IN-CYLINDER PRESSURE RECONSTRUCTION USING VIBRATION MEASUREMENTS AND DEEP CONVOLUTIONAL NEURAL NETWORKS

Amaury Bosso André, amaury.andre@gmail.com[1,2]
Jacques Wainer, wainer@ic.unicamp.br[1]
Eduardo Beltrame, eduardo@semeq.com.br[2]
Afonso Henriques Moreira Santos, afonso@ixconsult.com.br[3]

[1]Instituto de Computação - Unicamp, Av. Albert Einstein, 1251 - Cidade Universitária, Campinas - SP - Brasil
[2]Semeq, Av. Laranjeiras, 2392 - Egisto Ragazzo, Limeira - SP - Brasil
[2] iX Estudos e Projetos, R. Cel. Joaquim Francisco, 341 - Varginha, Itajubá - MG - Brasil

Abstract: *In-cylinder pressure signal, during the combustion process, is an important parameter for fault detection in internal combustion engines. It impacts in reliability and efficiency, as far as consumption and pollutant emission. Directly measure in-cylinder pressure has many drawbacks due to the harsh environment inside the combustion chamber: it needs a costly transducer, which has a very limited life-time. The use of indirect measurements have great potential, and many methodologies were proposed in the past. But they all need pre- or post-processing in vibration data, or depend on specific operational conditions. In this work, a deep Convolutional Neural Network (CNN) fed with raw vibration data is used to reconstruct the in-cylinder pressure signal. A single accelerometer per cylinder can be used for constantly monitoring the combustion process for large internal combustion engines used in a power generation plant.*
Key-words: *vibration, pressure, internal combustion, engine, convolutional neural network*

1. INTRODUCTION

Real time condition based monitoring of internal combustion engines, used in power generation plants, plays an important role in preventing unexpected breakdowns, and consequently stoppage in power generation. Continuously measuring combustion parameters permits a reduction in fuel consumption and in pollutant emissions. As most defects found in internal combustion engines are directly related to the combustion process, the in-cylinder pressure provides useful information in the detection of combustion phasing, leakages due to degradation in the piston ring or in the cylinder wall and injection problems.

Directly measuring in-cylinder pressure has several drawbacks: a high performance and highly resistant transducer is required due to the harsh environment that it is exposed in the cylinder combustion chamber. This makes pressure sensors considerably more expensive in comparison to other type of sensors, such as accelerometers and tachometers. The harsh environment significantly reduces pressure transducer lifetime when permanently mounted in the inspection point. Combustion chamber deposits on the transducer through time is also an important drawback for constant direct measurements. All these factors reduce the efficiency, accuracy and mainly the economic feasibility of the constant monitoring process using dedicated pressure sensors for direct measuring.

Indirect methods have great potential for engine diagnosis, and many methodologies were presented in the past with good accuracy. They use non-intrusive techniques and sensors, such as accelerometers and tachometers, instead of pressure transducers. These sensors are externally mounted on the engine block. The goal is to detect combustion events through vibration signals, as they happen in an integrated way. These events come from the cylinder pressure internal dynamics and are transmitted to the engine external surfaces Jia *et al.* (2015), such as valve opening and closing, fuel injection and burning, and mechanical abrasion.

A method that uses acoustic emission signal was presented in El-Ghamry *et al.* (2005). It reconstructs the pressure signal in a large two-cycle and in a small four-cycle diesel engines. The approximation results were satisfactory, both in time and in frequency domain. A cepstrum based modeling was used. It was concluded that the acoustic emission signal did not present a direct answer to the combustion process, and that, the extrapolation for load and rotation conditions different than the parameters tested in the work is a difficult task using only acoustic emission signals. Another work that uses acoustic signals for pressure reconstruction is Barelli *et al.* (2009a), but vibration signals are used in combination for diagnosing condition in internal combustion engines.

The angular speed variation of crankshaft is also an important indirect measurement for combustion monitoring. In Barelli *et al.* (2009b), a Recurrent Neural Network (RNN) is proposed for cylinder pressure reconstruction, but it is shown that single RNN is not capable of reconstructing pressure for complete operating domain of engine distributed over load torque and engine speed. Work presented in Weißenborn *et al.* (2011), adapts a non-linear model for rotational speed, to detect combustion parameters, such as maximum pressure and its angular location. In Taglialatela *et al.* (2013), combustion parameters identification is also performed through crankshaft speed, but a Multi-Layer Perceptron (MLP) neural network is used, with promising results.

Most of traditional techniques use vibration signal measured through externally mounted piezoelectric accelerometer pick-ups in the engine block. Some developed time-domain methods from vibration signals. Work presented in Businaro *et al.* (2015) estimates some combustion process parameters as maximum pressure peak amplitude and its relative location. Work presented in Zhu (2007) directly reconstructs the in-cylinder pressure signal using time-domain acceleration, through a Vibration Transfer Function (VTF). In Chiatti *et al.* (2017), one accelerometer vibration signal is used for parameter estimation in a multi-cylinder diesel engine. All these works promising results, show that vibrations contain information about the combustion phenomenon. But they all make use of preprocessing techniques to extract combustion related components and to improve signal to noise ratio.

Frequency Response Function (FRF) are also used to make in-cylinder pressure reconstruction from acceleration signal. In Jia *et al.* (2015), they concluded that a pure FRF did not give sufficiently accurate pressure signal approximation results, and so a combination of the proposed FRF with a Particle Sworm Optimization (PSO) algorithm brought the results closer to what was expected.

Neural networks based on Radial Basis Function (RBF) are very successfully used in pressure reconstruction and combustion parameters identification. Many works such as Bizon *et al.* (2015, 2011); Johnsson (2006); Jia *et al.* (2013), take advantage of the non-linear model provided by RBF networks. Although high accuracy are achieved, in most cases large training sets, in several different rotation and load conditions, are required in order to train the neural networks in the most different engine operation possibility variations. They also depends on pre- or post-processing signal techniques.

The main novelty of this paper consists in the application of deep Convolutional Neural Networks (CNN) for in-cylinder pressure reconstruction from time-domain acceleration signal. CNN are getting increasing attention in recent works as a robust and efficient feature learning model for condition monitoring. In Chen *et al.* (2015), faults in gearbox are classified using a CNN to learn from a set of 256 predetermined features extracted from vibration signals. In Janssens *et al.* (2016), fault detection in rotating machinery is performed by a CNN over vibration signals but converted in frequency domain. In Ince *et al.* (2016), a CNN fed with the raw vibration data, measured directly by an accelerometer, is used for motor fault detection. All these works show results that outperform classical feature-engineering based methods.

Results obtained in the literature show that vibration based methods are effective for the reconstruction of in-cylinder pressure, important for internal combustion engine monitoring. More recent work, show that representative features can be extracted automatically from the raw vibration signals. It avoids manual feature extraction or selection, which rely heavily on prior knowledge of specific machinery conditions such as rotation and load.

2. CONVOLUTIONAL NEURAL NETWORK

The convolutional neural network architecture presented in figure 1 shows how to perform pressure reconstruction from raw vibration signals. Thre are two distinct phases, the first responsible for feature extraction, that comprehends convolutional and pooling layers, and the regression phase itself, of a densely connected multilayer perceptron neural network.

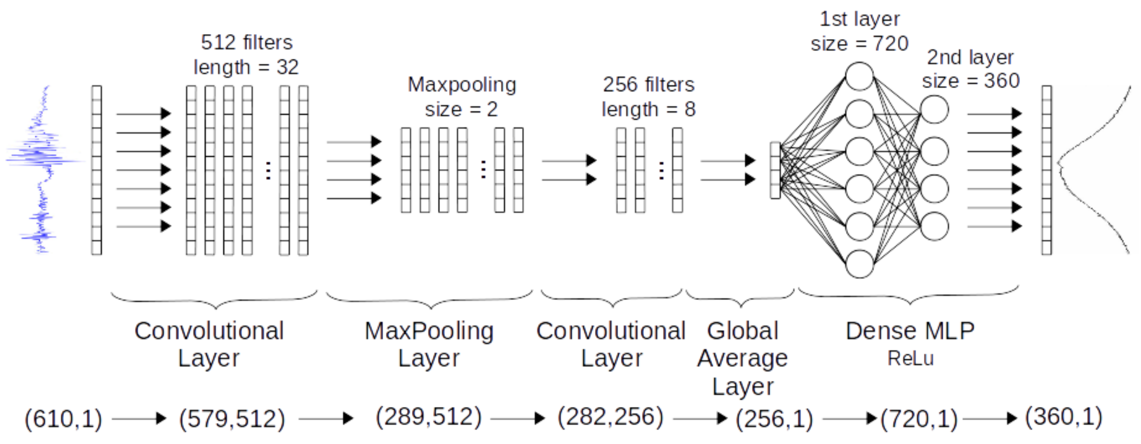

Figura 1: CNN architecture and hyper parameters used.

2.1 CONVOLUTION LAYER

This layer applies a convolution operation in the unidimensional vibration signal with filter kernels, followed by the activation unit to generate output features. Equation 1 shows the convolution operation of a filter f, with size of $2k$ to a unidimensional signal g.

$$(f * g)[n] = \sum_{m=-k}^{k} f[m]g[n-m] \tag{1}$$

The result of the convolution operation is passed to an activation unit. Rectified Linear Unit (ReLU) is used as activation unit to accelerate the convergence and to enhance the representation ability of the CNNs. The formulation of a ReLU unit is presented in equation 2.

$$r(x) = x^+ = max(0, x) \tag{2}$$

2.2 POOLING LAYER

CNNs have a pooling layer after the convolution operation to reduce size of the features extracted in the network. The most common pooling strategy is a max-pooling layer, which preserves the local max value over the input features. For each n values, the pooling layer keeps the max values and discards the others.

2.3 REGRESSION LAYER

The regression layer consists of a densely connected Multilayer Perceptron Neural Network. This layer uses the features automatically extracted from the convolutional and pooling layers before, and learns is weights to generate the correspondent pressure curves.

The regression layer uses the ReLU activation unit, the same used in convolutional layers before.

3. EXPERIMENTAL SETUP

The experiments were carried out in a power generation plant in Brazil, consisting of 38 Wärtsilä W20V32 engines (Figure 2). They run with fuel oil type B1, that has lower sulfur content and lower viscosity limit. Wärtsilä W20V32 is a vee engine with 20 cylinders divided in two banks: from A1 to A10, and from B1 to B10. Each engine has a generation capacity of $8,73MW$ at $60Hz$, while the whole power plant has a total capacity of $331,74MW$, and consumes more than 1600 ton/day of fuel oil. More engine specifications are listed below.

- Bore: 320mm
- Stroke: 400mm
- Con Rod: 850mm
- Rotation Speed: 720rpm

The data acquisition system used (figure 2) is able to record up to 8 channels simultaneously, with 13 bits of resolution and maximum acquisition rate of $1MS/s$. To run the experiments on the generators engines, three channels were used, each one with $24KS/s$ of sampling rate: one for the tachometer signal, measuring its rotation speed for synchronization purpose; one for the vibration signal from a piezoelectric accelerometer; and the third channel for the in-cylinder pressure reference curve.

The accelerometer used for vibration measurements is a piezoelectric one with $100mV/g$ of sensitivity, dynamic range of $\pm 50g$ peak and maximum shock protection of $5000g$ (peak). The accelerometer temperature range varies from -50 to 121^oC, while its frequency range response with $\pm 3db$ is 0.5 to $15000Hz$. To measure rotation speed, a laser photo tachometer with $0.25ms$ of answering time and work temperature range of -10 to 50^oC was used. In-cylinder pressure signal was acquired using an AVL sensor with $13mV/bar$ sensitivity, measuring range of 0 to $150bar$, and operating range of -10 to 110^oC.

Five different engines were measured in the power generation plant. For each one, the flying wheel had to be marked with a reflexive tape for tachometer readings of rotation speed. To guarantee repeatability, the reflexive tape was positioned in the same place for every engine, on the TDC point of the first cylinder A1, assumed as the zero degree reference. The angles, together with the cylinders sequence of combustion, were retrieved from empirical measurements of the engine geometry, and can be seen in table 1.

Tabela 1: Cylinders angles of TDC.

Cylinders angles from reference A1									
A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
0	232.5	155	77.5	670	310	465	540	592.5	387.5
B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
60	292.5	215	137.5	729.5	370	525	574.5	652	447.5

All engines were measured in operational condition, with $720rpm$ of rotation speed. It could not be changed during power generation, because the frequency of the generator is dependent upon its speed of rotation. Measures were taken

Figura 2: Wärtsilä engines in the power generation plant.

in 3 load conditions: 50%, 75% and 100%. Vibration data were measured by accelerometers positioned directly on the engine's block, nearest to the TDC point of each cylinder.

Every engine had each of its 20 cylinders measured, and 4 seconds of signal acquisition length were acquired. In four-stroke engines, there is one combustion cycle every two rotations of the crankshaft. Running at $720rpm$, which corresponds to $12Hz$, there are 6 combustion cycles per second of signal. Since 4 seconds are measured, there are a total of approximately 24 cycles per signal. For 20 cylinders, in 3 load conditions, for 5 different engines, a total number of cycles measured was around 7200.

The convolutional neural network used in this work consists of a convolutional layer, with 512 filters of size 32, followed by a polling layer that reduces to the half the number of extracted features. Then, another convolution layer is applied, of 256 filters of size 8, followed by an average pooling layer. Which results in a 256 length feature vector.

The regression layer consists of a MLP network of two layers, the first one with 720 units and the second one with 360 units, densely connected. Figure 1 shows the CNN used in this work. It also shows signal dimensions in each step of the network.

For comparison purpose, some commonly used algorithms for signal regression are used: Multi-Layer Perceptron (MLP), Extra-trees, K-Nearest Neighbor (KNN) Regressor, and Ridge Regressor. Two different comparisons were made: one with the same dataset used in the CNN Regressor training; and one with traditional preprocessing for vibration signal, as used in Chiatti *et al.* (2017).

3.1 SIGNALS PREPROCESSING

Convolution Neural Networks, as presented here, use only raw signals as inputs. However, the techniques used for comparison perform better with a preprocessing phase. For a fair comparison with the other techniques, the signal manipulation made for the other techniques are presented in this section. Raw signals measured simultaneously of vibration, in-cylinder pressure and rotation can be seen in figure 3.

Due to the high sampling rate used in the acquisition system $24kHz$, and also some noise in the acquisition process, the original pressure signal presents a non-smooth aspect. To eliminate this distortion, a Savitzky-Golay filter is applied to pressure data to increase the noise–signal rate without distorting the original waveform. This is obtained through a convolution, by coupling successive subsets of adjacent points with a low degree polynomial using the Linear Least Squares. The Savitzky-Golay filter has the following formulation:

$$Y_j = \sum_{i=-\frac{(m-1)}{2}}^{\frac{(m-1)}{2}} C_i y_{i+1}, \frac{(m-1)}{2} \leq j \leq n - \frac{(m-1)}{2} \tag{3}$$

In equation 3, C_i is a set of m convolution coefficients and n is the total number of signal samples. A total of 77 coefficients were used in this work, for a third degree approximation polynomial, to prepare the pressure signal. Therefore, the result of the pressure signal filtered with the use of equation 3 can be seen in figure 4 below.

The tachometer signal and the engine geometry shown in table 1 makes it possible to retrieve the relative crankshaft position for each cylinder. Vibration and pressure signals, acquired simultaneously, can be synchronized through every cylinder TDC, as can be seen in figures 5 and 6.

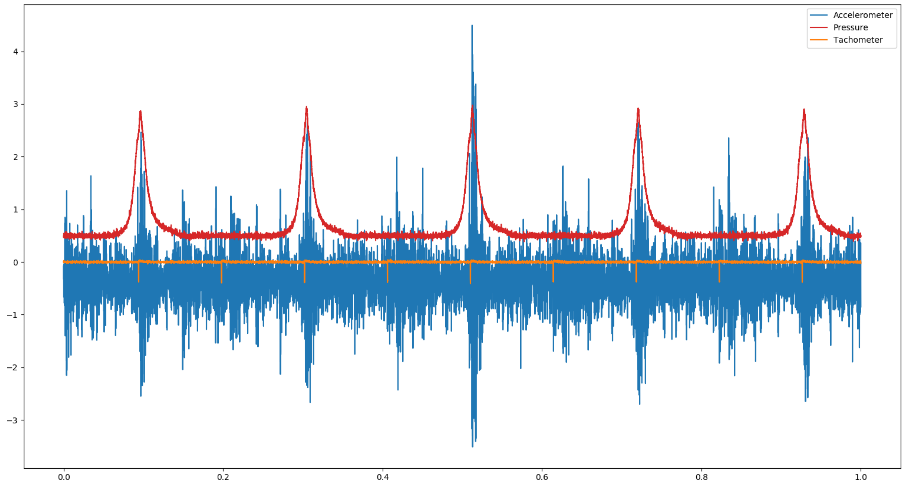

Figura 3: Waveforms acquired.

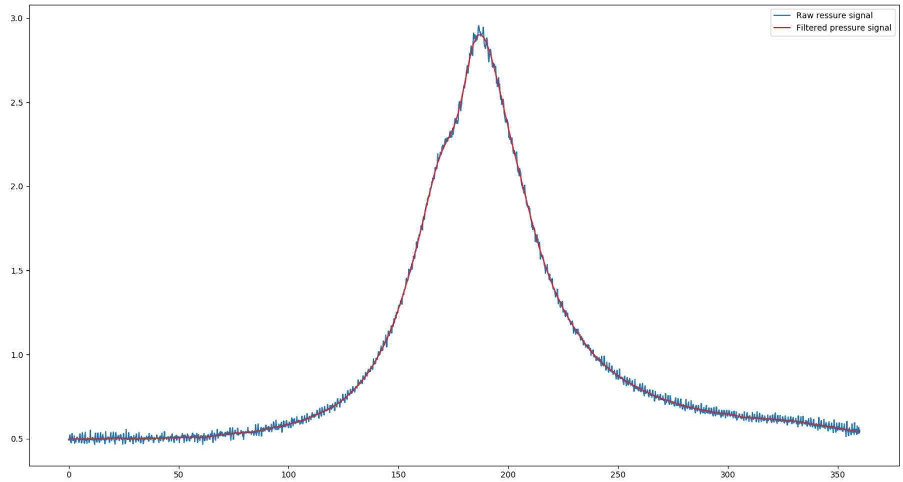

Figura 4: Pressure filtered for noise removal.

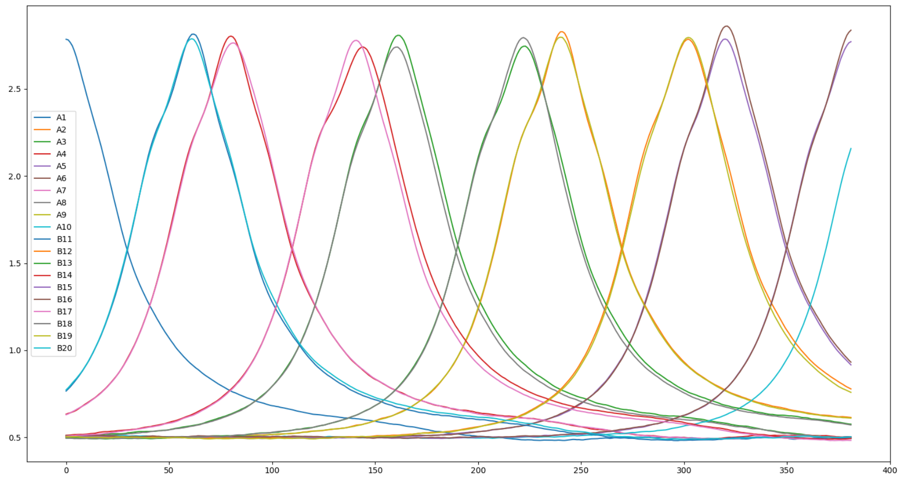

Figura 5: Pressure signal.

Figure 7 shows the pressure signal in one cylinder, overlapped with its accelerometer trace. It is possible to observe that accelerometer signal amplitudes suddenly increase in the presence of the combustion event.

The vibration preprocessing comprehends: a band-pass filter in vibration signal, with lower and upper frequencies selected through the coherence function analysis of vibration and in-cylinder pressure, followed by a subsample decimation factor of 5.

Preprocessing vibration signal comprehends a band-pass filter, with lower and upper frequencies selected by the coherence function of vibration and pressure signals, shown in figure 8. Coherence function is computed as the power spectral densities and the cross power density of the signals.

As can be seen in figure 8, two bands exists with high coherence of vibration and pressure signals. The first significant

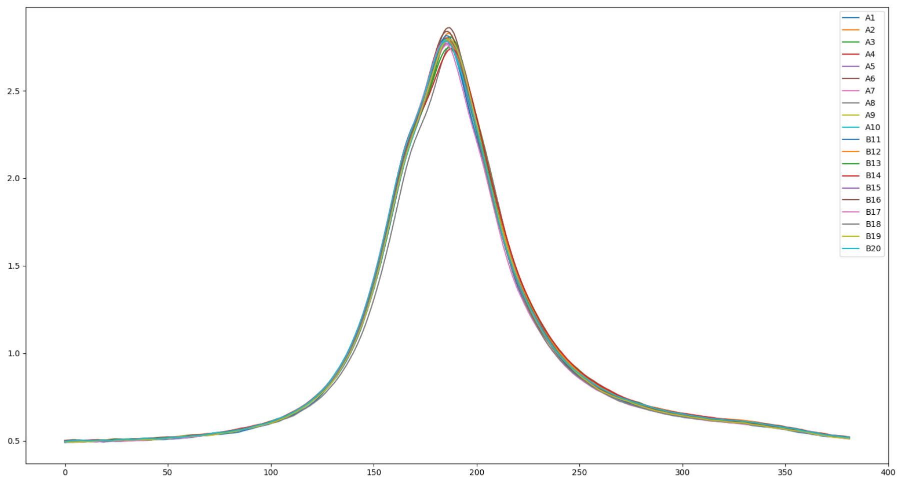

Figura 6: Synchronized pressure signals.

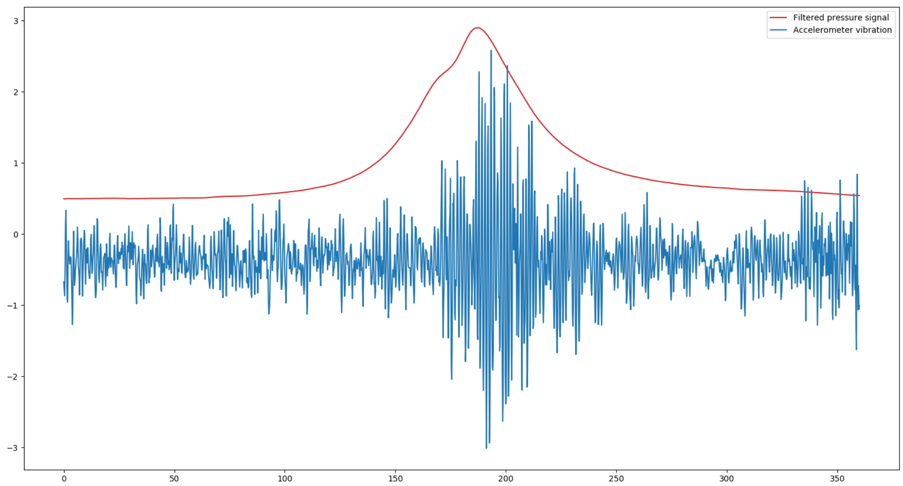

Figura 7: Pressure and accelerometer signal overlapped.

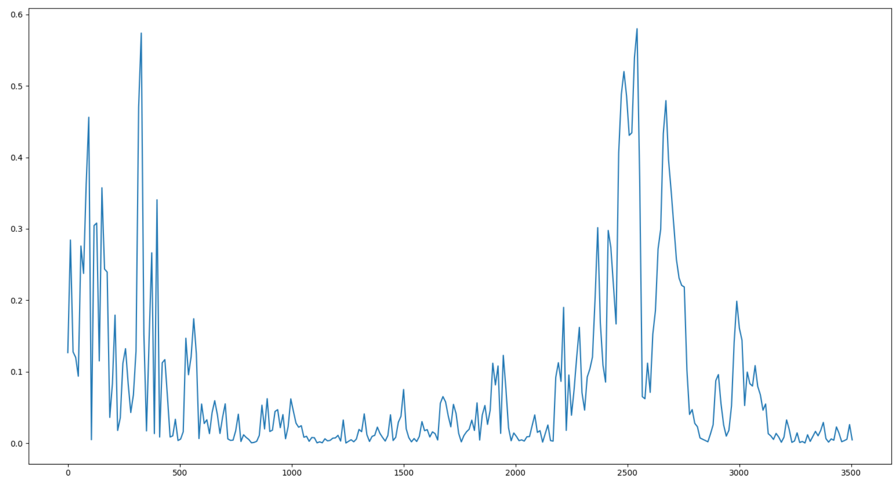

Figura 8: Coherence function of vibration and pressure signals.

band showed to result in better results for pressure regression, so vibration signals were band-pass filtered with lower and upper frequencies of 10 and $500Hz$ respectively. Filtering result for vibration signal seen in figure 7 is presented in figure 9.

A leave-one-out cross-validation (LOOCV) was performed, using 4 engines for training and the remaining one as the validation set. Therefore, a total of 5 rounds of training and testing is performed to measure the reconstruction accuracy of the algorithms used.

The error metrics used are:

- MAE (*mean absolute error*) – Represents the mean of the absolute difference from the reconstructed pressure in

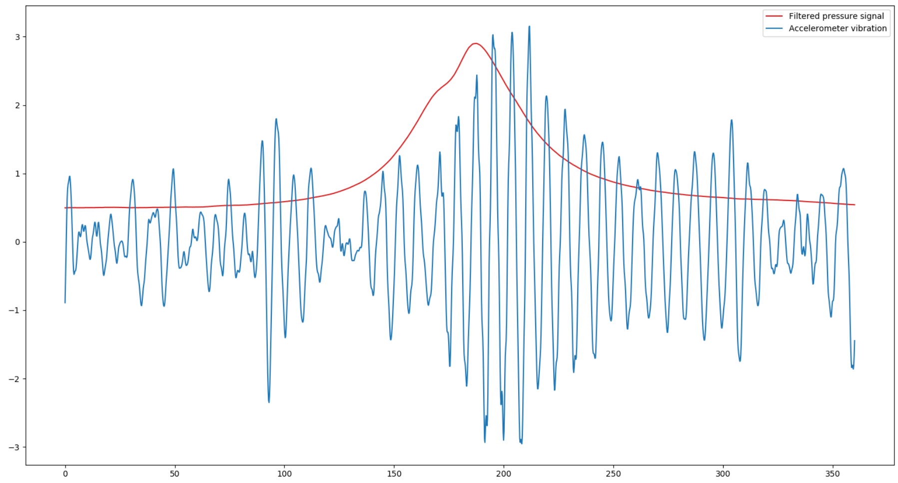

Figura 9: Vibration signal band-pass filtered.

comparison to the real pressure acquired
$MAE = \frac{\sum_{i=1}^{n} |p_r - p_e|}{n}$

- MSE (*mean squared error*) – Represents the mean of the squared difference from the reconstructed pressure in comparison to the real pressure acquired
$MSE = \frac{\sum_{i=1}^{n} (p_r - p_e)^2}{n}$
- R^2 (coefficient of determination) – Represents the proportion of variation from the reconstructed pressure in comparison to the real pressure acquired
$R^2 = 1 - \frac{\sum_{i=1}^{n} (p_r - \overline{p_r})^2}{\sum_{i=1}^{n} (p_r - p_e)^2}$

4. RESULTS AND DISCUSSION

The proposed approach is compared to other commonly used algorithms, such as Multi Layer Perceptrons Neural Networks, Extra Trees, K-Nearest Neighbor and Ridge Regressors. The results using all algorithms the same dataset, with no vibration preprocessing is shown in table 2. It shows the average and standard deviation resulting for the LOOCV. All algorithms were fed with raw data is this table.

Tabela 2: Comparison results with the same datasets (raw data) for all algorithms.

	MAE		MSE		R^2	
	μ	δ	μ	δ	μ	δ
MLP Regressor	5,127	1,156	124,653	48,375	0,934	0,030
Extra Trees	4,023	0,696	62,391	19,784	0,957	0,016
KNN Regressor	5,403	0,844	121,260	48,493	0,932	0,019
RidgeCV	4,634	0,737	93,248	24,047	0,946	0,016
CNN Regressor	3,832	1,273	61,547	32,274	0,965	0,023

Five engines were measured, so a leave-one-out cross-validation (LOOCV) was used to test the regression model accuracy. For that, one engine measurements were used as validation dataset, while the others were used to train the regression model. Three error quantifiers were used: the square of correlation coefficient (R^2), that represents the percent of data closest to the best fit for pressure signal; the mean average error (MAE), that summarizes the deviation from expected pressure signal; and the mean squared error (MSE), that is the squared deviation from expected pressure signal. Those metrics are commonly used to measure regressions accuracy.

The results of using filtered vibration signal as input for regression in Multi Layer Perceptrons Neural Networks, Extra Trees, K-Nearest Neighbor and Ridge Regressor are shown in table 3. For comparison purpose, CNN using raw data is compared in this table to other algorithms, but is this one, they are using preprocessed data.

In figure 10 is possible to see a randomly selected combustion cycle, with the real pressure signal as reference (blue line), together with pressure estimation results for the regressors used.

To show robustness for the proposed methodology, in figure 11, is presented the resultant reconstruction using the CNN-based Regressor for each load condition for a specific engine.

The cost of instrumentation with pressure transducers is more than 1.5 million dollars, for a power plant the size of Gera Maranhão, Having vibration accelerometers, instead of pressures transducer, the cost would be around 150 thousand dollars. When comparing the extremely low life of a pressure transducer, due to the very high temperatures and pressures

Tabela 3: Comparison results of CNN with raw data and the others with preprocessed vibration.

	MAE		MSE		R^2	
	μ	δ	μ	δ	μ	δ
MLP Regressor	4,389	0,960	88,996	33,096	0,951	0,020
Extra Trees	4,129	0,703	63,765	19,927	0,955	0,015
KNN Regressor	4,172	1,037	70,513	29,214	0,961	0,016
RidgeCV	4,574	0,796	93,991	19,436	0,946	0,015
CNN_Regressor	3,832	1,273	61,547	32,274	0,965	0,023

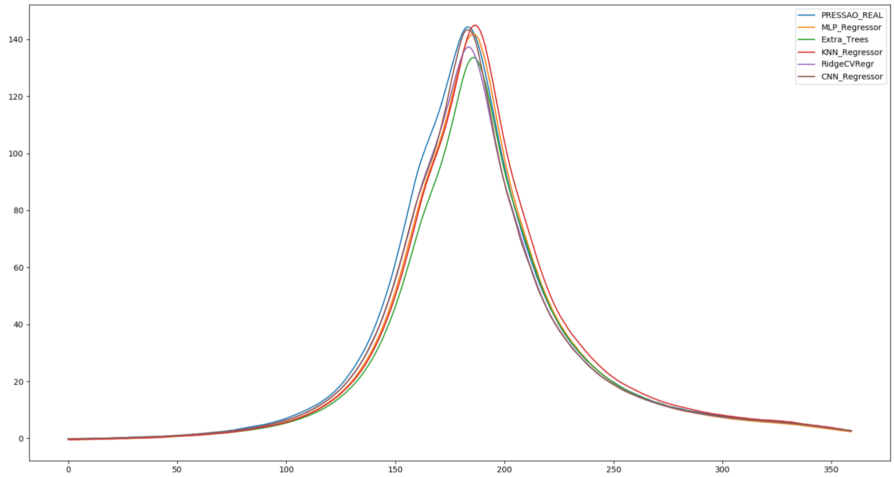

Figura 10: Visual comparison for pressure reconstructions.

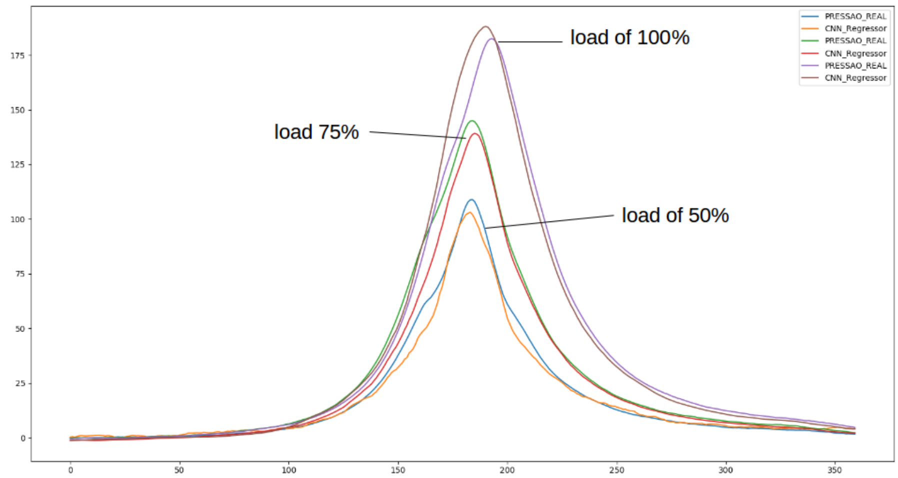

Figura 11: Visual comparison for pressure reconstructions.

that they are submitted, the cost of instrumentation becomes impracticable. In addition, with the results presented here, with accelerometers replacing pressure transducers, continuous monitoring is feasible for timing deviations detection on the combustion process, for example. The detection of a single engine with timing deviation problem, impacting in one percent of its fuel consumption, would allow savings of 400 kilograms of fuel per day.

5. CONCLUSIONS

In this paper, a CNN-based regressor for in-cylinder pressure reconstruction using raw vibration data as input was proposed. Experimental results in large internal combustion engines in a power generation plant, showed that representative features were learned directly from raw vibration signal. And, in comparison to commonly used regressors, such as MLP, KNN, Extra-Trees and Ridge Regressor, the proposed methodology had better regression accuracy in average. It outperformed its peer algorithms for different engines, and for different load conditions, all mixed in the same dataset.

In-cylinder pressure reconstruction from raw vibration data using convolutional neural networks is a robust way of indirect measure a parameter widely used in evaluating the combustion process. Due to the smaller cost of sensors used for this indirect measurements, their considerably longer life-time, the robustness and the accuracy of the methodology presented, is possible to constantly monitor large power generators, preventing breakdowns, excessive fuel consumption and pollutant emission.

6. ACKNOWLEDGEMENT

The work reported in this paper has been supported by Electric Power Sector Technological Development and Research Program – R&D, regulated by Brazilian ANEEL (National Agency for Electric Energy Sector) with code number PD-6492-0215/2015. Project under execution by the following entities: SEMEQ and iX Consultoria, and financed by Gera Maranhão, Geradora de Energia do Maranhão.

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8. AUTHORS RESPONSIBILITY

The authors are solely responsible for the content of this work.