VIBRATION BASED RECONSTRUCTION OF THE CYLINDER PRESSURE IN DIESEL ENGINES BY USING NEURAL NETWORKS

RECONSTRUCCIÓN DE LA CURVA DE PRESIÓN DE MOTORES DIESEL BASADO EN ANÁLISIS VIBRACIONAL Y REDES NEURONALES

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ABSTRACT

The cylinder pressure curve is a very important parameter for detection of malfunctioning of combustion process in diesel engines. It provides a considerable amount of information about the performance of the engine. The traditional method to get the cylinder pressure curve is to use a cylinder pressure transducer, which is inserted in the cylinder head of the engine. This method is both expensive because of the high cost of the transducer and lifetime limited due to the harsh working environment. Therefore, there is an increasing need of a new non-intrusive method, which can be applied for the reconstruction of the cylinder pressure.

The main objective of this paper is to perform the reconstruction of the cylinder pressure curve from vibration measurements by using the Neural Network Method (NNM). The cylinder pressure data obtained with transducers on operating engines was simultaneously recorded with vibration data obtained with external accelerometers at Scania Acoustic Laboratory in Stockholm (Sweden). The measured data were used to train the Neural Networks (NN), thereafter a new data set of vibration signals was enter to the NNs to get the reconstructed cylinder pressure signal. Finally, the results showed high accuracy and precision. The standard deviation of the average maximum cylinder pressures ($\bar{P}_{MAX}$) varied between 0.03 and 1.01 percent, much lower than those obtained with other methods i.e. Cepstrum Method and Multivariate Data Analysis (MVDA). The final goal to use the NNM for optimization of the combustion process and engine diagnostics was fulfilled.

RESUMEN

La curva de presión del cilindro es un parámetro muy importante para la detección del inadecuado funcionamiento del proceso de combustión en los motores diésel. Los parámetros proporcionan una cantidad considerable de información sobre el rendimiento del motor. El método tradicional para obtener la curva de presión del cilindro es utilizar un transductor de presión del cilindro, que se inserta en la culata del motor. Este método es caro debido al alto coste del transductor y la vida útil limitada debido al ambiente de trabajo duro del sensor. Por tanto, existe una necesidad creciente de un nuevo método no invasivo, que se puede aplicar para la reconstrucción de la presión del cilindro.

El objetivo principal de este trabajo es llevar a cabo la reconstrucción de la curva de presión del cilindro utilizando mediciones de vibración y el Método de Redes Neurales (MRN). Los datos de presión de los cilindros obtenidos con transductores en funcionamiento se registran de forma simultánea con los datos de vibración obtenidos con acelerómetros externos en el Laboratorio de Acústica de Scania en Estocolmo (Suecia). Los datos medidos se utilizan para entrenar las redes neuronales, a partir de entonces un nuevo conjunto de datos de señales de vibración ingresa al (MRN) para obtener la señal de presión del cilindro reconstruido.

Finalmente, los resultados mostraron una alta exactitud y precisión. La desviación estándar de las presiones máximas (P_{max}) de los cilindros varía entre 0,03 y 1,01 por ciento, muy inferior a los resultados obtenidos con otros métodos, es decir, Método Cepstrum y método de análisis de multivariables (MAMV). Se puede plantear que el objetivo final de este trabajo se cumplió al aplicar MRN para la reconstrucción de la curva de presión, y la posibilidad de aplicar los resultados en la optimización y diagnóstico del proceso de combustión del motor.

1. INTRODUCTION

There are increasing demands to reduce the noise and exhaust emissions in Diesel engines, and the combustion process is the main parameter which can be able to reduce requirements by optimization of its performance [1]. Knowing the exact behavior of the combustion process, its optimization can easily be performed. There is a standard method to collect the cylinder pressure curve. A cylinder pressure transducer has to be inserted in the cylinder head of the engine. The use of cylinder pressure has several disadvantages such as high cost and limited lifetime due to the harsh work environment, and some times it could be very difficult to find a place to insert the cylinder transducer in the cylinder

head of the engine. Therefore, there is a great need of non-intrusive detection methods, by using accelerometers in order to reconstruct the cylinder pressure curve from response measurements [2].

The main idea of this research project, Peña [5], was to use the Neural Network Method to reconstruct the cylinder pressure curve from the vibration response of the engine surface. NNM has never been used to solve this specific problem, so it is a completely new approach, even though it was already used for analyzing processes where it showed to be a versatile instrument in different fields (i.e. turbomachinery fault identification, vibration diagnostic system for rotation machinery and for detection of motor incipient fault detection [3], condition monitoring applications [4]).

The data (cylinder pressure and vibration response) analysis was carried out by an extensive pre-processing of the data to reduce the noise, before it was introduced to a Generalized Regression Network [6] for the prediction of the source (cylinder pressure). The network was trained under a supervised learning algorithm (where the input signal data and the desired response were known). An external validation was also carried out to see the robustness and accuracy of the Neural Network Method.

Finally, the reconstructed cylinder pressure curve showed a high accuracy. It is also important to mention that the obtained results do not change in accuracy and precision above 1600 rpm, where others methods failed i.e. Cepstrum Method and Multivariate Data Analysis MVDA [2], [7].

2. CYLINDER PRESSURE AND VIBRATION DATA

The engine data recording was carried out at the Scania acoustic laboratory in Stockholm (Sweden). Four diesel engines, in line 6 cylinders, turbo charged, 11 liters, were used for the experiments. The instruments used were accelerometers, piezo electric transducers, a magnetic sensor and AVL recording. The maximum sampling frequency was 32.768 Hz. The tests were conducted using 6 piezoelectric accelerometers mounted firmly onto cylinder head bolts. These six accelerometers were used in order to collect the signals for each cylinder. An inductive magnetic sensor was connected to the flywheel to locate the position of the piston in the cylinder. Two water-cooled quartz, AVL, pressure transducers were used to make combustion pulse measurements, it was necessary to move around the transducer to collect data for all cylinders.

The details of the experiment were extensively explained in an earlier paper [2]. In order to find the best measurements points in the diesel engine a coherence analysis was performed [2]. Figure 1 illustrates the holes where the transducers were inserted. It also shows the position of the magnetic sensor and the position of the accelerometers. The data processing was performed with Matlab$^®$ signal processing toolbox 6.5.

Cylinder pressure transducer   Accelerometers

Magnetic sensor
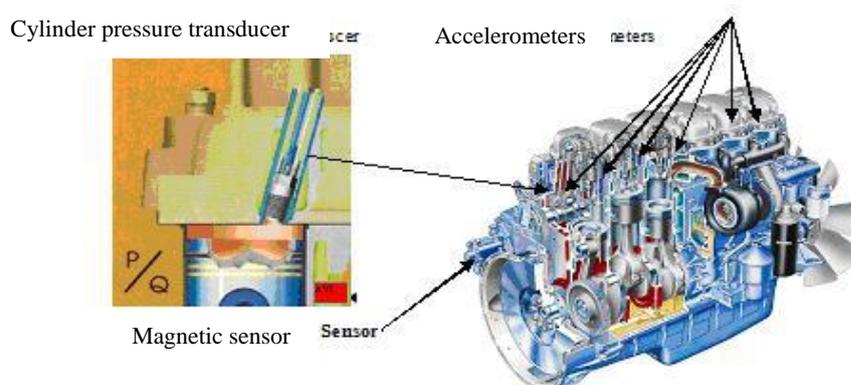
**Figure 1** - Measurement Set-Up.

3. NEURAL NETWORK METHOD

The theoretical basis of neural networks was developed in 1943 by the neurophysiologist Warren McCulloch at the University of Illinois and the mathematician Walter Pitts at the University of Chicago. They studied the potential and capabilities of the interconnection of components based on a model of biological neurons. In 1954 Belmont Farley and Wesley Clark of the Massachusetts Institute of Technology succeeded in running the first simple neural network [7].

The primary appeal of neural networks is their ability to emulate the brain's pattern-recognition skills. Since then, many different models and architectures have been developed and analyzed for a variety of applications. In 1986, the parallel distributed processing (PDP) group, Rumelhart and McClelland, published a series of results and algorithms that served as a catalyst for much of the subsequent research and applications of artificial neural networks in different engineering and scientific fields. The most important property of a neural network is its capacity to learn from the environment through by means of an interactive process of adjustments applied to its synaptic weights and bias levels. Ideally, the network becomes more knowledgeable about its environment after each iteration of the learning process. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze.

A possible disadvantage of this technique is the black box character that might appear. During the process of training of the Neural Network, also during the reconstruction of the cylinder pressure, the internal procedures and operations are not made available in a tangible form. Although the network matrix with its mathematical weighting and biases can be shown, together with all of the applicable training algorithms which are fully mathematical described, the Neural Network is still less transparent than other formula based modeling techniques.

Neural Network Analysis (NNA) has emerged as a powerful technique for modeling general input and output relationships and been used for many complicated tasks [8]. NNA can be used to learn to approximate any function and behave like associative memories using exemplar data that is representative of the desired task. NNA estimates a function without requiring a mathematical description of how the output functionally depends on the input as it 'learns from examples' or, more precisely, it learns from underlying input – output data mapping [8].

The neural network consists of the input layer of neurons (one neuron to each input), a hidden layer or several hidden layers of neurons and an output layer of one neuron for each output. A typical example can be seen in Figure 2.
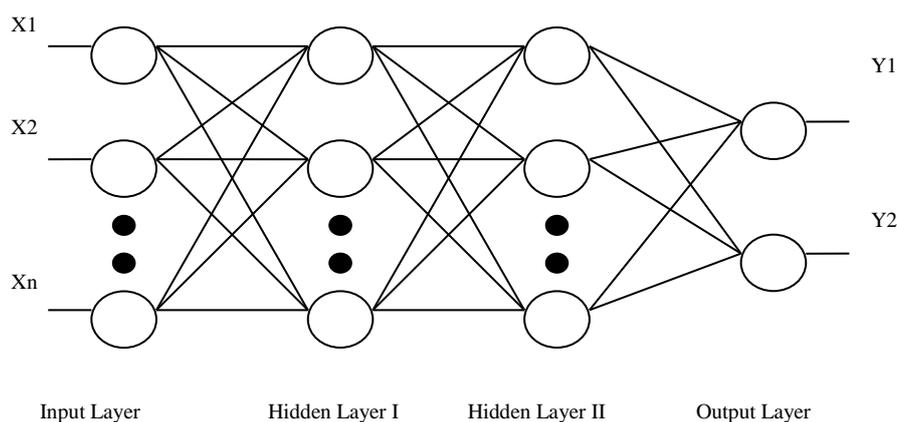
Figure 2 - Neural Network.

3.1 Radial–basis functions network

The design of a supervised neural network may be pursued in a variety of ways such as Back-Propagation and Radial–Basis Function (RBF) [3]. Back Propagation's algorithms are characterized for the design of a multilayer perceptron (under supervision) and may be viewed as the application of a recursive technique known in statistics as stochastic approximation. Radial Basis Function network has a complete different approach, it works by viewing the design of a neural network as a curve fitting (approximation) problem in a high-dimensional space. According to this point of view, learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for "best fit" being measured in some statistical sense. Correspondingly, generalization is equivalent to the use of this multidimensional surface to interpolate the test data. Such a viewpoint is the motivation behind the method of radial-basis functions in the sense that it draws upon research work on traditional strict interpolation in a multidimensional space.

In the context of a neural network, the hidden units provide a set of "functions" that constitute an arbitrary "basis" for the input patterns (vectors) when they are expanded into the hidden space, these functions are called radial–basis functions. Radial–basis functions were first introduced in the solution of the real multivariate interpolation problem. The construction of a RBF network, in its most basic form, involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to its environment. The second layer, the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space, in most

applications the hidden space is of high dimensionality. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer.

A mathematical justification for the rationale of a nonlinear transformation followed by a linear transformation may be traced back to an early paper by Cover [9]. According to this paper, a pattern-classification problem cast in a high–dimensional space is more likely to be linearly separable than in a low–dimensional space hence the reason for frequently making the dimension of the hidden space in a RBF network high. Another important point is the fact that the dimension of the hidden space is directly related to the capacity of the network to approximate a smooth input–output mapping by Niyogi and Girosi [10], the higher the dimension of the hidden space, the more accurate the approximation will be. Radial basis networks may require more neurons than standard feedforward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available.

3.2 Generalized Regression Neural Network (GRNN)

GRNN is among radial basis networks and has recently found many applications in regression and function estimation processes. It has been shown that given a sufficient number of neurons in the hidden layer, a GRNN can approximate a continuous function to an arbitrary precision.

The standard supervised network architectures (multilayer perceptrons and radial basis functions) infer a parameterized model (the weights forming the parameters) from available training data. The parameterized model (the network) is usually much smaller than the training data and can be executed quite quickly, although the time taken to train the model may be long. An alternative approach is to model the function more or less directly from the training data. This has the advantage that there is no need for training (or, at most, one can use "training" that is actually very simple and consisting of little more than changing the form in which the training data are held). Bayesian networks, often called Generalized Regression Neural Networks (GRNNs), are such methods. Regression networks train extremely fast.

The architecture for the GRNN is shown in Figure 3. It was created a two-layer network. It is similar to the radial basis network, but has a slightly different second layer. Here the nprod box shown (code function in Matlab, normprod) produces s^2 elements in vector n^2. Each element is the dot product of a row of a vector LW ^{2,1} and the input vector a^1, all normalized by the sum of the elements of a^1. Further information on GRNN can be found in Matlab$^{®}$ Manual [6].
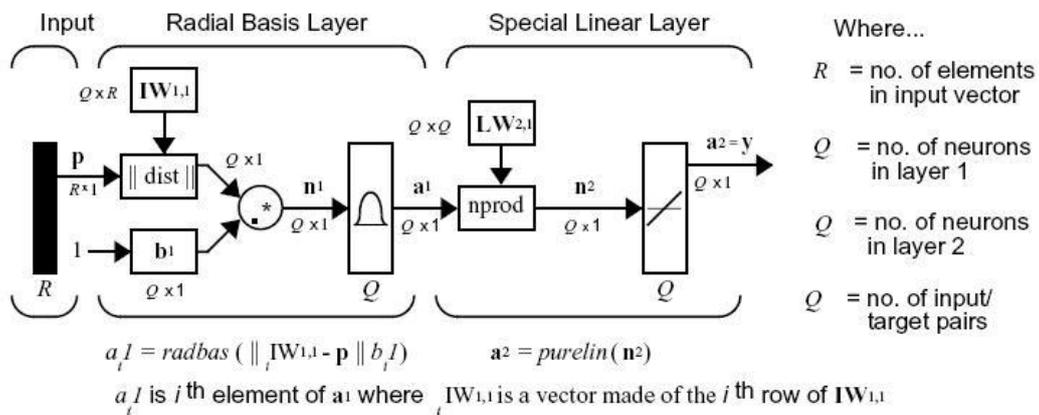

Figure 3 - Generalized regression network architecture [6].

There are many alternative forms of neural network systems and there are many ways NNA can be applied to a given problem. In this specific case, there is a vibration signal and a pressure signal, the goal is to teach a neural network how to reconstruct this pressure signal based on a vibration input. This case fits in the function approximation since there is a need to obtain a transfer function capable of converting the vibration on the engine surface into the cylinder pressure curve, so that The Radial Basis Function Network with the Generalized Regression Network was used.

4. ANALYSIS PROCEDURE

Before the introduction of data into NNM, an extensive pre-processing has to be applied to the row data, Figure 4.
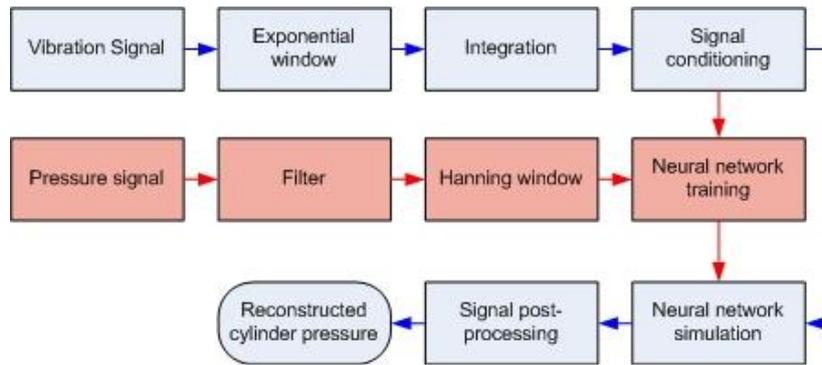
Figure 4 - The flow chart for the reconstruction of the cylinder pressure.

In order to reduce both the noise and the effects of overlapping of adjacent cylinders, a tailored window was applied to the pressure signal [2]. Figure 5 shows a typical example of the signals that were measured. Even if the signals were measured in the same running conditions (10% load and 800 rpm.), most of the variation can be seen between the peaks. This variation may introduce some errors in the Neural Network Modeling. To reduce this variation the vibration data were changed from acceleration to velocity. So that the input data into the neural network method was the velocity instead of the acceleration signal. The integrated data results can be seen in Figure 6, which shows smoother curves.
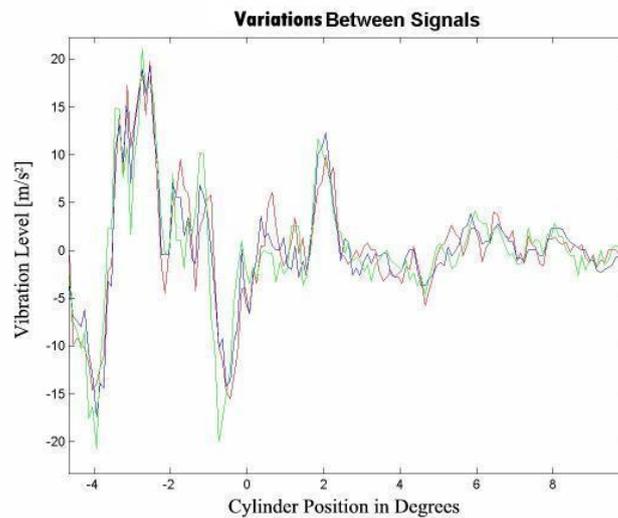
Figure 5 - Acceleration response curves.
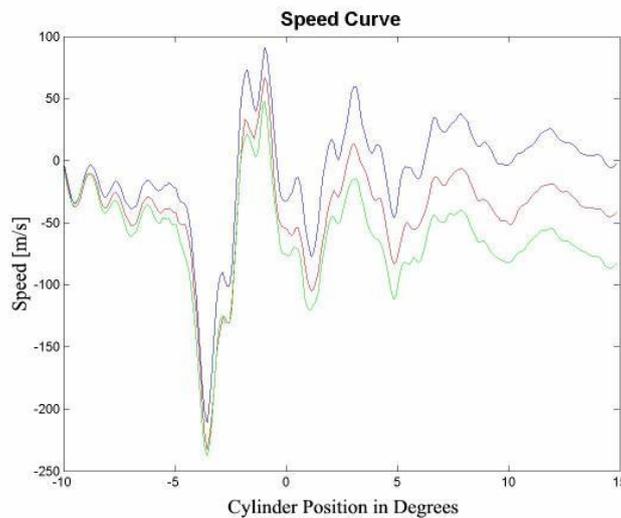
Figure 6 – Velocity response curves.

The cylinder pressure data signal is also filtered out with a tailored windowing combination between the Hamming window and the rectangular window [2]. In order to further reduce the noise in the input data, the pressure signals were submitted to a zero-phase digital filter which performs a zero-phase digital filtering by processing the input data in both the forward and reverse directions. After filtering in the forward direction, it reverses the filtered sequence and runs it back through the filter [11]. The resulting sequence has precisely zero-phase distortion and double filter order, see Figure 7a and 7b.

Finally, the filtered data was introduced to the NNM and the analysis process was performed using the Generalized Regression Neural Network.

5. RESULTS

The total amount of data signals for each cylinder and for each engine running conditions is 30. These signals were paired and a mean value taken, so as it became 15 data signals for each cylinder and for each engine running condition. From these 15 signals, 10 signals from engine 1 were used to train the network. The 5 remaining signals from engine 1 and the 15 signals from engine 2 were used for the external validation process. In order to reduce the variations between the signals the input data set has been normalized in the range of (-1, 1).

Finally, the pre-processed signals were ready to start the network training by using the learning algorithm generalized regression neural network (GRNN). Ten signals from engine 1 and cylinder 1 were used.

The results of the simulation process showed consistency, however they did not reproduce the cylinder pressure curve. An equalizer function was required. The equalizer function was obtained by using the difference of the average measured and the average reconstructed of the cylinder pressure curves. Six equalizer functions were needed, one for each cylinder. After the NNA, the final results were obtained by adding the equalizer function. The inverse process of the normalization made before the network training was applied to the simulation results. The obtained Neural Network models were tested to check out both the robustness and its capability to perform the reconstruction of the cylinder pressure from response measurements.
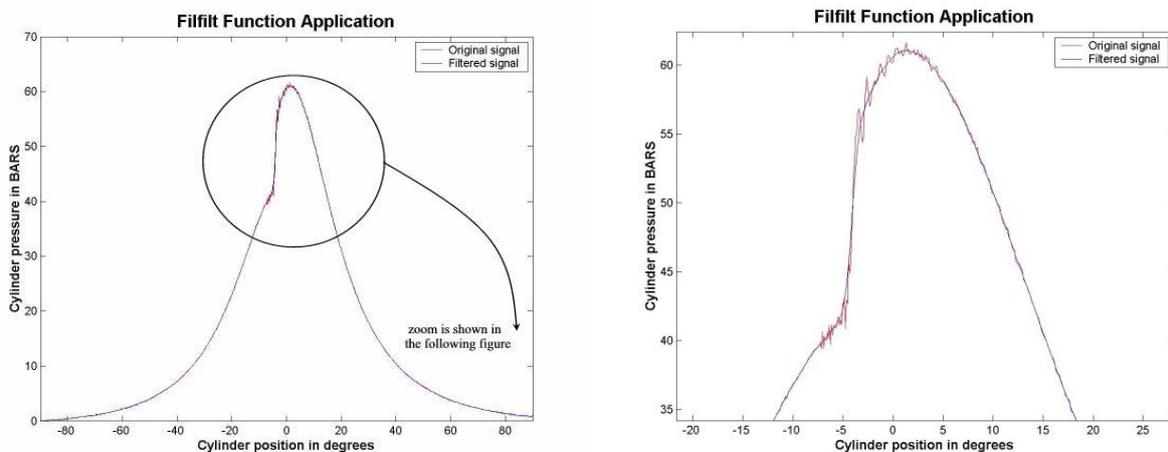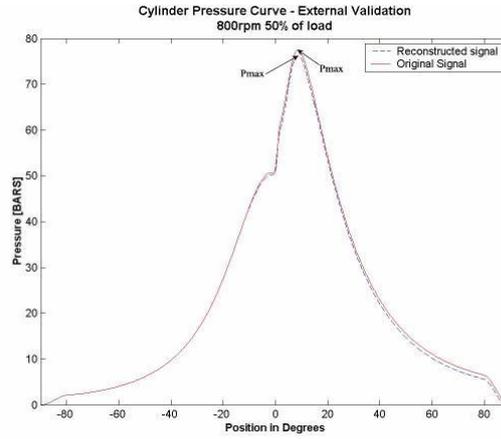

Figure 7 - Comparison between the original (curve with ripples) and the filtered (smoother curve) signals.

The external validation of the obtained model was performed in the following way: Nine old vectors were kept and a completely new data vector was entered to simulate the response of the model. Twenty new vibration responses were used for each cylinder with data acquired from two different engines. The results showed high accuracy proving the robustness of the obtained models, Figure 8 show typical results.
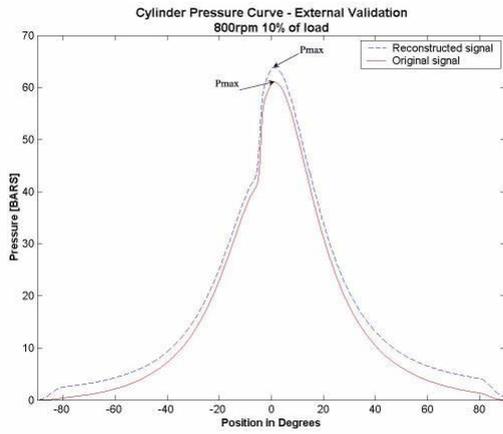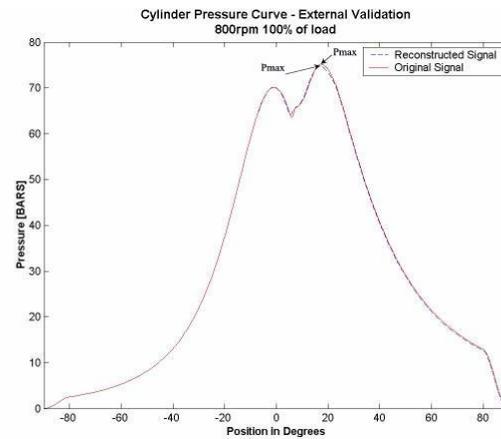
a) Cylinder pressure for 800 rpm and 10% load

b) Cylinder pressure for 800 rpm and 50% load.
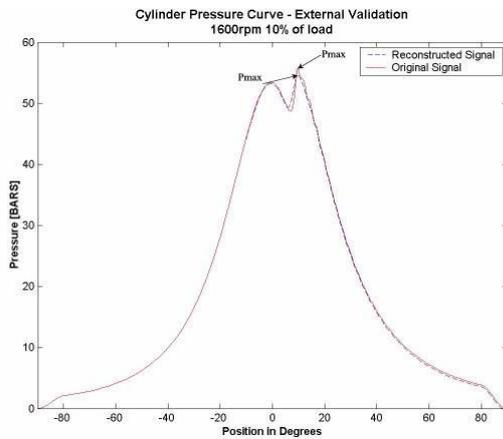
c) Cylinder pressure for 1600 rpm and 10% load

d) Cylinder pressure for 800 rpm and 100% load.

Figure 8 - Comparison between the reconstructed (doted line) and the original signals (continuous line).

The summery of the obtained results can be seen in Table 1 and Table 2. The average and standard deviation of the maximum cylinder pressure ($\bar{P}_{MAX}$) were selected for comparison.

TABLE 1 – COMPARISON BETWEEN THE AVERAGE OF THE MEASURED AND RECONSTRUCTED MAXIMUM CYLINDER PRESSURE ($\bar{P}_{MAX}$)

Average of the Maximun Cilinder Pressure (Pmax)		800 rpm			1600 rpm			2000 rpm		
		Carga			Carga			Carga		
		10%	50%	100%	10%	50%	100%	10%	50%	100%
Cil. 1	Medido	62.88	79.55	78.93	55.95	87.79	146.56	64.21	97.41	143.65
	Reconstruido	62.27	77.59	77.80	54.21	87.61	145.24	62.52	95.62	141.04
Cil. 2	Medido	63.78	78.26	79.30	56.35	87.95	146.13	65.10	97.20	143.40
	Reconstruido	62.41	78.69	78.28	56.22	87.67	146.13	63.66	95.59	141.96
Cil. 3	Medido	64.48	78.60	80.16	57.06	87.94	147.77	64.71	96.66	143.01
	Reconstruido	63.69	79.68	79.01	55.12	88.27	146.77	62.77	94.42	141.01
Cil. 4	Medido	65.05	81.73	80.08	58.49	89.60	149.02	67.49	103.81	154.35
	Reconstruido	64.38	80.70	79.28	57.72	89.76	147.86	66.28	100.51	150.13
Cil. 5	Medido	63.68	81.72	80.14	58.26	90.09	149.31	66.06	103.81	154.35
	Reconstruido	62.98	80.37	79.25	56.38	89.84	148.36	64.87	101.72	152.58
Cil. 6	Medido	65.18	81.06	79.77	58.86	90.36	149.82	70.83	105.05	153.42
	Reconstruido	64.63	80.28	79.05	58.84	90.17	148.86	69.56	102.89	150.90

Two of the most important qualities, adaptivity and fault tolerance, were determinant to choose neural networks for the new approach on the vibration based reconstruction of the cylinder pressure curve. So, if the model is robust and reliable, it should have these characteristics and, consequently, respond in a proper way when it is exposed to

completely unknown data. The obtained neural network models show outstanding results for the reconstruction of the cylinder pressure curve from vibration measurements. The new approach can be used for onboard engine diagnostics.

6. CONCLUSIONS

▪ The cylinder pressure curve was successfully reconstructed based on a response vibration signal by using Neural Network Methods.

▪ The noise reduction of the data was successfully handled by filtering and windowing techniques.

▪ The Neural Network Model proved to be very robust as it can work with absolutely unknown data and provide trustworthy results. The accuracy of the NNM results was not diminished at high engine speeds above 1600 rpm.

▪ Finally, the obtained results showed high accuracy, the standard deviation of the average maximum cylinder pressure ($\bar{P}_{MAX}$) varied between 0.03 and 1.01 percent.

TABLE 2 – COMPARISON BETWEEN THE STANDARD DEVIATION OF THE MEASURED AND RECONSTRUCTED MAXIMUM CYLINDER PRESSURE ($\bar{P}_{MAX}$)

Standard Deviation [%]		800 rpm			1600 rpm			2000 rpm		
		Load			Load			Load		
		10%	50%	100%	10%	50%	100%	10%	50%	100%
Cil. 1	Medido	0.92	0.67	1.85	0.88	0.62	0.69	1.54	1.87	1.17
	Reconstruido	0.09	0.05	0.13	0.37	0.13	0.02	0.47	0.09	0.02
Cil. 2	Medido	0.97	0.69	1.63	1.02	0.55	0.72	1.46	1.56	0.92
	Reconstruido	0.11	0.33	0.17	0.96	0.03	0.30	0.36	0.07	0.17
Cil. 3	Medido	1.19	0.93	2.38	1.37	0.38	0.86	2.08	1.75	1.40
	Reconstruido	0.03	0.03	0.12	0.07	0.25	0.07	0.36	0.10	0.07
Cil. 4	Medido	1.57	2.09	1.95	1.47	0.72	0.58	0.99	1.18	1.01
	Reconstruido	0.13	0.13	0.03	0.45	0.16	0.007	0.32	0.28	0.10
Cil. 5	Medido	0.61	3.65	1.62	1.49	0.76	0.58	0.99	1.18	1.01
	Reconstruido	0.07	0.05	0.08	0.28	0.02	0.06	0.36	0.04	0.27
Cil. 6	Medido	1.67	2.10	1.01	1.45	0.66	0.55	1.38	1.20	0.57
	Reconstruido	0.05	0.27	0.09	1.01	0.06	0.06	0.14	0.07	0.17

7. ACKNOWLEDGEMENTS

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