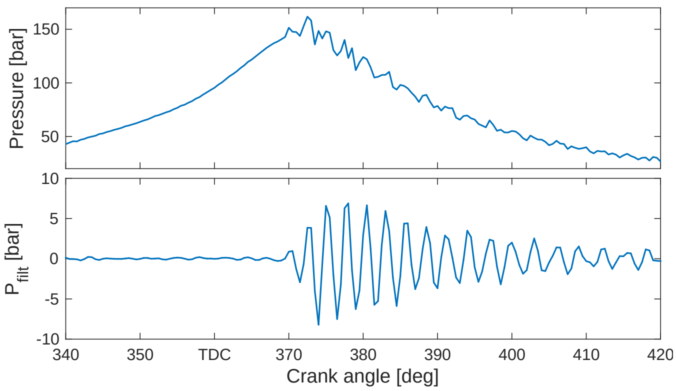

Fig. 2. Knocking pressure cycle (upper plot) and band-pass filtered version (lower plot).

The band-pass filtered pressure is then processed in two ways. On the one side, the $MAPO$ is computed according to:

$$MAPO_j = \max |p_{filt,j}(\theta)| \quad \text{where } \theta_{min} \leq \theta \leq \theta_{max} \tag{2}$$

where θ_{min} and θ_{max} define a region of interest in the crank angle domain. On the other side, the filtered pressure signal energy is evaluated by means of the Root Mean Square (RMS) value (3): this precaution - usually not discussed in scientific papers - in practice helps to make the knock detection more robust, avoiding false detections due to mechanical vibrations or electromagnetic induced disturbances:

$$RMS_j = \sqrt{\frac{1}{\theta_{max} - \theta_{min}} \sum_\theta p^2_{filt,j}(\theta)}. \tag{3}$$

Both indicators are used to assess the cycle knocking behavior. In the present context, the two variables are used following a genuine classification approach using logistic regression. This choice is motivated by the fact that such approach proves to be effective also when the covariates are not gaussian-distributed, which is the case for the $MAPO$ (2) and the signal energy (3).

2.1 Parameters and tuning

The red-shadowed boxes of Figure 1 represent the tunable part of the standard knock detection algorithm. The band-pass filter features two parameters: the first one is the frequency f_{osc} whereas the second is the filter order n. Both should be tuned in order to extract in the most effective way the pressure oscillations. Despite being related to engine geometric characteristics, in fact, pressure waves due to self-ignition show a non trivial frequency content: as a result, usually the design of such parameter is shepherd by the spectral analysis of knocking and not-knocking cycles. An example is reported in the upper plot of Figure 3, where it is clearly visible the high frequency content of pressure waves during knocking cycles. However, given the wide range of frequency excited, the selection of the band-pass filter frequency f_{osc} is not immediate: as a matter of fact, the most common approach is to set f_{osc} in the location of the peak of the high-frequency knock content. It should be remarked how the pressure waves spectrum varies not only for different engine geometry, but also when slight changes of the operating conditions occur, for example for different boost pressure, intake temperature, air/fuel ratio; moreover, given the random nature of knock, see Jones et al. (2013), the pressure wave spectrum is expected to change from cycle-to-cycle. This means that the inspection of different knocking cycles spectra might lead to a different settings for the parameter f_{osc}: this is for example what happens in Figure 3, where for cycle number 1 f_{osc} is set equal to 2584Hz, whereas inspecting cycle number 2 the corresponding f_{osc} would be 2704Hz. The filter order selection (n) is less straightforward than

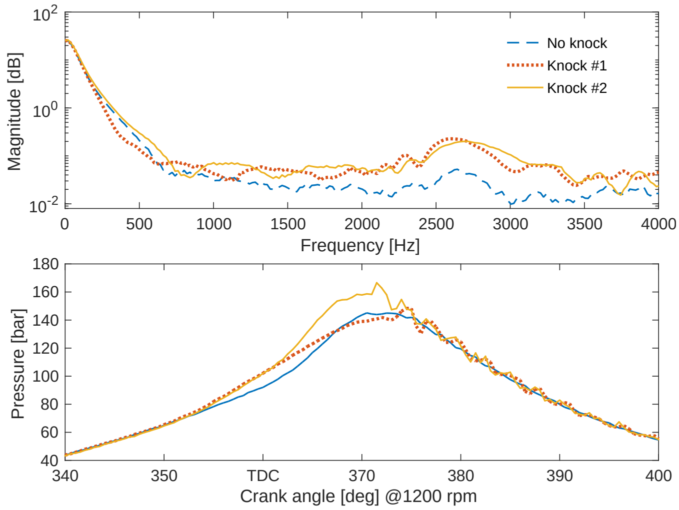

Fig. 3. Comparison of the spectral content (top plot) of three different pressure traces (bottom plot).

the choice of its band-pass frequency. As it can be seen from Figure 3, to preserve most of the spectral content a low order (less selective) filter should be chosen. A higher filter order could be set to narrow the harmonic analysis only around the main components of the oscillations: however, given the width of the spectrum even around the main oscillation frequency, with the selected band-pass filter structure (1) a small increase of n might lead to an excessive filtering. For this reason, the design of n is typically made by trial-and-error, aiming at maximizing the knock detection performances.

The logistic regression classification requires the design of the parameters of the hyperplane that divides the features hyperspace in two regions respectively referred to the knocking and the not-knocking cycle label. In the present context, the two features used to classify the cycle knocking behavior are (2) and (3). The tuning of the decision boundary parameters is accomplished by maximizing the conditional likelihood $\mathcal{L}$:

$$\mathcal{L}_{\alpha,\beta} = \mathcal{P}\left(y_1, \dots, y_k \,|\, \mathbf{x_1}, \dots, \mathbf{x_k}\right) = \prod_{j=1}^{k} \frac{e^{(\alpha+\boldsymbol{\beta}\mathbf{x_j})y_j}}{1+e^{(\alpha+\boldsymbol{\beta}\mathbf{x_j})}}$$

where, $\mathbf{x_j}$ is the feature vector of the j-th cycle, y_j its knocking status ($y_j = 1$ for knock, $y_j = 0$ for no knock), α and $\boldsymbol{\beta}$ the parameters which define the hyperplane. In the present work, the Matlab *glmfit* method was used to solve such maximization problem.

3. EIGENPRESSURE KNOCK DETECTION

The rationale behind the proposed eigenpressure approach lies in the fact that a given pressure profile ($p_j(\theta)$) can be described as a linear combination of basis functions, the so called eigenpressures $\bar{p}_i(\theta)$:

$$p_j(\theta) = \sum_{i=1}^{l} \gamma_{i,j} \cdot \bar{p}_i(\theta) \tag{4}$$

where $l = (\theta_{max} - \theta_{min})/\Delta_\theta = 720$ is the length of the pressure trace vector. Such basis functions are computed offline performing a *PCA*, via a Singular Value Decomposition (*SVD*), on a set of experimental pressure profiles. Once the basis are defined, for any j-th measured pressure profile the coefficients of the linear combinations $\gamma_{i,j}$ are computed as its projection on the i-th eigenpressure. From a more intuitive perspective, such decomposition aims at describing the pressure profile in terms of its “most important” components. In fact, the eigenpressures can be sorted in terms of their relevance in describing the pressure profile: the *SVD* procedure, along with the eigenpressures, provides the singular values which naturally perform this ranking. To provide a visual interpretation, in Figure 4 the singular values of the *SVD* performed over 2000 pressure profiles are shown: it is interesting to notice how the first eigenpressure - depicted on the lower plot - has the typical “bell shape” of a pressure profile, which is indeed the most relevant characteristic of any pressure trace. By truncating

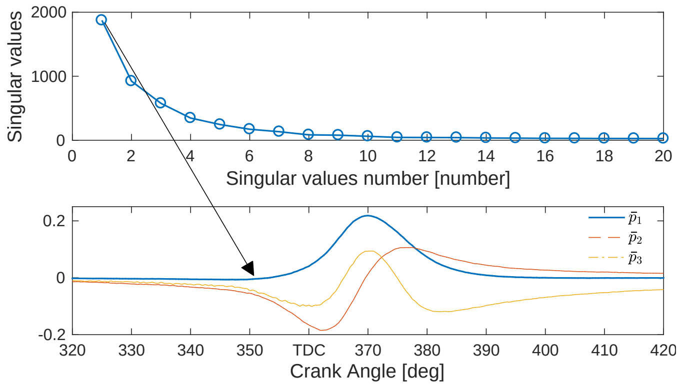

Fig. 4. Singular values of SVD performed over 2000 pressure traces.

the sum of weighted basis in equation (4), one can obtain an *approximated* pressure profile:

$$\tilde{p}_j(\theta) = \sum_{i=1}^{n} \gamma_{i,j} \cdot \bar{p}_i(\theta), \qquad n \leq l. \tag{5}$$

As a matter of fact, by using a very limited amount of basis, it is possible to approximate a pressure profile with a satisfactory accuracy: in Figure 5 the average maximum and root mean squared reconstruction error are shown, along with an example of pressure profile approximation using 1 and 20 eigenpressures. The approximation capability of the eigenpressures approach was successfully used in the literature, mainly to reduce the complexity in modeling and regression problems, see *e.g.* Formentin et al. (2014); Henningsson et al. (2012). In the present context, the motivations to employ this method are different. In fact, the oscillations in the pressure trace of a knocking cycle can be seen as a *minor* component in the overall

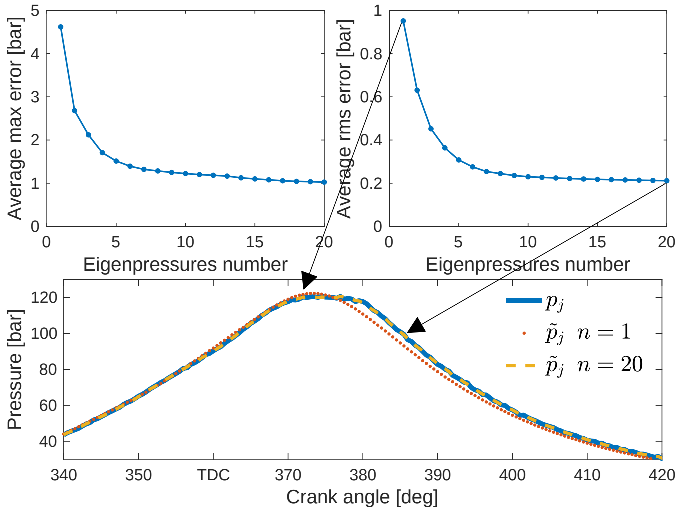

Fig. 5. Average RMS and maximum reconstruction error (top diagrams) as function of the number of eigenpressures (n). The crank angle reconstruction of a sample pressure profile for $n = 1$ and $n = 20$ is shown in the lower panel.

pressure curve trend and will thus likely not be captured in a reconstructed pressure profile. Thus, the idea is to extract the pressure oscillations by inspecting the residual signal of the pressure profile reconstruction:

$$p_{res,j}(\theta) = p_j(\theta) - \tilde{p}_j(\theta). \tag{6}$$

In Figure 6, an example of the proposed approach is shown and applied to the same pressure trace shown in Figure 2. Once the residuals are computed, they are used in the

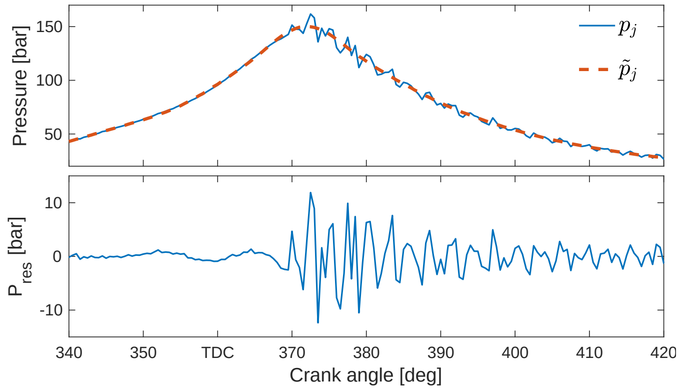

Fig. 6. Knocking pressure cycle (solid) and reconstructed eigenpressure profile (dashed) in the upper plot. Residuals (6) in the lower plot.

same fashion as the filtered data $p_{filt,j}$ of Section 2: the maximum value, as in (2), and its energy (3) are computed and used as describing features to feed the cycle knocking behavior classifier.

3.1 Parameters and tuning

The eigenpressure knock detection algorithm is represented in Figure 7, where the red-shadowed blocks refer to the tunable part of the algorithm. The calculation of $\tilde{p}_j(\theta)$ requires the sole choice of the number of eigenpressures n used to truncate the sum in (4). On the one side, having a high value of n is desirable, so to have an overall precise

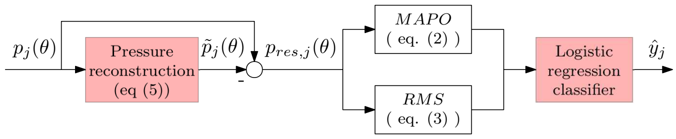

Fig. 7. Block diagram of the eigenpressure knock detection algorithm.

pressure profile reconstruction. On the other side, when the number of eigenpressures increases, the waves become an *important* part of the pressure profile, which is left over by low order approximations. As a matter of fact, higher values of n lead to a reconstructed pressure profile which includes also knock-induced oscillations: in the perspective of computing a signal for knock detection this is not a wise choice since the pressure oscillations disappear in the computed residuals (and it is likely that it will not be easy to detect knock from their analysis). This situation is shown in Figure 8: it is clearly visible how the $\tilde{p}_j(\theta)$ built with $n = 11$ eigenpressures is capable of describing the pressure waves; in the corresponding residuals the pressure oscillations (which are clearly visible in the residuals computed using $n = 10$) disappear.

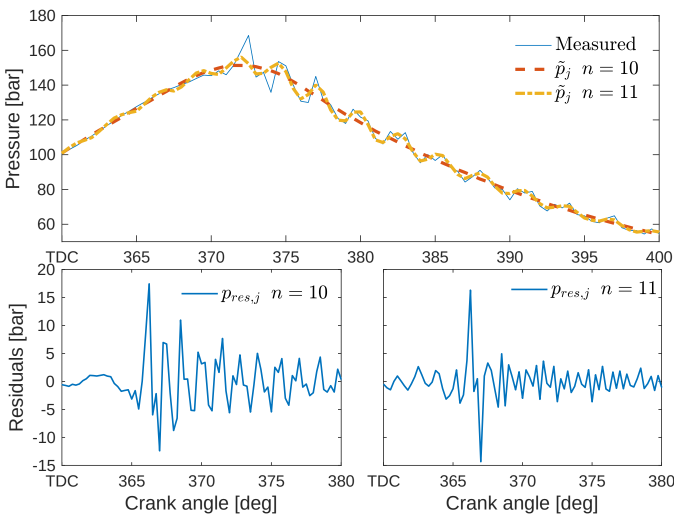

Fig. 8. Comparison of pressure reconstruction using a different number of eigenpressures. The corresponding residuals (6) are shown in the lower plots.

The selection of the proper value of n does not actually require the pressure profile reconstruction analysis, but can be carried out by a straightforward inspection of the eigenpressures $\bar{p}_i(\theta)$. For the present case (see Figure 9), all the eigenpressures from $i = 1$ to 10 are characterized by a smooth shape, which describes the overall pressure trace trend in the crank angle domain. Conversely, for values of $i \geq 11$ high frequency oscillations are clearly visible in the eigenpressures. This reveals that from $n \geq 11$ the accuracy of the knock detection algorithm is expected to decrease, for the previously discussed mechanism.

The other parameters of the algorithm which must be tuned are those of the logistic regression block. Being based on the same choice of classification features, this part of the algorithm can be tuned following the same automatic procedure suggested in Section 2.1.

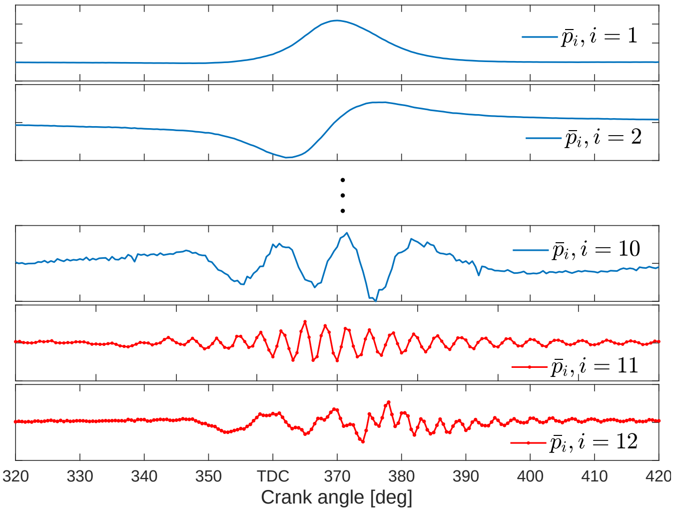

Fig. 9. Eigenpressures $\bar{p}_i$ for $i = 1, \ldots, 12$.

4. DATA-DRIVEN KNOCK DETECTION

When dealing with internal combustion engines, it is common practice to employ simplified physics based models to relate in-cylinder pressure measurements to relevant engine quantities. Given the difficulty in finding physics-based values for the parameters of such models, an alternative is to directly train data-driven models without imposing any model structure but with the sole goal of achieving the best performance. In general, the data-driven modeling approach shows very poor validation results when too many regressors are used: the eigenpressure decomposition, in this perspective, leads to more effective results since it allows a pressure profile description using only few parameters (compared to the number of samples needed to define the pressure profile in the crank angle domain, equal to $l = 720$). This fact was efficiently exploited in in-cylinder pressure data-driven modeling: for instance in a recent paper of the authors this approach was applied to engine knock probability modelling (Panzani et al. (2016)) and control (Panzani et al. (2017)), in Formentin et al. (2014) and Henningsson et al. (2012) to estimate the NO_x emissions of a diesel engine and the air/fuel ratio, and finally in Moser et al. (2013) to control the delivered engine torque.

The last approach proposed to knock detection is to directly employ the eigenpressures coefficients $\gamma_{i,j}$ to feed the logistic regression, pursuing a pure data-driven classification. The only parameter that must be tuned by the practitioner is the number n of considered eigenpressures: considering the reconstruction capabilities shown in Figure 5 a maximum value of 20 eigenpressures is selected.

5. COMPARISON AND DISCUSSION

The proposed knock detection algorithms are tested on real data acquired from a dual fuel in-line six cylinders marine engine, provided by Wärstilä and characterized by: a power output of 1200kW at 1000rpm, a cylinder bore of 200mm, and a piston displacement of 8.8l/cyl. A total amount of 2994 engine cycles were recorded, inducing different knocking conditions by means of main fuel injection duration changes. To assess the actual cycle knocking status, all the cycles were first analyzed by an expert and cross-checked with other sensors (see the Introduction) installed on the test bench equipment: 984 cycles were classified as knocking (more than 30%).

To validate the classification performances a K-fold data cross validation is performed, with $K = 10$; no significant difference is observed by increasing or reducing the value of K. In each K-th fold, an average of 30% of knocking cycles are kept, so as to avoid extreme and unrealistic situations with no knocking cycles in the validation dataset. In this scenario, the average percentage misclassification error:

$$\varepsilon_{\%} = \frac{1}{K} \sum_{k=1}^{K} \frac{1}{p} \sum_{j=1}^{p} (y_j - \hat{y}_j) \tag{7}$$

is used to compare the different detection algorithms. In equation (7), for each K-th fold, p is the validation set size, y is the true knocking behavior and $\hat{y}$ is the classifier outcome. Index (7) provides an estimate of the average probability of misclassification for a new observed data.

A summary of the classification performance is shown in Figure 10, where for each algorithm, a sensitivity analysis with respect to the parameter n is done. For the standard algorithm (Section 2) n is the band-pass filter order, for the eigenpressure algorithm (Section 3) n is the number of eigenpressures used in (5), and for the data-driven algorithm (Section 4) n is the number of eigenpressures used to directly feed the classifier. The

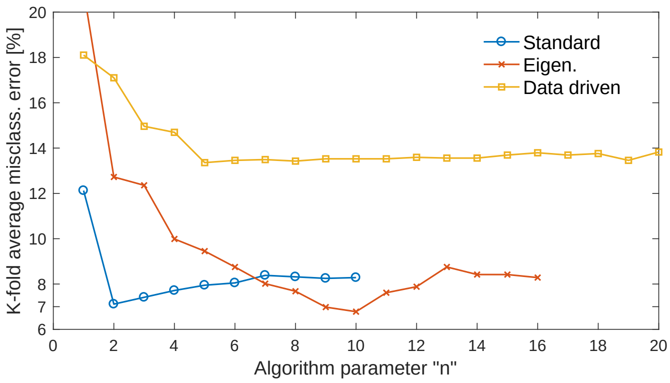

Fig. 10. Misclassification error (7) for the three proposed algorithms, as function of the parameter n, which assumes a different meaning according to the selected algorithm (see Section 2, 3, and 4).

overall best classification performances are obtained by the eigenpressure algorithm, which provides an averaged (over the K folds) misclassification error below 7%; the standard method performs slightly worse. In addition, by inspecting each of the K classification performances, it can be seen that the standard methods performs better than the eigenpressure one only in the 30% of the times. The worst classification performances are obtained for the data-driven approach which reaches only a lower value of $\varepsilon_{\%} \approx 13\%$. Thus, despite the excellent modeling performances of data-driven methods shown by different authors, this approach does not fit for the knock detection task: this could be explained considering that a linear classifier is not capable of extracting complex information like the maximum oscillations amplitude and their energy from the reconstructed pressure profile.

The eigenpressure approach error $\varepsilon_{\%}$ as function of n confirms the reasoning proposed in Section 3.1: the best classification performance is obtained with $n = 10$ which is the number of eigenpressures that allows for a precise approximation of the pressure profile, without including the pressure waves oscillations. The interpretation of the misclassification performances of the standard method is more difficult. The upper plots of Figure 11 clearly explain the poor results obtained when a low order band-pass filter is used: indeed the residuals (left-upper part of the diagram) show a significant low frequency component, not related to the fuel self-ignition, which leads to a false knock detection. The right-upper plot, which shows the spectral analysis of the pressure trace before and after filtering, confirms the same result. Conversely, when $n \geq 2$ is considered, the residual inspection is no longer useful in interpreting the classification results, as they look very similar in the two cases despite the spectral analysis clearly reveals a difference in the spectral content of the two signals. In other words, the proper choice of the band-pass filter order is highly related to the classification performance and cannot be anyhow done in advance, leading to a more difficult and iterative tuning process.

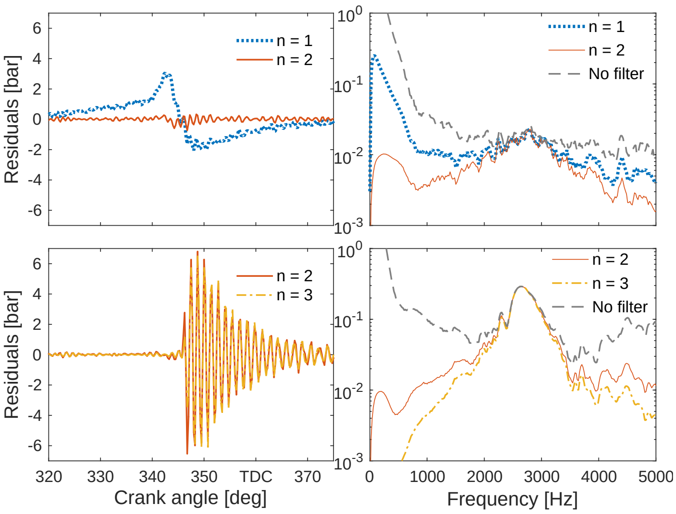

Fig. 11. Filtered pressure $p_{filt,j}$ for different values of the band-pass filter (1) order (left plots). Spectral analysis of the unfiltered and filtered pressure traces (right plots).

6. CONCLUSIONS

In this paper, a *PCA* of in-cylinder pressure traces is used to develop an algorithm for knock detection. Compared on real experimental data with a standard band-pass filtering approach, the eigenpressure decomposition proves to extract in a more precise way the knock-related oscillations of the pressure profile; moreover it is shown how the effort to tune the algorithm is minimal, due to the straightforward interpretation of its parameters in terms of misclassification error. The proposed algorithm is also prone to an actual engine online implementation: in fact it requires only the cycle-per-cycle calculation of (5) and (6), since the *SVD* can be performed off-line on a batch of collected data. Moreover, it does not require any operating point parameter adaptation as it is required for the band-pass filter approach (see Section 3). A pure data-driven classification approach is also tested. Experimental results show worse performances of such approach, suggesting the possible use of more complex (nonlinear) classification approaches for a pure data-driven knock classification.

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