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ROBUST IDENTIFICATION OF PRESSURE OSCILLATIONS IN THE COMBUSTION CHAMBER OF A HEAVY-DUTY TURBINE

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Abstract: *The flame instability of the combustion in heavy-duty gas turbines may result in pressure oscillations in a frequency range that can damage both combustors and downstream hot-gas-path components. This paper contributes with a nonlinear identification based on a black-box model approach for modelling the maximum values of the pressure oscillations inside the combustion chamber of a heavy duty gas turbine. The methodology is based on a robust data filtering combined with a Volterra-Series model obtained using the Forward Regression with Orthogonal Least-Squares (FROLS) algorithm. The models obtained are simulated and the samples are compared with the original data in terms of the Sum of the Absolute Errors (SAE) and two modified versions of it. The obtained model is validated on sixteen individual combustors simultaneously and the robustness of the simplified generic model is discussed.*

Keywords: *Heavy-Duty Gas Turbine, Combustion Chamber, Pressure Oscillations, Nonlinear System Identification.*

1. INTRODUCTION

The use of heavy-duty gas turbines is growing due to its high combined cycle efficiency, higher power output, lower emissions, fuel flexibility and its lower initial capital expenditure cost (Vyncke-Wilson, 2013). As a result of the mentioned advantages, this group of gas turbines has been widely used in the energy generation industry. In such huge machines, predictive and preventive actions and the maintenance schedule and procedures are essential in order to diminish gas path components faults and outage probabilities, aiming to maintain desired efficiency levels.

Among a huge variety of problems related to the gas turbines maintenance, such as fouling in the air filter and compressor, aging of gas path components, excessive clearance due to rubbing and malfunctions (Lemma *et al.*, 2016), pressure oscillations were one of the most explored by researchers in the past few decades, as seen in Sen *et al.* (2010); Lieuwen (2003); Schildmacher *et al.* (2006); Yang and E. C. Culick (1986). It consists on the high frequency differential of pressure generated by the flame instability of the combustors stages (Iurashev *et al.*, 2017). The high amplitude of pressure can damage the equipment, while the continuous oscillations in the natural frequency of the physical system can provoke resonance, which could cause the destruction of the structure.

In order to avoid this phenomena, a model that describes the oscillations as a function of input variables is sought. The first issue is that a commercial physical system modeling is more complicated due to the fact that a lot of information is not available in service manuals (Nelles, 2001). Considering the analyzed heavy-duty gas turbine, the missing information might be components dimensions, inlet air mass flow and the control scheme, etc. Moreover, as the pressure oscillations occur in high frequency, it requires a dedicated hardware for collecting the desired data. On the other hand, some physical features as the ambient temperature and the gas mass flow are not updated in such frequency. Hence, there is an inconsistency between the oscillation's and physical data, which are represented in the frequency and time domain, respectively.

Therefore, the most recommended solution for the mentioned problem is a nonlinear identification based on black-box models, which is a widespread approach that treats the physical system as a block with inputs and outputs without knowing what is inside that box. Based on experimental data (inputs and outputs), there are numerous techniques available in the specialized literature that has been successfully used in many other areas (Ayala and Coelho, 2016; Olsson, 1976; Stoev and Schoukens, 2016; Schoukens and Tiels, 2017; Noël and Kerschen, 2017; Cham *et al.*, 2017; Mezghani *et al.*, 2017; Prangishvili *et al.*, 2016). There are some research related to nonlinear identification and simulation of gas turbines (Lyantsev *et al.*, 2017; Iurashev *et al.*, 2017; Hamid Asgari, 2015), however a black-box model of the pressure oscillations inside a combustion chamber has not yet been presented.

This paper exposes a nonlinear robust identification methodology based on black-box models tested on the generic identification of the combustion chamber pressure oscillations in a heavy-duty gas turbine. The procedure is described step-by-step from the data filtering to the model's quality evaluation. The maximum filter of image treatment is adopted, while the Forward Regression with Orthogonal Least-Squares (FROLS) (Chen *et al.*, 1989) algorithm is used to select the model's terms and the Sum of the Absolute Error (SAE) with two variants is used to measure the model's generalization.

The rest of this paper is organized as follows. Section 2 contains the general information about the combustion chamber, the data acquisition system and the pressure oscillations phenomena. The proposed methodology is described in Section 3, while the results obtained are exposed in Section 4. Finally, the final remarks are shown in Section 5.

2. COMBUSTION CHAMBER

This section contains the technical information about the combustion chamber studied, as well as the oscillations phenomena and the data acquisition system.

2.1 Heavy-Duty Gas Turbine

The combustion chamber studied in this paper is part of a heavy-duty gas turbine used for power generation in a gas power plant, as illustrated in Figure 1.a. The gas turbine operates using natural gas in a combined cycle. In other words, the hot gases generated by the combustion in the gas turbine are used to move a steam turbine. The combustion system is a composite of sixteen combustion chambers arranged in a circular pattern, as shown in Figure 1.b.

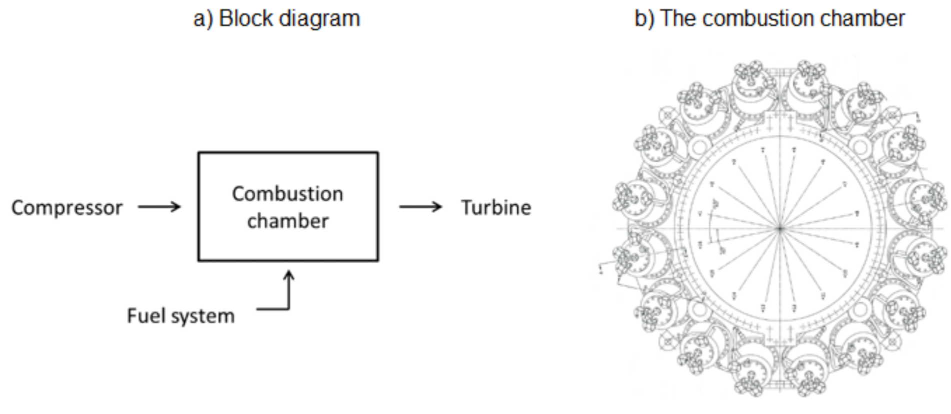

Figure 1. a) The block diagram of the combustion system studied in the present paper and b) The circular positioning of the combustors (Raja, 2016).

2.2 Pressure Oscillations

One of the most crucial factors in combustion instabilities is the level of dynamic pressure oscillations that can occur in the combustion chamber. These oscillations are produced due to pressure waves amplitude and frequency properties, which are susceptible to heat release and pressure fluctuations within the combustion gas mixture. This phenomenon is described by the Rayleigh criterion, shown in Equation 1 as the Rayleigh integral form (Putnam and Dennis, 1954), where *p'* represents the local pressure fluctuation, *q'* the local unsteady heat release and *T* the period of oscillation. The

Rayleigh criterion states that energy is supplied to the combustion chamber mass flow when the magnitude of the phase between heat release fluctuations and pressure fluctuations at the flame is less than ninety degrees (Farhat and Al-Taleb, 2010), as indicated by a positive value in the Rayleigh's index R (Lieuwen, 2005). In this scenario, pressure oscillations are magnified, leading to an unstable combustion process, while a negative index represents an attenuation of the pressure oscillations (Khanna, 2001).

$$R = \int_0^T p'(t)q'(t)dt \tag{1}$$

The frequency band analyzed in this paper is the one between 100 and 160 Hz, due to the higher pressures observed within this frequency range.

2.3 Data Acquisition System

The research data handled in this paper stemmed from the Combustion Dynamics Monitoring System (CDMS) from Siemens, which performs a continuous monitoring of the combustion dynamics levels in the combustion chambers. This system has a high frequency response, identifying and taking measurements at frequencies up to 5kHz, making full use of fast response dynamic pressure transducers to monitor around the clock nine bands of frequencies for each combustor, storing the maximum value read in each band. The collected values are then stored second by second in a database, as well as other numerous variables such as ambient temperature, turbine gross power and fuel gas manifolds configuration, which are collected using an industrial MODBUS (serial communications protocol) network and an OPC (Open Platform Communications) server, also being stored on a per second basis.

3. Robust Identification Procedure

The adopted methodology consists on the robust identification of the combustion chamber's pressure oscillations from the suitable dataset treatment to a final generic model to describe this phenomena for all the sixteen components of the chamber. The robust identification procedure is described in the following subsections.

3.1 Independent Variables Selection

The pressure oscillations in the combustion chamber studied can be described as a consequence of dozens of physical and mechanical conditions, which are measured and stored in the database as independent variables. However, many of those variables are the result of another sub process of the system and/or cannot be controlled by the operator. The combustion chamber exhaust temperature illustrates that situation. The main issue is that the complexity and sensitivity of the final simulation model increases with the number of sub-process models in cascade, along with a decrease in the model's precision and robustness. (Ninness and Hjalmarsson, 2004; Rojas *et al.*, 2011).

In order to overcome this problem, the objective of this step of the identification process is to select only the variables that do not depend on other sub-models, such as the ones that can be controlled by the operator and those ones from the ambient, which must be the primary and independent variables of the final simulation model. In this research, the power set point, the ambient temperature and the gas mass flow in the four different intakes of the combustion chamber (A, B, C and pilot) are chosen as the independent simulation variables. These variables are referred in the discrete time domain (k) respectively as $Pot(k)$, $T(k)$, $A(k)$, $B(k)$, $C(k)$ and $P(k)$, as illustrated in Figure 2.

3.2 Data Filtering

Due to the necessity of a robust identification, the The Running Maximum Filter (RMF) has been used in this paper. It is part of a common class of filtering methods, along with Minimum and Median filters, which can be found in several applications in image processing, although these filters are also applied to one dimensional data such as in time series and sound processing (Zhu and Shasha, 2003; Keogh and Ratanamahatana, 2005). The filter works by picking the maximum value through a sliding window of size w and using it as a new value in the filtered signal. In this paper context the filter is used to extract only the pattern of the maximum values of pressure oscillation at the combustion chamber within some time window, making it possible to evaluate the maximum oscillation range with a given set of inputs.

3.3 Candidate Terms Definition

In order to obtain the most robust model possible, the auto-regressive terms were disregarded. This means that the candidate terms are only the current (non-causal model) and the past values of the inputs. In dynamic systems, modelling an equation relying only on past values of system inputs $u_n(k)$ is known as Finite Impulse Response (FIR) model. Its value decreases until reaching zero within the period of time after an impulse signal is applied to the system input. When adding a zero order term θ_0 into the equation, it becomes a first-order Volterra-Series model. In the case of higher ordered

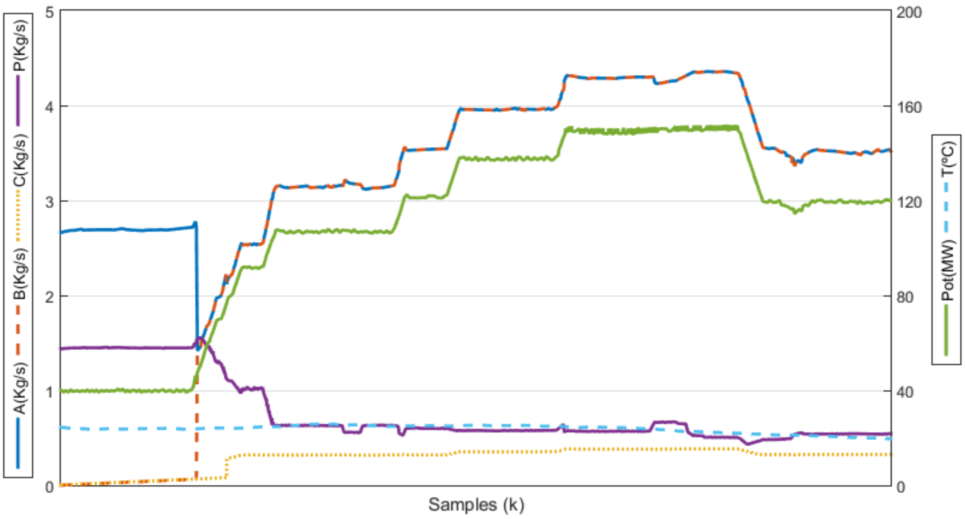

Figure 2. Inputs considered in the discrete time domain k.

terms $(n > 1)$, Volterra-Series are able to represent nonlinear systems and these models are also named Nonlinear FIR (NFIR) (Billings, 2013; Nelles, 2001).

The Volterra-Series based modelling has been used in many engineering applications (Cheng *et al.*, 2017; Prawin and Rao, 2017) and a second order representation can be written as:

$$y(k) = \theta_0 + \sum_{m_1=0}^{M} \theta_1(m_1)u(k-m_1) + \sum_{m_1=0}^{M}\sum_{m_2=0}^{M} \theta_2(m_1, m_2)u(k-m_1)u(k-m_2), \quad (2)$$

where $y(k)$ is the output, $u(k-m_i)$ the lagged inputs, M is the maximum time lagged inputs, and $\theta_i(.)$ are the parameters, also called Volterra Kernels. In this paper, the Volterra-Series model is treated as a Multiple Inputs and Single Output (MISO) system, due to the combustion chamber physical aspects.

3.4 Identification Process

Calculating the coefficient values for linear-in-the-parameters models is often an easy operation, since the well-known Least Squares Estimator can be used. However, finding the most significant terms to such model is a more complex task, since we need to know the contribution of each part in its accuracy. In the 1980's the Orthogonal Least Squares (OLS) method was developed aiming to address this issue. OLS is able to calculate the coefficients of auxiliary models independently, as they are orthogonal to the estimated data set. So they are classified by the Error Reduction Ratio (ERR), a metric used to determine how much each part can contribute to a final model (Chen *et al.*, 1989; Billings, 2013).

Although the OLS method is able to give information over the ERR, these values depends on the order and position of each term in the equation. The Forward Regression OLS (FROLS) was designed to overcome this situation by performing a full evaluation of the ERR after every step. In other words, after one term is selected the OLS is applied once again to a new set of candidates which excludes the previously selected one. This procedure is taken until a desired Error-to-Signal Ratio (ESR) or maximum number of terms is reached (Chen *et al.*, 1989; Billings, 2013; Nelles, 2001).

3.5 Model Validation

In order to check the model quality, the generic models must be compared with all the sixteen combustors data individually. Its accuracy is evaluated through the Sum of the Absolute Error (SAE) value from Equation 3, which can be written as:

$$SAE = \sum_{i=1}^{N} |y_i - \hat{y_i}|, \quad (3)$$

where N is the number of samples compared, y represents the original data and $\hat{y}$ the estimated sample.

As the objective is to obtain the most robust models, two SAE variations have been used: the Superior SAE (S-SAE) and the Inferior (I-SAE). The first one considers only the subset with the estimated samples above the original data, while the second one takes into account the values under the oscillation curve. The ideal model should present null SAE, S-SAE and I-SMAE, however this condition might not be possible to achieve. Thus, the alternative condition is to reduce all error, mainly the I-SAE.

4. RESULTS

In this section the identification setup, the filtered data, the selected terms and the final robust model are exposed and discussed.

4.1 Identification Setup

The number of samples used in the filter is defined as 60 (30 forward and 30 backward). Among the candidate terms are all the input variables with ten possible delays (re-sampling data by 60) and maximum second order. The total number of candidates is 1890. Further, the maximum number of terms defined in the FROLS algorithm is 20.

4.2 Filtered Data

The pressure data filtered using RMF provided a new sequence above the original one which has less high frequency oscillation, as illustrated in Figure 3. Since the main concern is to predict the maximum pressure magnitude in the combustion chamber within a given operation condition, the filtered data is more significant. Further, the variance has also been significantly reduced, mainly for the samples with higher pressure amplitude and also for the ones with high power. Both sequences have been used as training data sets, where the original data and the filtered data have been used for the identification of the conventional model, which are referred as the Non-filtered Model and the Filtered Model.

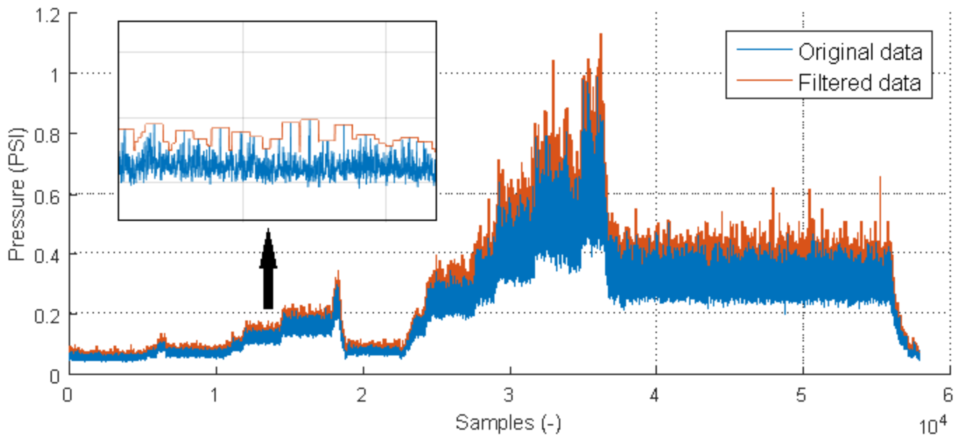

Figure 3. Filtered data.

4.3 Terms Selection

According to the Error Reduction Ratio (ERR), the FROLS algorithm has selected the most relevant terms for both models (as previously mentioned, the maximum number of terms allowed is 20). The terms are shown in Table 1 in descending order, that is, from the highest to the lowest ERR. In both models, the second order terms $A(k) \times Pot(k)$ and $Pot(k) \times T(k)$ have appeared, respectively, as the first and the second most relevant terms to describe the oscillations. Because of its double appearance, it is important to notice the influence of the $Pot(k)$ in the oscillation models found. Looking back at the input variables graph (Figure 2), it is noticeable that the variance increases as $Pot(k)$ and $A(k)$ increase. This seems to justify the appearance of $Pot(k)$ in both top terms.

Moreover, the second order terms $T(k)^2$ and $A(k) \times P(k)$ have also appeared in both models on top of the list, which means that the involved variables have some influence in the output, mainly $A(k)$ and $T(k)$. The correlation of the variable $P(k)$ with the output is not evident, however it appears in some second order terms and also isolated in the first half of the Filtered Model's list of terms. $B(k)$ is clearly the less significant variable in both cases, while $C(k)$ is the most distinct between the models. In the Filtered Model, $C(k)$ appears twice in the top of the list, isolated and squared, while it does not even integrate the top of the Non-filtered Model's list.

Furthermore, the correlation between the filter's variance reduction and the term's orders can also be identified. In the Filtered Model almost all possible first order terms appear in the top 20 list, while in the Non-filtered Model only $Pot(k)$ appears as the last term of the list. In fact, the Error Reduction Ratio (ERR) of these terms is minimal, as seen in Figure 4.a, wherein all terms ERR are shown for both models. In the Sum of ERR (SERR), shown in Figure 4.b, it is possible to see the settled values for both models and how the first terms contribute more than the others.

Another important information is that the delayed terms are almost not relevant in the models. Indeed, there are only two second order with delay terms that appear only in the Non-filtered Model ($C(k-240) \times C(k-480)$ and

Table 1. Resulting terms from the FROLS algorithm (the models also have the zero order term not displayed in this table).

Term	Filtered Model	Non-filtered Model
1	$A(k) \times Pot(k)$	$A(k) \times Pot(k)$
2	$Pot(k) \times T(k)$	$Pot(k) \times T(k)$
3	$C(k)$	$T(k)^2$
4	$C(k)^2$	$A(k) \times P(k)$
5	$T(k)^2$	$A(k) \times T(k)$
6	$A(k) \times P(k)$	$C(k) \times P(k)$
7	$P(k) \times T(k)$	$A(k) \times C(k)$
8	$B(k) \times C(k)$	$A(k)^2$
9	$C(k) \times Pot(k)$	$B(k) \times T(k)$
10	$P(k)$	$P(k)^2$
11	$A(k) \times C(k)$	$P(k) \times T(k)$
12	$C(k) \times T(k)$	$B(k) \times P(k)$
13	$Pot(k)$	$B(k) \times C(k)$
14	$A(k)^2$	$C(k)^2$
15	$P(k)^2$	$A(k) \times B(k)$
16	$B(k)$	$C(k) \times Pot(k)$
17	$B(k) \times T(k)$	$P(k) \times Pot(k)$
18	$P(k) \times Pot(k)$	$C(k-240) \times C(k-480)$
19	$T(k)$	$A(k-60) \times A(k-300)$
20	$C(k) \times P(k)$	$Pot(k)$

$A(k-60) \times A(k-300)$). According to the graphic shown in Figure 4.b, the SERR of the Non-filtered Model converged to approximately 97%, while the SERR of the Filtered Model exceeded the goal, which has been defined as 99%. As the Filtered Model needs only eight terms to achieve the goal, this is the number of terms considered for this model, while the Non-filtered Model considers all the 20 terms. It means that the Filtered Model has 60% less terms compared to the Non-fitlered Model, reducing the model's complexity and the noise exposition/vulnerability.

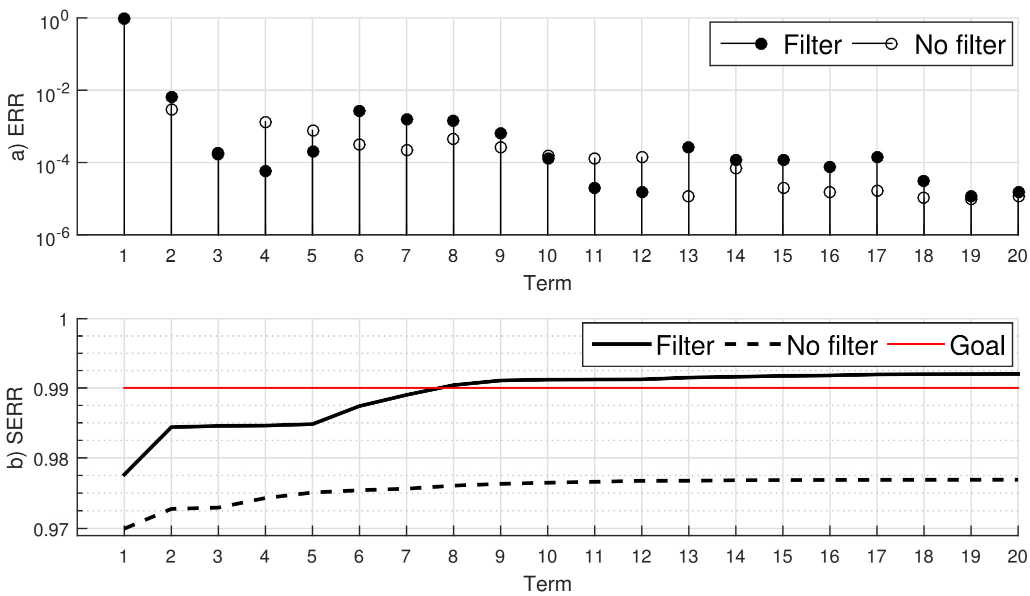

Figure 4. a) The Error Reduction Ratio (ERR) of each term and b) The Sum of ERR (SERR) of each model and the desired value (the red line).

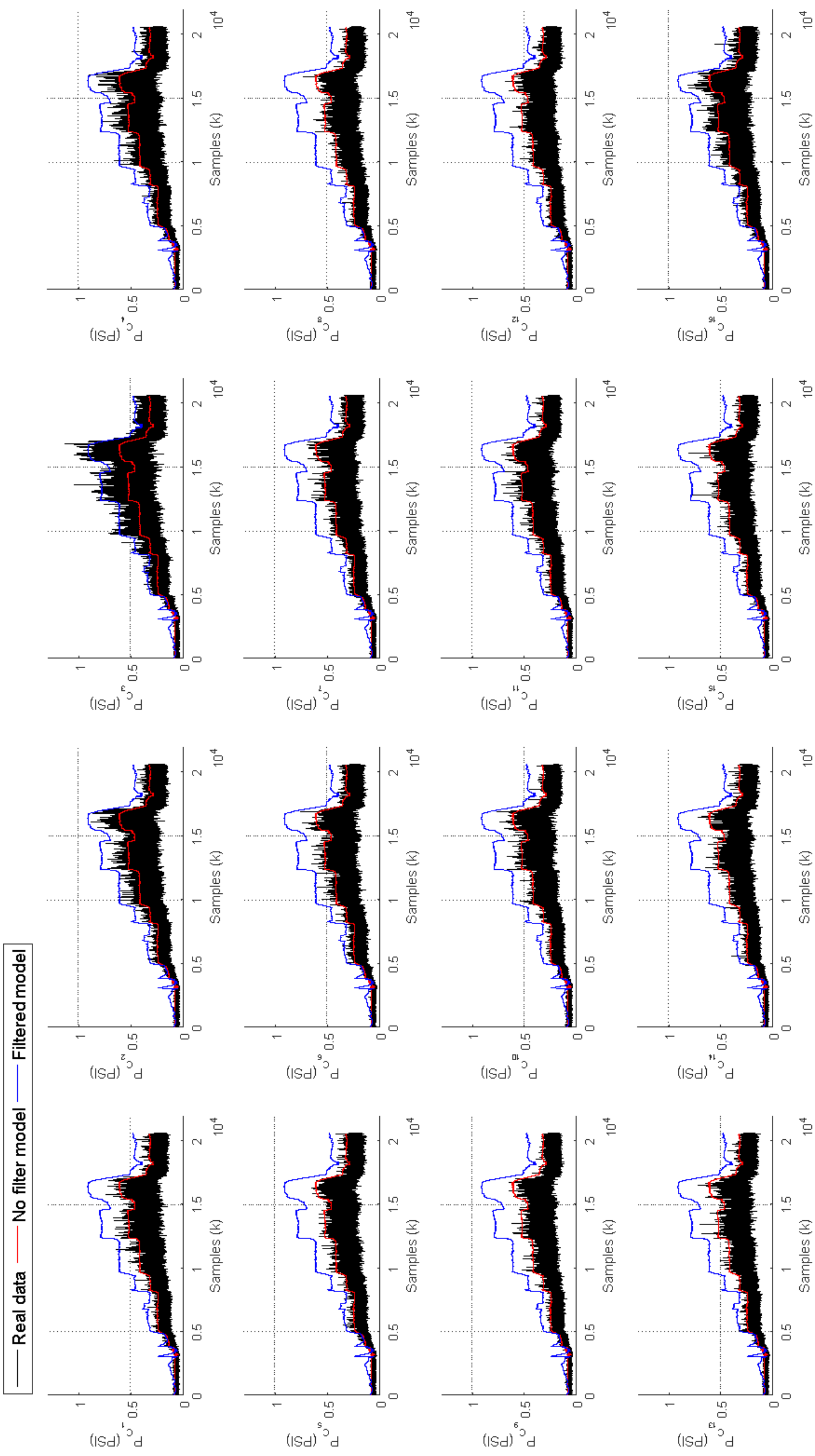

Figure 5. Identification results for the sixteen combustors in the discrete time domain.

4.4 Resulting Models

The pressure oscillations in the considered frequency band are referred as P_{C_n} for all the combustors $n \in \{1, 2, \ldots, 16\}$, as seen in Figure 5. For comparison purposes, the filtered and the non-filtered generic models estimated outputs have been drawn overlapped with the real data in blue and red color, respectively. Although all the combustors are geometrically equivalent and the input variables have the same values, the pressure amplitudes and the variance are quite different depending on the combustor.

The most relevant difference between these models is related to the mean values of the filtered and the Non-filtered model, which are, respectively, above and around the real data. Hence, the SAE and the S-SAE of the Non-filtered model are lower than the Filtered model's one, as shown Table 2. However, the I-SAE and the percentage of original data covered by the estimated samples, which we call Covered Percentage (CP), are higher than the Filtered model's ones. In fact, there is significant difference between the Filtered and Non-filtered model. Treating the combustors as samples and performing the Wilcoxon statistical test Conover (1999), the null hypothesis (H_0, which states that the samples belong to the same population) is rejected for significance level $\alpha = 0.05$ with p-values 1.54e-06, 1.54e-06, 5.59e-06 and 1.54e-06 for SAE, S-SAE, I-SAE and CP, respectively.

Table 2. The calculated errors from the obtained models (Non-filtered/Filtered).

Combustor	**SAE**	**S-SAE**	**I-SAE**	**CP**
1	1.05E-01 / 2.49E-01	2.13E+03 / 5.09E+03	1.38E+01 / 4.76E+00	96.4% / 99.1%
2	8.90E-02 / 2.31E-01	1.78E+03 / 4.71E+03	4.20E+01 / 4.35E+00	94.3% / 99.3%
3	6.63E-02 / 1.91E-01	1.14E+03 / 3.90E+03	2.21E+02 / 1.00E+01	81.9% / 98.6%
4	9.03E-02 / 2.32E-01	1.80E+03 / 4.74E+03	4.26E+01 / 4.27E+00	94.0% / 99.2%
5	1.10E-01 / 2.54E-01	2.23E+03 / 5.20E+03	9.58E+00 / 4.23E+00	97.5% / 99.3%
6	1.03E-01 / 2.47E-01	2.09E+03 / 5.05E+03	1.63E+01 / 3.84E+00	96.6% / 99.4%
7	1.01E-01 / 2.45E-01	2.05E+03 / 5.01E+03	1.48E+01 / 4.21E+00	96.7% / 99.3%
8	1.16E-01 / 2.61E-01	2.37E+03 / 5.35E+03	5.00E+00 / 3.80E+00	98.4% / 99.3%
9	1.16E-01 / 2.61E-01	2.37E+03 / 5.34E+03	5.05E+00 / 4.43E+00	97.9% / 99.3%
10	1.06E-01 / 2.50E-01	2.15E+03 / 5.11E+03	1.11E+01 / 4.36E+00	96.7% / 99.1%
11	1.02E-01 / 2.46E-01	2.06E+03 / 5.03E+03	1.32E+01 / 3.95E+00	97.0% / 99.3%
12	1.15E-01 / 2.60E-01	2.34E+03 / 5.31E+03	7.36E+00 / 4.22E+00	97.4% / 99.2%
13	1.17E-01 / 2.62E-01	2.38E+03 / 5.35E+03	7.14E+00 / 4.42E+00	97.6% / 99.2%
14	1.12E-01 / 2.57E-01	2.28E+03 / 5.25E+03	8.74E+00 / 4.25E+00	97.2% / 99.2%
15	1.12E-01 / 2.57E-01	2.28E+03 / 5.25E+03	6.67E+00 / 3.77E+00	98.2% / 99.4%
16	9.59E-02 / 2.39E-01	1.93E+03 / 4.88E+03	2.95E+01 / 4.32E+00	95.7% / 99.3%
Avg.	1.03E-01 / 2.46E-01	2.09E+03 / 5.04E+03	2.83E+01 / 4.57E+00	95.8% / 99.2%
Std.	1.33E-02 / 1.78E-02	3.18E+02 / 3.65E+02	5.26E+01 / 1.47E+00	3.9% / 0.2%
Wilcoxon	1.54e-06	1.54e-06	5.59e-06	1.54e-06

5. CONCLUSION

This paper presented an approach for robust identification of a general model of the pressure oscillations in the combustion chamber of a heavy duty gas turbine. The real data has been treated using a maximum filtering process. Further, the FROLS algorithm has been used to select the model's terms, which could be non-linear order two and also regressors of the inputs. The performances of the filtered and non-filtered based models have been compared in terms of the errors SAE, S-SAE and I-SAE of the sixteen combustors of the combustion chamber.

Through the results obtained it can be asserted that the generic models presented in this paper can approximately describe the oscillation phenomena for all the combustors in the frequency band studied. Moreover, the model found without the use of filtered data presented smaller SAE, while the model obtained using filtered data has shown better results in terms of I-SAE and CP. The Wilcoxon test has shown that the error samples for both SAE and I-SAE have statistical significant difference, which means that the Non-Filtered model is more accurate, while the Filtered Model is more robust. Hence, due to its robustness and reliability, the Filtered Model is considered better than the first one in the desired context.

The topics of future research are: the identification of individual models for each combustor or the inclusion of an adaptive system for adjusting each model from the generic one proposed in this paper; the Multi-Input Multi-Output (MIMO) system identification considering the physical-mechanical co-influences; and, the identification considering the errors presented in this paper simultaneously through advanced techniques of Computational Intelligence.

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