Proceedings of the 6th European Conference of the Prognostics and Health Management Society 2021 - ISBN – 978-1-936263-34-9

Lean Blowout Sensing and Processing via Optical Interferometry and Wavelet Analysis of Dynamic Pressure Data

Gianluca Nicchiotti[1], Krzysztof Solinski[2], Fabrice Giuliani[3]

[1,2]*Meggitt SA, Energy Sensing & Controls, Fribourg, 1700, Switzerland*
gianluca.nicchiotti@ch.meggitt.com
krzysztof.solinski@ch.meggitt.com

[3]*Combustion Bay One e.U. advanced combustion management, Graz, Austria*
Fabrice.Giuliani@CBOne.at

ABSTRACT

More stringent environmental requirements for gas turbine pushed towards the development of new methodologies to sense and monitor the combustion process.

New dynamic pressure sensors based on optical interferometry have been developed to improve performances of traditional piezoelectric sensors at low frequency and high temperature which limit their capability of detecting impending blowout conditions.

By acting on combustion settings, equivalence ratio has been varied to produce lean combustion regimes under which optical and piezo sensors performance have been compared.

The data collected were analyzed with two wavelet-based signal processing methods designed to represent flame health indicators. The first algorithm simply exploits the well-known wavelets time/frequency analysis capability to carry out an investigation of signal variations at a lower frequency range up to 40 Hz. The second uses wavelets to extract non-linear characteristics of the signal related to the fractal dimension of the signal itself.

The flame health indicators computed on data acquired by the optical sensor, reacted to changes in combustion dynamics preceding the blow out event. This was not the case with the data set acquired from the piezoelectric technology.

The combination of optical sensing and wavelet analysis allows to define quantities that can be associated to the health of the flame and give hints about the imminence of the flame extinction.

1. INTRODUCTION

Increasingly restrictive emission standards compel power generation systems to operate within lean combustion limits in order to reduce the formation of NOx. Under lean conditions, the combustion process becomes more vulnerable to small dynamic pressure perturbations caused by load changes, variations in air temperature or humidity. When the air-fuel ratio shifts towards a lean mixture the flame speed gradually decreases from its value at stoichiometric conditions. Once the flow velocity of the fuel mixture exceeds the local flame speed of the reacting components, the flame becomes unstable and can be swept away by the flow from the unburned reactants and blowout can take place. A blowout event, i.e., the disappearance of the flame, caused by an excessive leanness of the reacting mixture is generally referred to as a lean blowout (LBO) and may occur due to a flame blow-off or flame extinction. LBO represents the main challenge when operating combustors in lean conditions (Lieuwen & Yang, 2006) and it is a serious problem for operations of land-based gas turbines, which may lead to engine shutdown, impacting productivity and generating revenue losses.

Currently the risk of LBO is mitigated by operating the combustor with a wide margin above the uncertain LBO limit. The ability to sense or detect LBO precursors would provide significant benefits in terms of engine reliability and operability. Trustworthy blowout precursors would enable optimal performance by reducing maintenance, shutdown time and operating costs overall, while increasing the engine life expectancy.

The present paper is structured as follows. The first part gives an overview of the current methodologies used for LBO precursor's detection. Subsequently, a dynamic pressure measurement technology based on optical interferometry is introduced. The improvements brought to the low frequency analysis, when compared to piezoelectric sensors are then described in details. Afterwards, two different algorithmic approaches used to identify LBO precursors are proposed. In conclusion, we will examine the results obtained during an "ad hoc" test campaign aimed at studying the behavior of the pressure signal in the vicinity of the LBO, where the proposed algorithms have been used to analyze data recorded by the interferometric optical sensing system.

2. LBO Sensing: State of the Art

Development of data acquisition and analysis schemes and strategies requires a thorough understanding of the flame characteristics which precede LBO.

Numerous schemes (Glassman, Yetter, & Glumac, 2014), (Cheng & Kovitz, 1958) and (Peters & Williams, 1983) have been suggested to explain blowout, focusing on the thermal balance between heat release rate and heat loss rate.

Three main mechanisms have been proposed to explain the LBO phenomenon. According to Kalghatgi and Gautam (1981) blow-out occurs when the local reactant flow velocity exceeds the maximum premixed turbulent burning velocity. Broadwell, Dahm and Mungal (1985) identified, among other causes, the reaction time not keeping the pace of the changes in mixing time, whilst Kim, Williams and Ronney (1996) suggested that intrinsic flame-front instability may lead to the blowout. In general, burning velocity, flame thickness and flow dynamics seem to be the most fundamental parameters that govern flame processes close to its extinction. Their presence determines changes in thermo-acoustic patterns, chemiluminescence and ion emissions, in addition to the changes in flame temperatures. These physical quantities can be detected by readily available sensors and can be used to determine impending blowout identification.

Chemiluminescence provides information on the presence of the combustion process and its energy, as its measurements are linked to reaction rate and heat release rate. Therefore, chemiluminescence is commonly employed for monitoring the flame stability and blowout detection (Keller & Saito, 1987), (Lawn, 2000), (Roby, Hamer, Johnsson, Tilstra, & Burt, 1995), (Mehta, Ramachandra, & Strahle, 1981) and (Khanna, Vandsburger, Saunders, & Baumann, 2002). In this case, the primary chemiluminescent species of interest in a hydrocarbon flame are electronically excited OH. This method depends on the optical interface, supposedly having constant properties, while in practice it may blacken or lose transparency, which is a shortcoming regarding embedding such sensors in combustors.

Particle Image Velocimetry (PIV) is a quantitative flow visualization technique, used by Chaudhuri, Kostska, Renfro and Cetegen (2010), Raffel, Willert and Kompenhans (1998) and Stohr, Boxx, Carter and Meier (2011), to determine the instantaneous whole-field fluid velocity, which is one of the key parameters characterizing combustion instabilities. This is a laboratory method, also requiring large optical access. Moreover it results extremely demanding in computation time.

High-speed intensified Charge-Coupled Device (CCD) cameras employed to measure flame shape, in conjunction with edge detection image processing algorithms, can also provide information about the flame health.

Each of the above sensing technologies features drawbacks like: maintainability, operating temperature limits or slow response time, which makes pressure sensors based on piezo-electric effect, the most widely adopted systems for this kind of application.

Dynamic pressure is proportional to the temporal rate of change of heat release and many ground-based systems are instrumented with dynamic pressure piezoelectric transducers (Pressure Sensors, 2021), (Pressure Transducers, 2021) and (Dynamic Pressure Sensors, 2021). With respect to other sensing technology their main advantage lies in the possibility of placing them near the fuel injectors in the combustor front-end.

3. LBO Sensing: Piezo Limitations

When combustors operate in lean conditions, oscillations arise as the equivalence ratio is reduced. Observations and numerical simulations have shown that oscillations are characterized by high amplitude pressure fluctuations caused by the local flame blowout and re-ignition events, happening at low frequencies. The occurrence of these partial extinction and re-ignition events increases as the flame approaches lean blowout.

All predicted (Yi & Gutmark, 2009) and observed (De Zilwa, Uhm, & and Whitelaw, 2000), (Muruganandam & Seitzman, 2012) and (Nair & Lieuwen, 2005) frequencies are below 40 Hz, hence the precise observation of low frequency pressure signal is central for the analysis of LBO phenomena.

Piezoelectric (PE) phenomenon has been utilized for decades in dynamic pressure measurements. Various piezoelectric materials have extensively been researched for high-temperature (HT) applications (Cavalloni, Sommer, & and Waser, 2011) and each one of them has its own unique advantages and drawbacks for use in HT sensors.

PE pressure sensors exploit the property of piezoelectric materials to produce charge output proportional to pressure.

However the way in which piezoelectric materials react to high temperatures or temperature transient conditions may affect sensor performance at low frequencies.

In general, PE sensors cannot produce output proportional to static pressure. The charge created by applied static pressure will eventually leak through the material and disappear. The pace of the electric charge leakage shapes the sensor sensitivity to low frequency pressure changes, i.e., its low frequency response. The resistance, which drops with temperature increase at about a factor 10 every 100°C (Jiang, Kim, Zhang, Johnson and Salazar, 2014), accelerates the charge leakage through the PE crystal, hence dropping the sensitivity to low frequency pressure changes. At the same time at high temperatures, phenomena like twinning and pyro-electricity arise increasing the measurement noise.

The combination of all these factors makes quantitative and qualitative evaluation of low frequency measurements at temperatures above 450°C with PE sensors difficult or even not possible in certain particular cases.

4. LBO Sensing: Optical Interferometry

Physical limitations of PE based technologies were the driving factors for exploration of pressure sensors designs based on Fabry-Pérot interferometry (Hernandez, 1986), (Berthold & Lopushansky, 2014). In addition to enhanced sensitivity at low frequency, optical interferometry should provide advantages over piezoelectric sensing also for their inherent insensitivity to external perturbations, such as electromagnetic interferences and vibrations.

The interferometric pressure sensing system can be subdivided into an optoelectronic interrogator and an optical transducer. The subsystems are connected together through an optical fiber, so that light signals can be exchanged, as shown in Figure 1.

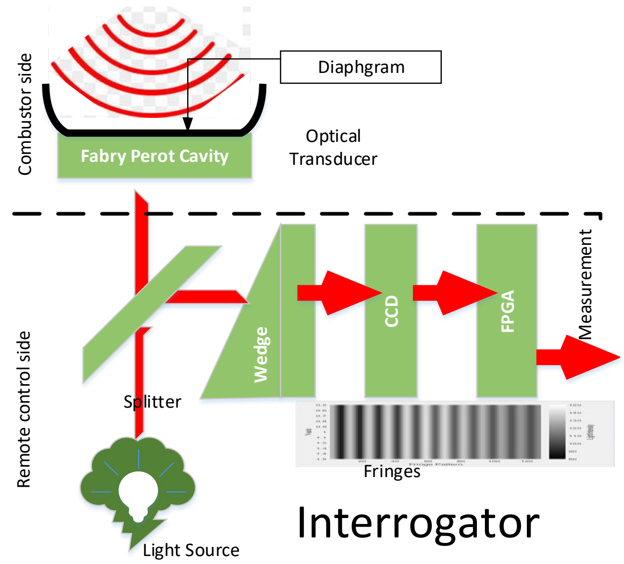

Figure 1: Interferometric system working principle

The interrogator sends a light signal out to the Fabry-Pérot cavity. The cavity is composed of two semi-reflecting glass mirrors. One mirror is directly connected to the optical fiber and the other is bonded to a diaphragm, such that the cavity dimension varies when it is subjected to pressure.

Within the Fabry-Pérot cavity, the light is frequency-modulated by the applied external pressure and returned to the remote control side. The interrogator converts the frequency modulation of the light into spatial modulation by means of a Fizeau wedge interferometer (Born & Wolf, 1999), that produces a fringe signal. The spatially modulated light is recorded by a CCD, whose signal is then processed to extract the dynamic pressure measurement.

5. LBO Processing: Low Frequency Analysis Of Non-Stationary Signal

With any type of sensor, implementing a LBO precursor detection technique, requires inserting a software module into the existing monitoring system.

A valid LBO precursor should display at least three key features:

- a fast time response,
- increase monotonically as blowout is approaching,
- robustness against noise and small deviation of signal parameters.

Based on the phenomenology of an imminent LBO, three main signal-processing methods have been used for extracting precursors: conventional spectral or wavelet-based time-frequency analysis (Farge, Kevlahan, Perrier, V., & Goirand, 1996), statistical analysis and threshold crossing analysis (Muruganandam, et al., 2002). As previously discussed, in the vicinity of LBO, transients in the low frequencies band occur and there is a marked increase in power in the 10-50 Hz range. The power in these spectral bands increases by a factor of nearly 60 near blowout (Nair S. , 2006).

The primary limitation of a conventional examination of the spectrum through Fourier Transform is its insensitivity to time-localized events. This shortcoming can be avoided with time-frequency data analysis using the wavelet transform, for instance.

5.1. Wavelets

Wavelets are zero average waveforms with compact support. Continuous Wavelet Transform (CWT) is the result of convolving the signal $X(t)$ with appropriately scaled and shifted versions of the mother wavelet $\boldsymbol{\psi}$(t):

$$C_x(a,b) = \int X(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \qquad (1)$$

It determines how much the signal in some localized interval around time b, matches the wavelet basis function ψ(t) at the scale a. Thus, it can be used for detection of features with certain prescribed characteristics and time scales.

CWT can be viewed as a generalization of short time Fourier transform, which can be recovered by replacing the so called mother wavelet $\psi(t)$ by the complex exponential e^{-it}, and the scale factor is the inverse of the frequency.

Continuous wavelet coefficients $C_x(a,b)$ in Equation (1) are the sum of signals, over time, multiplied by scaled and shifted versions of the mother wavelet. The higher the C_x, the closer the similarity between the signal and the wavelet. Hence, by selecting an appropriate wavelet characteristics, the CWT can be used to extract precursors from noisy data, with precise signal localization.

If the chosen wavelet belongs to the orthogonal family the Discrete (or Dyadic) Wavelet Transform (DWT) can be used to reduce the number of coefficients whilst keeping the full reconstruction capability of the original signal. DWT limits to powers of 2 the variation in scales and shifts. Hence the two wavelet parameters are defined as $a = 2^{-j}, b = k2^{-j}$

Where j and k are integers. Equation (1) becomes:

$$C_{j,k} = \int X(t)2^{j/2}\psi(2^j t - k)dt \qquad (2)$$

5.2. Wavelet Flame Health Indicators

A practical question is often which orthogonal wavelet to use and why. In addition to the popular Morlet wavelet, a variety of analytic wavelets have been proposed, including the Cauchy, Derivative of Gaussian, lognormal or log Gabor, Shannon, and Bessel wavelet (Holschneider, 1995) and (Mallat, 1999). For our application, Morse wavelet basis has been used. The generalized Morse wavelets were introduced by Daubechies and Paul (1980) as the eigenfunctions of a time/frequency localization operator. Morse wavelets are particularly useful for analyzing localized discontinuities and events. They can be parametrized with two values, which makes them more versatile than other wavelet families, such as Morlet wavelets. Morse wavelets are defined in the frequency domain as:

$$\Psi_{\beta,\gamma}(\omega) = \int \psi_{\beta,\gamma}(t)e^{-i\omega t}\,dt \qquad (3)$$

where γ > 0 is the shape parameter and β > 0 is the oscillation control parameter. In our tests, we set the values γ = 0.1 and β = 22, which approximates Bessel wavelet (Lilly & Olhede, 2012).

Based on the computed Morse wavelet coefficients, we developed two flame health indicators whose objective is to behave as LBO precursors. The rationale is to track in time the relative wavelet energy within the low frequency band between 3 and 40 Hz; a strategy recalling the wavelet entropy approach (Rosso, Blanco, & al., 2001).

The former indicator compares the relative intensity of the wavelet coefficients $C_{j,k}$ with scale parameter j, spanning a frequency range between 3 and 40 Hz. We named it hard indicator I_H:

$$I_H = \begin{cases} 0, & if\ (max(|C_{j,k}|) - min(|C_{j,k}|)) < mean(|C_{j,k}|) \\ \dfrac{max(|C_{j,k}|) - min(|C_{j,k}|)}{mean(|C_{j,k}|)}, & else \end{cases} \qquad (4)$$

where *max*, *min* and *mean* indicate the maximum, minimum and average operations, respectively.

The latter follows the evolution of the statistical dispersion of the coefficients $C_{j,k}$ in the same range of frequencies defined above and we named it soft indicator I_S:

$$I_S(t) = \frac{std(|C_{j,k}(t)|)}{mean(|C_{j,k}(t)|)} \qquad (5)$$

where *std* indicates the standard deviation operation.

6. LBO Processing: Nonlinear Properties Of LBO Transition

Nonlinear time series analysis approach inspired by chaos theory is becoming an increasingly reliable tool for clarifying the nonlinear properties of complex dynamics (Henry, Lovell, & Camacho, 2001). Investigating nonlinear dynamics of combustors, Kabiraj and Sujith (2012), Gotoda, et al. (2012) and Nair and Sujith (2014) showed that the 'combustion noise' generated by the flame is not composed by merely stochastic fluctuations and possesses multifractal characteristics. The transition to blowout exhibits dynamically rich behavior, more specifically, prior to blowout, the system switches from low-amplitude periodic fluctuations to high-amplitude chaotic fluctuations.

Noiray and Schuermans (2013) showed that the 'noise', which in general is either filtered out or treated as stochastic background, contains relevant information about the dynamical state of the system and can be used to understand the combustion health. As a consequence, the separation of the measurements into a signal and noise may lead to loss of valuable information because the 'noise' might be a direct consequence of inherent complexity of turbulent combustion dynamics.

Nonlinear dynamical systems are characterized by invariant measures, which can be estimated from observed time series. The invariant measures are associated with the complexity of the underlying system dynamics. The effectiveness of the fractal description in detection of pressure fluctuations preceding the LBO has been initially presented by Gotoda, et al. (2012). Taking advantage of better quality signals from the interferometric optical sensors, as a measure of nonlinear signal correlation multifractal features, pressure data have been extracted and analyzed in quest for LBO precursors.

6.1. Multifractal analysis and Holder exponent

The term 'fractal' (Mandelbrot, 1974) is used to describe objects that have a fractional dimension. Fractal structures appear naturally in dynamical systems. The analysis of these structures provides knowledge about the relation between systems, uncertainty and indeterminism. They are especially effective for obtaining information about the future behavior of complex systems (Aguirre, Viana, & Sanjuán, 2009).

Fractals are objects presenting self-similarities across different scales, which implies long-term memory persistence. Mathematically, for a fractal time signal X, holds:

$$X(ct) = X(t)/c^H \qquad (6)$$

for some scaling c and a constant H. H is called Hurst exponent and its value lies between 0 and 1. Hurst exponent quantifies the persistence of the signal, and characterizes scaling behavior in the time domain. For completely uncorrelated noise (white noise), H = 0.5, whereas persistence in the random time series yields H > 0.5 and anti-persistence yields H < 0.5. Hurst exponent can be estimated from sampled data and it is linked to fractal dimension D by the equation D = 2 – H.

Low-frequency trends and scaling behavior can also be seen in the frequency domain. As opposed to broadband white noise, low frequencies dominate for persistent noise. More precisely, a time series that exhibits scaling behavior follows the frequency-domain scaling behavior described by:

$$A(\nu) \propto \nu^{-|\beta|} \qquad (7)$$

where A is the magnitude of the frequency spectrum and ν the frequency. The negative sign in the exponent indicate an amplitude decay with higher frequencies. For a time signal, mono dimensional, the scaling exponent is related to the Hurst exponent through:

$$\beta = 1 - 2H \qquad (8)$$

The scaling exponent β can be determined by fitting a regression line into the log-transformed data points of the spectral magnitude over the frequency. These reveals the key role played by a precise measurement at low frequencies provided by the interferometric optical sensor.

The Hurst exponent H, describing scaling behavior in random processes, can also be determined as a local property when a single window of variable length *t* remains centered on the observational point in time t_0. In this case, H is referred to as the local Holder exponent as opposed to the Hurst exponent, which applies to a global property. The rescaled range analysis yields one value of the Holder exponent for each observational point in time and therefore provides a time series H(t).

Wavelet Leader Multifractal Analysis (WLMA), also known as Wavelet Transform Modulus Maxima (WTMM) (Jaffard, 2004) (Muzy, Bacry, & Arneodo, 1993), is a method which allows to estimate the scaling exponents and the corresponding fractal features of the signal.

The Holder exponents of signal X and its singularity spectrum can be determined from wavelet leaders (Jaffard, Lashermes, & Abry, 2006). Wavelet leaders are constructed from the wavelet coefficients, by selecting a subset of wavelet transform coefficients $c_{j,k}$, representing the local maxima of the coefficients across adjacent dyadic segments (Hytönen & Kairema, 2013). The wavelet leader at t_0 at the scale j is defined as:

$$d_j(t_0) = max\{|c_{j',k'}|:\lambda_{j',k'} \in 3\lambda_{j,k}(t_0)\} \qquad (9)$$

where $\lambda_{j,k}(t_0)$ is the dyadic segment at the scale j, containing t_0 and $3\lambda_{j,k}(t_0)$ is a three times enlarged version of $\lambda_{j,k}(t_0)$, i.e., it consists in the union of $\lambda_{j,k}(t_0)$ and its 2 neighbors at scale j. The Holder exponent h_X of X at t_0 is then given by:

$$h_X(t_0) = \lim_{j\to+\infty} min \frac{\log d_j(t_0)}{\log 2^{-j}} \qquad (10)$$

Again the limit can be computed through a regression requiring long range time scale ($j \to +\infty$), hence high quality data at low frequency are crucial for the correct estimation of the parameter.

Following the concepts of nonlinear time series analysis presented by Kabiraj, Saurabh, Wahi and Sujith (2012), (De, Bhattacharya, Mondal, Mukhopadhyay and Sen (2020) and Gotoda et al. (2012), Holder exponent time-evolution has been evaluated as a possible flame health indicator to detect impending LBO events.

Tests on pressure signals recorded with the optical sensor, whilst varying combustion equivalence ratio and approaching LBO will be presented in the next sections.

7. LBO MONITORING: TEST SETUP

To assess the performance of the flame health indicators described above, we used the data collected during the tests presented in Nicchiotti, et al. (2021). The main objective of this study was to compare the optical sensing system with its piezo-electric counterpart in a controlled, precise and repeatable environment, while running several realistic scenarios representative of gas turbine combustion.

For the flame health indicators, the results obtained by processing pressure data from both piezo-electric and optical sensors will also be compared. A schematic representation of the test rig is shown in Figure 2. The two-stage burner generates a swirl stabilized premixed flame of air and propane. The pilot and main burner are coaxial and the flame evolves in a glass liner of 100-mm diameter and 400-mm length. Sensors locations are shown in Figure 3.

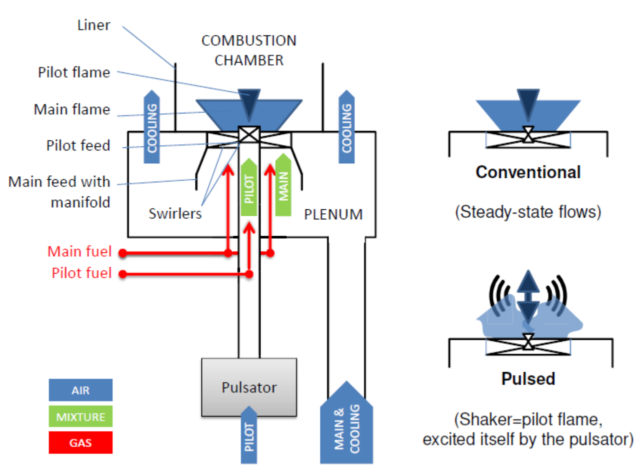

Figure 2: Schematic representation of the test rig.

Tests were run up to 20 kW thermal power. Both burning air (pilot + main air) and cooling air mass flow rates could be set up to 8 g/s. Acting on combustion parameters, cooling slots and the pulsator parameters, the test rig allows to create conditions for premixed to diffusive flame transitions, thermoacoustic instabilities, flashbacks and LBO.

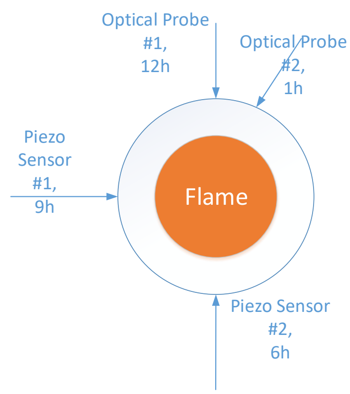

Figure 3: Sensors locations; all sensors are flush mounted at 75 mm downstream from the burner front plate.

Controlled LBOs are initiated at 16 kW by gradually increasing the mass flow of burning air, until a strong flame dynamic moving up and down along the liner is observed, while a characteristic coughing noise is heard. The air mass flow rate is maintained over periods of half a minute. The lean flame fights for stabilization and loses its footing while the combustor walls cool down, moving the heat strain downstream in the flame tube.

LBOs were observed at equivalent ratio $\Phi \cong 0.6$ at low power, degrading down to the $\Phi \cong 0.7$ at high power.

8. LBO MONITORING: TEST RESULTS

Six different controlled LBO tests were performed. For each of them the proposed flame health indicators were computed for both optical and piezo-electric sensors. An initial analysis of scalograms confirms that higher levels of noise at low frequencies are observed with piezo-electric sensors. Figure 4 shows scalograms produced with optical (top) and piezo-electric (bottom) sensors recordings. On the optical sensor scalogram, the flame “cough” phase or pattern, where the main flame detaches and reattaches to the flame holder, is clearly observable and the LBO event can be clearly seen at time t = 9s. On the contrary, with the piezo-electric data, such phenomena are partly hidden by the low frequency noise, represented by the lighter areas of the scalogram.

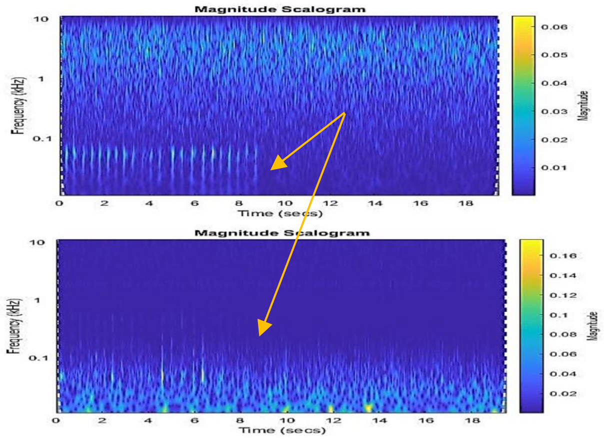

Figure 4: Scalograms in proximity of the LBO event for both the optical (top) and piezo-electric (bottom) sensors; arrows indicate the LBO time event at t = 9s.

8.1. Low Frequency Wavelet Indicators

Behavior of the hard and soft indicators, as described in Paragraph 5.2, has been investigated. The hard indicator I_H is displayed in Figure 5 and shows sharp and well visible peaks approaching the LBO event. In this test, peaks start appearing about 10 seconds before the event and increase in size as the flame extinction approaches. The hard indicator I_H has a low response far from the blow out, mitigating the risk of false alarms. However, it does not appear really appropriate for a continuous measurement of the health of the flame due to its discontinuities.

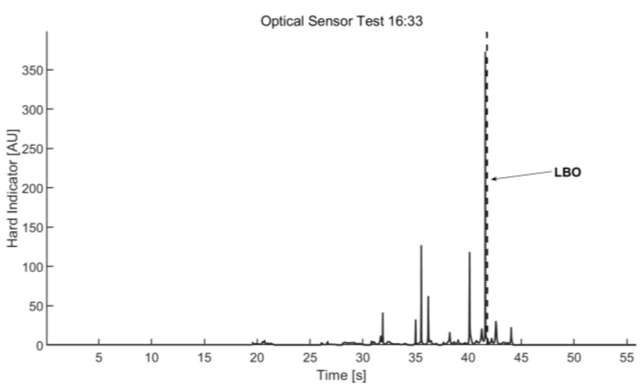

Figure 5: Hard indicator I_H derived from the optical sensor measurements at low frequency; AU stands for Arbitrary Units.

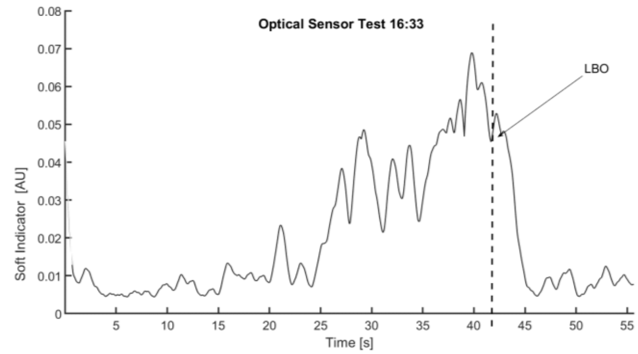

Figure 6: Soft indicator $\boldsymbol{I_S}$ derived from the optical sensor measurements at low frequency; AU stands for Arbitrary Units.

Instead, the soft indicator I_S has a more gradual response to an impending LBO and it starts "reacting" about 15 seconds prior to the event, as displayed in Figure 6. The transition is not as sharp as for the hard indicator I_H, but it increases smoothly as the event approaches. The soft indicator I_S seems to be able to better represent the state of health of the flame at the expense of producing some spurious peaks, as Figure 7 (top) indicates.

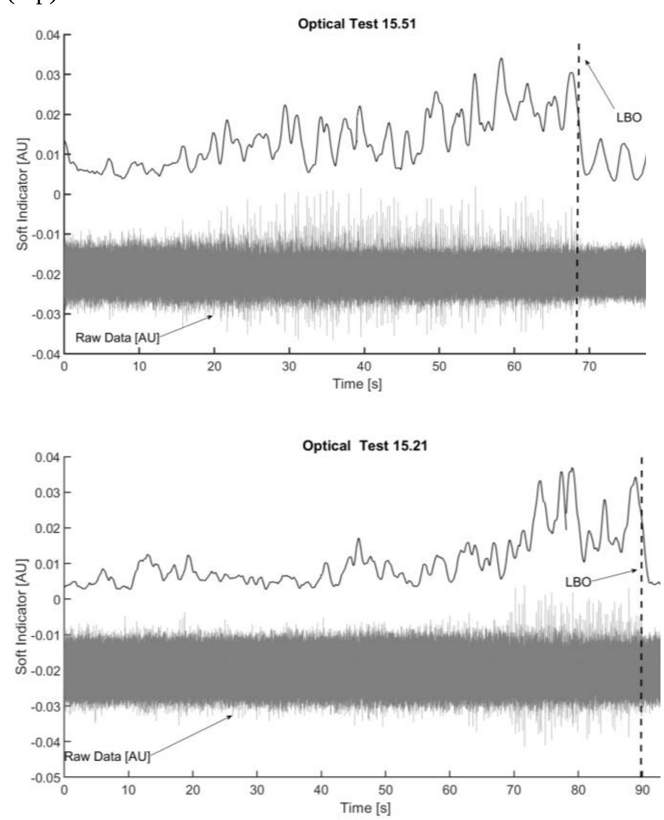

Figure 7: Two test results displaying the soft indicator $\boldsymbol{I_S}$ (curve on top) and the raw data (bottom signal) in Arbitrary Units (AU).

The two indicators have also been computed with the piezo-electric sensors data. As expected, the lower measurement quality at low frequency carried out with these sensors affects the indicator performance. Figure 8 shows the two indicators computed with the piezo-electric data obtained during the same test presented in Figure 5 and Figure 6 for the optical measurements. In this case, the LBO event is not visible at all.

Wavelet based health indicators show an overall good capability to react as the LBO is approaching, across all tests. However they respond more efficiently when the blow-out is preceded by a phase, where the main flame detaches and reattaches to the flame holder and less when it occurs in a smooth, continuous and silent way. Another limitation of such indicators is that they do not produce comparable peak levels before each LBO. This makes difficult to set thresholds for operating a control loop or managing alerts. On the contrary, Holder exponent, introduced in Paragraph 6.1 above, produces peak values more similar across different LBOs, as we are going to show in the next paragraph.

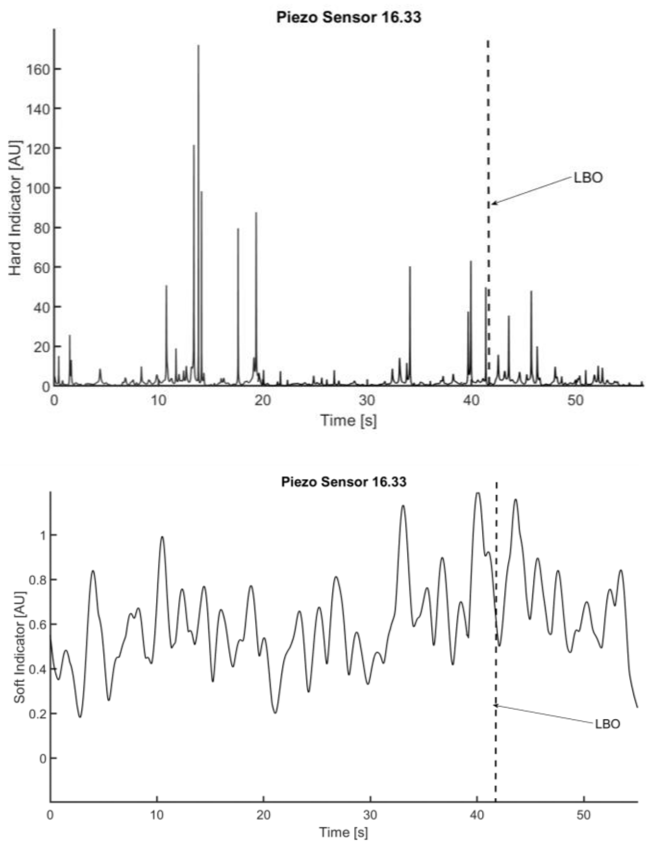

Figure 8: The hard (top) and soft (bottom) indicators derived from the piezo-electric sensor measurements at low frequency; AU stands for Arbitrary Units.

8.2. Holder exponent

The Holder exponent was computed for all available LBO tests. The general behavior, shown in Figures 9 to 12 (top), is quite repeatable. The Holder exponent value stays around 0.6 far from the blow-out event, which corresponds to a white noise situation, and then increases to 0.7-0.8, indicating persistence in the time-series when the flame becomes more unstable and comes nearer to extinction.

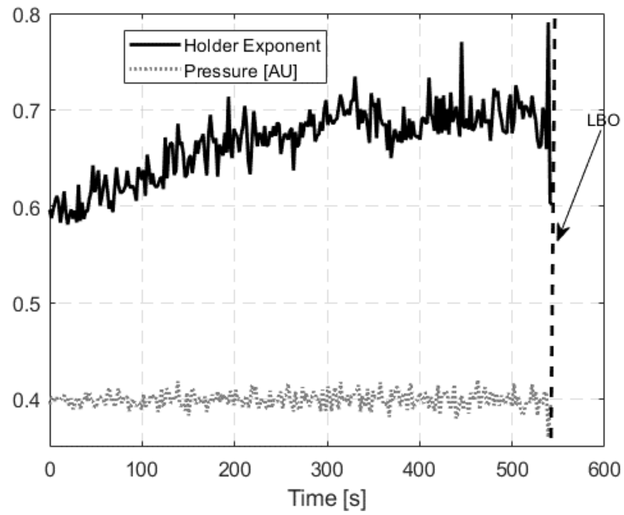

Figure 9: Behavior of the Holder exponent, derived from optical sensor measurements at low frequency, approaching the LBO event; pressure values in arbitrary units are plotted below (dotted line).

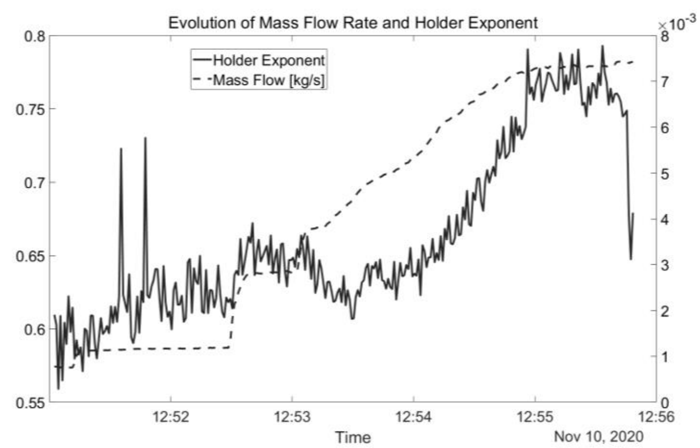

Figure 10: Values of the Holder exponent, derived from optical sensor measurements at low frequency, and the mass flow rate (dashed line), approaching the LBO event.

In our tests, the Holder exponent increases with the increase of air mass flow, whilst fuel rate is kept constant. This affects the equivalence ratio and the flame stability. Figure 10 shows both the mass air flow and holder exponent plotted as a function of time. Decreasing the equivalence ratio by increasing air flow rate brings the flame closer to extinction, which happened at about 12:55:45. The plot shows that flame health deterioration is well captured by the Holder exponent.

A comparison with the data obtained with the piezo-electric sensors was performed and is presented in Figure 12. As it happened for wavelet indicators, even in this case the values computed with the piezo-electric data are affected by noise, as they required low frequency information. As a consequence, the corresponding Holder exponent shows values randomly oscillating around 0.5, which represents the value expected for uncorrelated noise, as discussed in Paragraph 6.1 above.

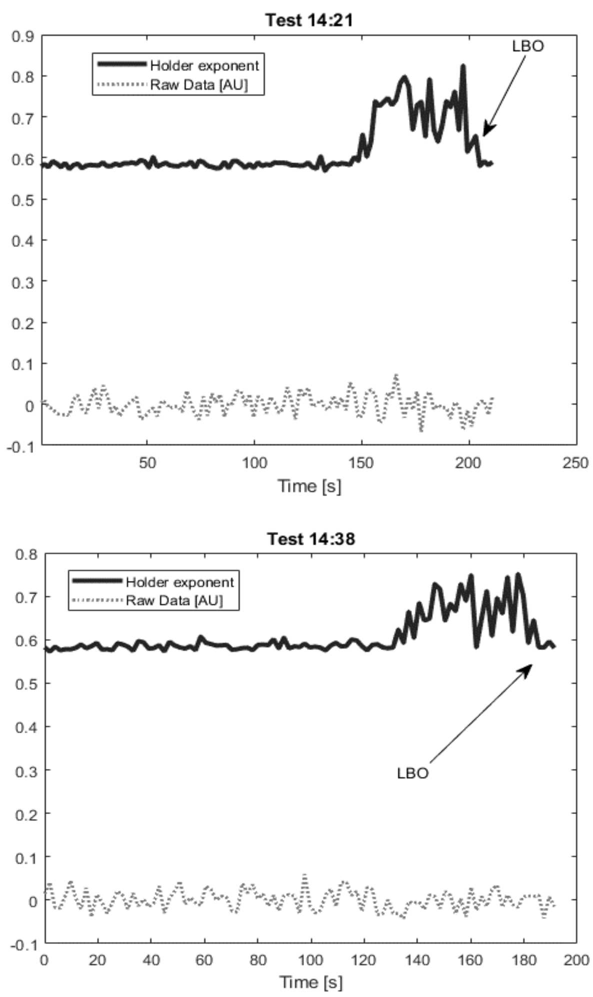

Figure 11: The Holder exponent, derived from optical sensor measurements at low frequency, approaching the LBO event; pressure values in arbitrary units are plotted below (dotted line).

9. CONCLUSIONS

Dynamic pressure sensors, based on optical interferometry, provide good quality, low frequency data at temperatures exceeding 450°C. This capability offers a reliable foundation for impending LBO indicators estimation.

This paper introduced three different flame health indicators based on low frequency analysis to detect and/or predict flame extinction. When deriving these indicators from low frequency measurements from the optical sensing system, it enabled the design of flame condition monitoring strategies with promising results for LBO detection and prognostics. This could lead to a new generation of monitoring tools, probably outperforming the current state-of-the-art, when applied to extremely aggressive environments, such as the hot core of a gas turbine.

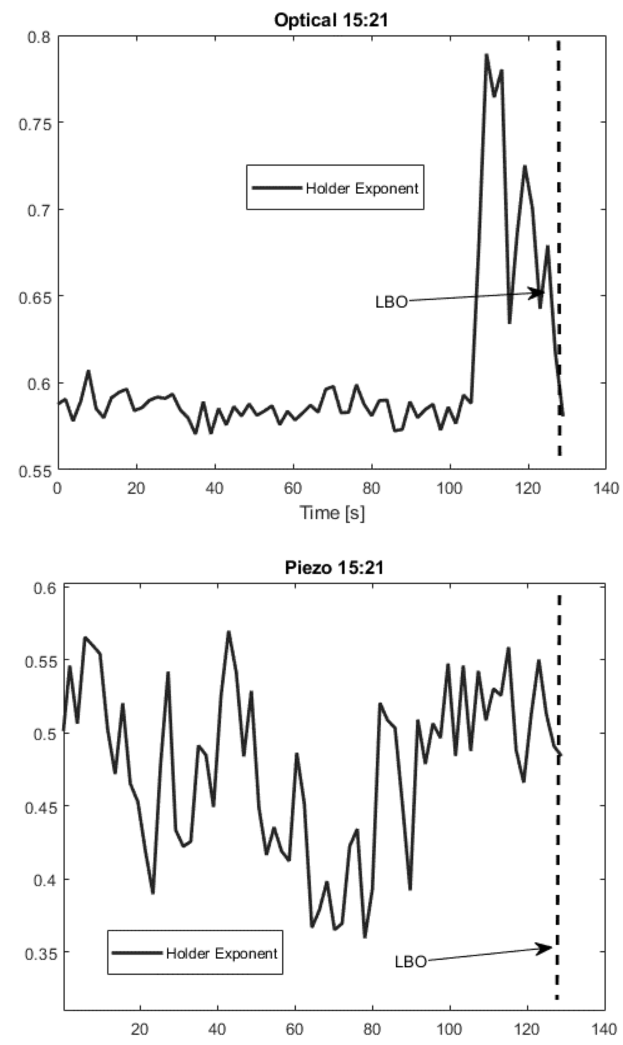

Figure 12: The Holder exponent, derived from both optical (top) and piezo-electric (bottom) sensor measurements at low frequency, approaching the LBO event.

ACKNOWLEDGEMENTS

Special thanks to Nina Paulitsch from CBOne, Lukas Andracher from FH Joanneum GmbH University of Applied Sciences, Graz and to Stéphane Page from Meggitt, who supported this experimental study.

REFERENCES

Aguirre, J., Viana, R. L., & Sanjuán, M. A. (2009). Fractal structures in nonlinear dynamics. *Review of Modern Physics*, 333-386.

Berthold, J. W., & Lopushansky, R. L. (2014). Overview of Advanced Fiber Optic Sensor Equipment for Energy Production Applications. *Proceedings of SPIE*, 197-205.

Born, M., & Wolf, E. (1999). *Principles of Optics.* New York: Cambridge University Press.

Broadwell, J. E., Dahm, W. J., & Mungal, G. M. (1985). Blowout of turbulent diffusion flames. *Symposium (International) on Combustion* (pp. 303-310). Elsevier.

Cavalloni, C., Sommer, R., & and Waser, M. (2011). D1. 1-high temperature stability of new single crystal piezoelectric sensors. *SENSOR 2011*, (pp. 520-525).

Chaudhuri, S., Kostska, S., Renfro, W., & Cetegen, B. (2010). Blowoff dynamics of bluff body stabilized turbulent premixed flames. *Combustion and Flame*, 790–802.

Cheng, S., & Kovitz, A. (1958). Theory of flame stabilization by a bluff body. *Symposium (International) on Combustion*, (pp. 681-691).

Daubechies, I., & Paul, T. (1980). Time-frequency localisation operators: a geometric phase space approach II. The use of dilations and translations. *Inverse Problems*, 661–680.

De Zilwa, S. R., Uhm, J. H., & and Whitelaw, J. H. (2000). Combustion oscillations close to the lean flammability limit. *Combustion Science and Technology*, 231-258.

De, S., Bhattacharya, A., Mondal, S., Mukhopadhyay, A., & Sen, S. (2020). Application of recurrence quantification analysis for early detection of lean blowout in a swirl-stabilized dump combustor. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 30(4), p. 043115.

Dynamic Pressure Sensors. (2021, March 9). Retrieved from https://catalogue.meggittsensing.com/dynamic-pressure-sensors-cp.html

Farge, M., Kevlahan, N., Perrier, V., & Goirand, E. (1996). Wavelets and turbulence. *Proceedings of the IEEE*, 639-669.

Glassman, I., Yetter, R., & Glumac, N. G. (2014). *Combustion 5th Edition.* San Diego: Academic Press.

Gotoda, H., Amano, M., Miyano, T., Ikawa, T., Maki, K., & Tachibana, S. (2012). Characterization of complexities in combustion instability in a lean premixed gas turbine model combustor. *Chaos*.

Henry, B., Lovell, N., & Camacho, F. (2001). Chapter 1 Nonlinear Dynamics Time Series Analysis. In M. Akay (Ed.), *Nonlinear Biomedical Signal Processing: Dynamic Analysis and Modeling* (pp. 1-37). New York: Institute of Electrical and Electronics Engineers.

Hernandez, G. (1986). *Fabry-Perot interferometers.* New York: Cambridge University Press.

Holschneider, M. (1995). *Wavelets: an analysis tool.* Oxford: Oxford University Press.

Hytönen, T., & Kairema, A. (2013). What is a cube? *Annales Academiæ Scientiarum Fennicæ Mathematica*, 405-412.

Jaffard, S. (2004). *Wavelet techniques in multifractal analysis.* Paris: Tech. rep., Paris University.

Jaffard, S., Lashermes, B., & Abry, P. (2006). Wavelet leaders in multifractal analysis. In *Wavelet analysis and applications* (pp. 201-246). Springer.

Jiang, X., Kim, K., Zhang, S., Johnson, J., & and Salazar, G. (2014). High-temperature piezoelectric sensing. *Sensors*, 144-169.

Kabiraj, L., & Sujith, R. (2012). Nonlinear self-excited thermoacoustic oscillations: intermittency and flame blowout. *Journal of Fluid Mechanics*, 376-397.

Kabiraj, L., Saurabh, A., Wahi, P., & Sujith, R. (2012). Route to chaos for combustion instability in ducted laminar premixed flames. *Chaos: An Interdisciplinary Journal of Nonlinear Science*.

Kalghatgi, A., & Gautam, T. (1981). Blow-Out Stability of Gaseous Jet Diffusion Flames. Part I: In Still Air. *Combustion Science and Technology*, 26(5-6):233-239.

Keller, J., & Saito, K. (1987). Measurements of the Combusting Flow in a Pulse. *Combustion Science and Technology*, 137-163.

Khanna, V. K., Vandsburger, U. R., Saunders, W., & Baumann, W. T. (2002). Dynamic analysis of swirl stabilized turbulent gaseous flames. *ASME*, (pp. GT-2002-30061).

Kim, J., Williams, F., & Ronney, P. (1996). Diffusional-thermal instability of diffusion flames . *Journal Fluid Mechanics*, 273-301.

Lawn, C. (2000). Distributions of Instantaneous Heat Release by the Cross-Correlation of Chemiluminescent Emissions. *Combustion and Flame*, 227-240.

Lieuwen, T., & Yang, V. (2006). *Operational Experience, Fundamental Mechanisms, and Modeling.* American Institute of Aeronautics and Astronautics.

Lilly, J., & Olhede, S. (2012). Generalized Morse Wavelets as a Superfamily of Analytic Wvelets. *IEEE Transactions on Signal Processing*, 6036-6041.

Mallat, S. (1999). *A wavelet tour of signal processing, 2nd edition.* New York: Academic Press.

Mandelbrot, B. B. (1974). Intermittent turbulence in selfsimilar cascades: divergence of high moments and dimension of the carrier. *Journal of fluid Mechanics*, 331-358.

Mehta, G. K., Ramachandra, M. K., & Strahle, W. C. (1981). Correlations between Light Emission, Acoustic Emission and Ion Density in Premixed Turbulent Flames. *Proc.Comb. Inst.*, 1051-1059.

Muruganandam, T. M., & Seitzman, J. (2012). Fluid mechanincs of lean blowout precursors in gas turbine combutors. *International journal of spray and combustion dynamics*, 29-60.

Muruganandam, T., Nair, S., Neumeier, Y., Lieuwen, T., & Seitzman, J. (2002). Optical and Acoustic Sensing of Lean Blowout Precursors. *AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit.* American Institute of Aeronautics and Astronautics, .

Muzy, J., Bacry, E., & Arneodo, A. (1993). Multifractal formalism for fractal signals: The structure-function approach versus the wavelet-transform modulus-maxima method. *Physical review E*, 875-887.

Nair, S. (2006). *Acoustic Characterization of Flame Blow Out Phenomenon.* Georgia Institute of Technology.

Nair, S., & Lieuwen, T. (2005). Acoustic Detection of Blowout in Premixed Flames. *Journal of Propulsion And Power*, 32-39.

Nair, V., & Sujith, R. (2014). Multifractality in combustion noise: predicting an impending combustion instability. *Journal Fluid Mechanics*, 635-655.

Nicchiotti, G., A. Page, S., Solinski, K., Andracher, L., Paulitsch, N., & Giuliani, F. (2021). Characterisation And Validation Of An Optical Pressure Sensor For Combustion Monitoring At Low Frequency. *Proceedings of Turbomachinery Technical Conference & Exposition,ASME Turbo Expo 2021*, (pp. GT2021-59103).

Peters, N., & Williams, F. (1983). Liftoff characteristics of turbulent jet diffusion flames. *AIAA Journal*, 423-430.

Pressure Sensors. (2021, March 9). Retrieved from https://www.avl.com/pressure-sensors

Pressure Transducers. (2021, March 9). Retrieved from http://www.pcb.com/TestMeasurement/Pressure/Extreme_Environ.aspx

Raffel, M., Willert, C., & and Kompenhans, J. (1998). *Particle Image Velocimetry: A Practical Guide.* Berlin: Springer-Verlag.

Roby, R. J., Hamer, A. J., Johnsson, E. L., Tilstra, S. A., & Burt, T. J. (1995). Improved Method for Flame Detection in Combustion Turbines. *Transactions of the ASME*, 332-340.

Rosso, O., Blanco, S., & al., e. (2001). Wavelet entropy: a new tool for analysis of short duration brain electrical signals. *Journal of Neuroscience Methods*, 65-75.

Stohr, M., Boxx, I., Carter, C., & Meier, W. (2011). Dynamics of lean blowout of a swirl-stabilized flame in a gas turbine model combustor. *Proceedings of the Combustion Institute*, 2953-2960.

Yi, T., & Gutmark, J. (2009). Stability And Control Of Lean Blowout In Chemical Kinetics-Controlled Combustion Systems. *Combustion Sci. and Tech.*, 226-244.

BIOGRAPHIES

Gianluca Nicchiotti received an MSc in Physics from Università di Genova, Italy in 1987 and an MSc in Applied Science from Cranfield University UK in 2013. Since 2005, he has been working for Meggitt Energy Sensing & Controls as Sr. System Engineer. Prior to Meggitt, he managed an image processing research team for offline cursive handwritten recognition at Elba Research Center and developed algorithms for sport video special effects at Dartfish. His career started at Elsag Bailey R&D in underwater acoustic cameras field. He is author of more than 50 papers and 5 patents. His current research interests are interferometric pressure sensors, signal processing and machine learning.

Krzysztof Solinski Senior Applications Engineer and combustion monitoring subject matter expert at Meggitt Energy Sensing & Controls, he received an MSc in Mechanical Engineering from Poznan University of Technology (2009). Since 2011, has been working at Meggitt in positions related to domains of vibration measurements, condition and combustion monitoring. He is involved in research on development of novel higher order spectra based digital signal processing methods for early machinery fault detection.

Fabrice Giuliani studied mechanical engineering at ESSTIN in Nancy, France, and at the University of Strathclyde in Glasgow, UK (graduation in 1997). After his Diploma Course in 1998 at the von Karman Institute for Fluid dynamics he did his PhD on combustion stability at ONERA Centre de Toulouse, and graduated from SUPAERO in 2002. He worked on kerosene fuel injection systems at DLR Cologne, Germany as a researcher and was then appointed head of department about gas turbine combustion at TU Graz, Austria (Habilitation to direct research, venia docendi, 2010). In 2012, he founded Combustion Bay One e.U., which provides expertise, research and development services in advanced combustion. As of 2021, F. Giuliani is still active in research and education. He is author or co-author of about 60 scientific papers and 4 patents.