# COMBUSTION SOUND ANALYSIS TO CONTROL THE BURNING QUALITY

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<u>Abstract</u>: The quality of the burning process may be investigated by using different means, such as visual inspection, employing electro- chemical transducers or analyzing the sound generated by the burning process. This paper reveals attributes regarding a method to detect the different states of combustion in progress by analyzing sound analogy. These results may be then used in order to take appropriate decisions to maintain the burning process in an optimal state. The first results are very promising and encourage continuing this research in the acoustic relevance in burning quality detection. Due to the fair computational requirements of the method this may be implemented on low cost solutions like microcontrollers.

Key words: combustion quality, instability, acoustic relevance, TESPAR, archetypes.

### I. INTRODUCTION

Acoustic relevance for combustion could be identified in relation with two main different causes:

- Noise coming from inside thermo-acoustic sources of the species production (NITAS);

- noise produced from external sources like the vibrations associated with the hazardous cavitations in the flowing water/steam throw the burner envelop; and/or induced by some leakage at the mechanical components (NEHCL).

After the initial stoichiometry conditions are set up by the use of a gas analyzer, there are several certain running situations in which the acoustic monitor might be useful when comparing with the tardy gas analyzers sensors – as they are inertial electro-chemically based.

In certain conditions thermo-acoustic instabilities might be associated with effects on the draft and by consequence with combustion balance. Rehabilitation of the stabile stoichiometric conditions request sometimes fast and proper decisions in order to remake the efficiency of flow-path through Burner\_Furnace\_Heat exchanger BFH (having turbulences promoters), and to avoid flame breakdown. As it is well known, the gas-dynamic of the premixing zone is the one driving the noisy (NITAS) behavior of combustion.

Just for easier understanding reasons, the image below presents the most noiseless laminar structure (Bunsen based flame), where it is very easy to see that flames become very instable and noisy by rescuing the premixed air access. Finally this instability rises to a sudden inevitable flame brake-down. The following snapshots illustrate the transition from lack of air to lean combustion by progressively raising the premixed air Figure 1.

In certain industrial burners such risking performing conditions imply NITAS and demand fast decisions. That is way acoustic analogy of combustion could be of a real interest when comparing with the tardy electrochemical gas analyzer. Preliminary controlling tests in disjoining the NEHCL impacts were done by the use of a speaker joining the entering flow rate (Fig.2). First idée was to perform tests within as lowered as possible flowing constrain (i.e. a Bunsen based flame). Tests were very hard to be monitored on the Bunsen lean performing conditions, as repetitiveness was almost impossible. Nevertheless the use of a speaker proves to be profitable not for a flow rate corrector but for giving the opportunity of inducing certain extra complementary reference sources.

In order to have the strongest but at the same time easily to be controlled noisy combustion (domestic) instabilities, we have made our option for exploring the primitive (highly NOx engender) 'cup based' burner. In comparing with Bunsen, the 'cup based' burner gives a widely stable thermogas-dynamic geometry. By tuning the premixed air admission or by adjusting slightly the fuel injection, we might setup three distinct steps in moving from noiseless (rich flame) through stoichiometry to lean –very noisy combustion stage.

Data acquisition concerns with three gradual premixed air supplies for the case of two different fuel flow rate  $(1m^{3}CH_{4}/h \text{ and respectively } 2m^{3}CH_{4}/h)$ . Medium air flow rate data acquisition corresponds to stoichiometry (1:9.7 the CH<sub>4</sub>/Air ratio) and the other two data bases refer to the tuning path from less to lean combustion conditions.

The aim of the tests was to reveal the scalable range of acoustic relevance, in disturbing the initial stoichiometric performing conditions. Experimental logistic was gathered around a cylindrical furnace enveloped with cooling water (Figure 2).

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Figure 1. Flame pictures at different mixtures for Bunsen burner and a real furnace

It is very well-known that a heat exchanger should be designed as finned as possible, but avoiding the limit of the narrowness that could be so poky as to introduce undesirable main pressure loses. Thus NEHCL affect the draft and might involve damages of the stoichiometry functioning conditions. The running characteristic point of the fan might be slightly displaced, as effect of extra fluctuating pressure. The exhaust main stream will effectively depend on the viscosity effect, as flow path in-between two fins/walls –take place predominant at the limit layer. Pressure waves will influence more or less the exhaust gases flowing rate at the proximity (limit layer) of the finned walls.

Repeating data from performing credible tests on acoustic analogy for the thermo-acoustic instabilities in combustion, determined us to use a speaker as a reference for the NEHCL source.

It was placed at the bottom of the cylindrical burner, in the way of interfering with the air assisted inlet. The speaker was used to induce noise at different frequencies and magnitude –in order to facilitate the possibility to repeat measurements at any desired conditions /moments. A microphone was used for the spectral data acquisition. The database was used in revealing acoustic accurateness influences coming from the two different NITAS and/or NEHCL sources. Each or all (at once) noise sources, will interfere in the air flow rate, disturbing the combustion conditions more evidently as more weakly in backpressure constrained – the furnace is [3].

In order to have some credible references, accurate tests were performed first on a Rijke-Tube – the simplest specific device for the thermo-acoustic relevance in combustion. Acoustic control steps were tested by obstructing premix zone, to draw the reference data base for the three specific combustion conditions: lack (of air), stoichiometry, and respectively lean fuel [1].



Figure 2. Furnace diagram employed in experiments

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An important part of the work done was related to the CFD prediction capabilities in the evaluation of the thermoacoustic impact. For computational economy reasons the entire interest domain was split in to two distinguish parts. The first one is represented by furnaces contour from the bottom-input burner conditions, to the top line delimiting the exhaust, and i.e. the entering conditions in the second interest zone - represented by the narrowness finned heat exchanger. The thermo-acoustic induced fluctuation in the pressure field should be finally mirrored in-around this path line of the above mentioned zones of interest. Once the heat exchange flux through the finned path could be accurate predicted, the back pressure could be kept in relatively low levels in concordance with the fan running characteristic point. This might give us the possibility to highlight the thermo-acoustic instabilities - as consistent they are in altering the flow-rate performances.



Figure 3. Furnace picture used in experiments

In fig. 4 one may observe a combustion sound capture generated during a specific state of the furnace (high flow  $CH_4$  lean fuel mixture).



Figure 4. Combustion sound capture

### II. THE SIMPLE TESPAR MODEL

TESPAR coding was first proposed by King and Gosling [4]

as a simplified digital language for coding speech. TESPAR coding can be applied for any band limited signals e.g. seismic vibrations ranging from fractions of hertz to radio domain and up to GHz domain and above.

The key idea of TESPAR coding is to use those zeros that can be easy to determine from the waveform by visual inspection. The easiest zeros to find are the zeros of the signal in time domain and associated with the real zeros in the zero domain, other easy to find zeros are the complex zeros associated with the minimum and maximum points on the waveform [8].

In the simple TESPAR model there is a term that must be defined before proceeding forward, an *epoch* (Figure 5) refers the portion of the waveform situated between two successive zero crossings of the signal [5]. There are two descriptors in the model associated with an epoch:

 $\mathbf{D}$  – The "*duration*" descriptor. The duration descriptor is related to the real zeros, it describes the number of samples in an epoch, in other words the number of samples between two successive zero crossings of the waveform.

S - The "*shape*" descriptor. As the name implies this descriptor is somehow related with the shape of the epoch – it is the number of local minima found in an epoch.

The band limited nature of the signals that TESPAR applies poses several limitations on the duration and shape of each epoch. The longest epoch is approximately equal to half of the period of the lowest frequency while the shortest epoch might have a duration of about half of the period of the highest frequency [6]. Obviously short epochs will generally have fewer minimums than longer epochs; generally the short epochs will be simpler epochs. If we regard an epoch as a two dimension vector an epoch is a point in the D-S plane. Because of the finite bandwidth the epochs all are situated in a finite zone of the plane.

#### THE TESPAR ALPHABET

Why was the finite zone mentioned before? Having a finite zone in the plane D-S is important for the next step where a vector quantization method is used to obtain a symbol table based on which for each epoch characterized by the two descriptors D and S one symbol is associated. The symbols in the table form the *TESPAR alphabet*.

The vector quantization algorithm is applied on a training set that captures the statistical distribution of the TESPAR epochs in the D-S plane. The training set is specific to a class of signal e.g. human speech, seismic vibrations, the training set must be specific in order to minimize the overall distortion.

Of course compression is obtained from this process, usually a small code-book is required 29 symbols are sufficient for most of the applications [4]. To further increase the compression, "alike" epochs can be associated with the same symbol. To generate this alphabet, a combustion sound record sampled at 16 kHz with 16bits resolution was employed. In order to limit the epoch descriptors, the following values were employed, for D=45 and for S=12. Using these limits more than 98% of the

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epochs are included in these ranges. Approximating the epochs with a symbol will eliminate the small disturbing discrepancies from the signal contributing thus to the overall robustness of the method. A 32 symbols alphabet was generated from the combustion sound records.



Figure 5. Signal inspection and descriptors (D, S) assignation to epochs.

D\S	0	1	2	3	4	5	6	7	8	9	10	11	12
1	32	-	-	-	-	-	-	-	-	-	-	-	-
2	24	-	-	-	-	-	-	-	-	-	-	-	-
3	28	28	-	-	-	-	-	-	-	-	-	-	-
4	12	12	-	-	-	-	-	-	-	-	-	-	-
5	20	20	20	-	-	-	-	-	-	-	-	-	-
6	4	4	4	-	-	-	-	-	-	-	-	-	-
7	30	30	30	30	-	-	-	-	-	-	-	-	-
8	14	14	14	14	-	-	-	-	-	-	-	-	-
9	22	22	22	22	22	-	-	-	-	-	-	-	-
10	6	6	6	6	6	-	-	-	-	-	-	-	-
11	6	26	26	26	26	26	-	-	-	-	-	-	-
12	26	10	10	10	10	18	-	-	-	-	-	-	-
13	10	10	10	18	18	18	2	-	-	-	-	-	-
14	31	18	18	18	18	2	2	-	-	-	-	-	-
43	9	9	9	9	9	9	9	9	17	17	17	17	1
44	9	9	9	9	9	9	9	1	1	1	1	1	1
45	9	9	9	9	9	9	9	1	1	1	1	1	1

Table 1. TESPAR symbol alphabet generated for combustion sound, sampled at 16 KHz

#### **TESPAR MATRICES**

The *TESPAR coder* breaks the signal in epochs described by the D-S parameters. Further on, by using a codebook, each epoch is approximated with a symbol, so at the output of the TESPAR coder we have a stream of symbols that need further analysis, figure 5 [4].

The TESPAR symbols stream can be organized in *fixed sizes* TESPAR matrices - essential for classification methods like artificial neural networks or archetypes based classifications. Two of these matrices are presented as follows.

The first TESPAR matrix called "*TESPAR S matrix*" simply keeps the number of repetition for each symbol in the stream figure 6. As we can see from the graphical representation the S matrix does not contain any information about the signal's time evolution.

Another matrix is the "TESPAR A matrix". This matrix

is a two dimensional matrix that counts the number of symbols pairs that appear at an L distance. The L parameter is called "*lag*" and introduces temporal information in the A matrix. Note that temporal information is the main difference between the two matrices. A small lag (< 10) will offer information on the short time evolution of the signal while a higher lag (> 10) will offer information on the long time signal properties. It is obvious that the A-Matrix offers more information than the S-Matrix, but at the same time it needs a lot more computational time than the S-Matrix (N times longer time). Consequently, a compromise has to be made between the computational time and the accuracy of the results.

Adding further dimensions to the matrices may lead to the increasing of classification power. However at this point the high power of discrimination displayed by these two matrices has proven that the use of three dimension matrices

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is unnecessary [4].

A significant advantage of representing the time-varying speech signal with TESPAR matrices is the fact that TESPAR matrices have the same size, regardless the length of the utterance. TESPAR-S matrices (vectors) were employed for the performed experiments.

In the classification process, one can employ the distance calculation between the archetypes and test matrices or the MLP neural networks. In the experiments the distance calculation between the archetypes and test matrices were used.

This property of TESPAR matrices to have constant dimension made possible the use of archetypes to improve the accuracy of the classification process. An archetype matrix results by averaging two or more matrices resulted from the same sentence uttered in different conditions and at different timings. These archetypes tend to underline the common characteristics and to diminish the different anomalies that may exist in different versions of utterances. The archetype created at once may be stored in an archetype database and used subsequently. In the classification process, a new matrix is generated and then compared with the archetype. Different forms of correlation may be used to carry out the classification. To decide if the two matrixes are similar enough a threshold is imposed and the archetype with the best score is considered to be the winner after this score is compared with the threshold. In fig. 7 the archetype generation and the classification process are presented [5].



Figure 6. TESPAR coding process from signal to TESPAR S and A matrices



Figure 7. TESPAR S and A matrices

# **III. EXPERIMENTS AND RESULTS**

In order to evaluate the efficiency of the TEPAR method in classifying the different sounds produced in the combustion process two types of experiments were made.

The first one, employed the sound produced by a **Rijke-Tube** - the simplest specific device for the thermo-acoustic relevance in combustion. For this burner six different situations were considered. By using two different debits of  $CH_4$ , the air flow was changed. For every  $CH_4$  flow, three different combustion mixtures were used: rich (lack of air), around stoichiometry level and lean (poor fuel) mixture.

Other experiments were performed on the furnace presented in figures 2 and 3. Some sounds samples were recorded depending on different thermo-energetic water flow rates and combustion in progress stages. The processing flow in the experiments was the same for both tests and followed the following steps:

- some recorded files from every type were employed to generate the alphabet for every system;
- the other files were coded by the TESPAR coder using the alphabet the TESPAR S and A matrices were generated;
- three files of every type were employed to generate the archetypes (TESPAR S and A matrices) for every specific state of the burning system;
- Then all the recorded files were classified as belonging to the different states of the system.

In our work we have used an external sound board, Creative Professional model, E-MU0404USB (24-bit/ 192kHz A/D and D/A converters, with 113dB SNR the A/D and 117dB SNR the D/A) and E-MU XTC Class-A ultra-

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low noise preamplifiers. The hardware zero-latency direct monitoring allows you to record and overdub with no annoying delay plug-and-play operation. The microphone is an Audio-Technica AT2010 type with 20Hz-20 kHz band, high sensitivity with capture directivity in solid angle of 15°. The Creative Professional sound board was connected to a

PC by the USB interface. The recorded files for the different states of the system were stored on the computer and then they were employed in the classification experiments. All the models generated for the different system states are system dependent, so for every system we have to generate the models.



Figure 8. Archetype generation and the classification process

### **EXPERIMENT 1 - RIJKE-TUBE**

The experiment started with combustion sound acquisition. For every considered state 25 files of approximately one second were recorded using a sampling frequency of 16 kHz with 16 bits resolution. Therefore for this experiment 150 files were recorded for the six different considerate states of the system.

A first goal was to observe the differences between the recorded files type by computing the power spectral density. So for two states of the system these distributions can be observed in figure 8. These two spectra, which are quite different, describe two similar states of the system, when stoichiometric mixtures are burning but having different CH<sub>4</sub> flows rates. Employing the TESPAR S and A archetypes for the three different combustion stages at each of the two different flow rates, six specific files were then classified, using the Euclidian distances. For the TESPAR A matrices a lag=2 was used. The tables 2 and 3 synthesize the classification task. All the files were correctly classified (100%) for both types of archetypes.

If the signals were a priori filtered by a low pass filter (5 kHz the cutoff frequency, Butterworth filters, order 10), 3% of the files were misclassified when TESPAR S archetypes were employed but no change was observed when TESPAR A archetypes were used. So the signal filtering has negative effects on the classification results.



b) low CH<sub>4</sub> flow-rate Figure 9. The power spectrum magnitude for stoichiometric mixture

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b) low CH<sub>4</sub> flow-rate Figure 10. The TESPAR S archetypes for two stoichiometric mixture states

TESPAR S matrix	Ι	Π	III	IV	V	VI
high CH <sub>4</sub> flow-rate	25	0	0	0	0	0
lean fuel mixture (I)						
high CH <sub>4</sub> flow-rate	0	25	0	0	0	0
Stoichiometric mixture(II)						
high CH <sub>4</sub> flow-rate	0	0	25	0	0	0
Lack air mixture (III)						
Low CH <sub>4</sub> flow-rate	0	0	0	25	0	0
lean fuel mixture (IV)						
Low CH <sub>4</sub> flow-rate	0	0	0	0	25	0
Stoichiometric mixture (V)						
Low CH <sub>4</sub> flow-rate	0	0	0	0	0	25
Lack air mixture (VI)						

Table 2. Combustion sound classification for the Rijke-Tube burner

# **EXPERIMENT 2**

# EXPERIMENTAL MODEL OF A REAL FURNACE

This experiment was made on the furnace presented in figures 2 and 3. For this experiment 100 records of the burning system were stored to describe the five considered states of the furnace. These files describe the following states:

- lean fuel mixture
- stoichiometric mixture
- lack air mixture
- cooling water sound
- cooling water sound with soundproofing.

We used the same parameters for the signals acquisition as in the first experiment. In the next figure one cam observe the power spectral density for two states of the system and the archetypes for these states.



Figure 11. The power spectrum magnitude for two system states



Figure 12. The TESPAR S archetypes for two system states

The results of files classification are presented in table 3 for TESPAR S archetypes. Only seven of the recorded files

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were misclassified. We see that the misclassification was made between the closest states. For the TESPAR A matrices all the files were been correctly classified (100%), so this proved to have a better power of classifying. Thus for the real furnace these results are very promising.

We experimented also on the influence of filtering on the signal classification. Applying a low pass filter (4 kHz, Butterworth filters, order 10) led to a percentage of the signals misclassification of 7% when the TESPAR S archetypes were employed and also to no misclassification for the TESPAR A archetype. A lag=2 was employed for the TESPAR A matrices. Note that for the descriptors (S, D) the same limits were observed.

TESPAR S matrix	Ι	II	III	IV	V
lean fuel mixture	18	2	0	0	0
<b>(I</b> )					
lack air mixture	1	19	0	0	0
(II)					
stoichiometric mixture	0	0	20	0	0
(III)					
cooling water sound	0	0	0	19	1
with soundproofing					
(IV)					
cooling water sound	0	0	0	3	17
(V)					

 Table 3. Combustion sound classification for the furnace from fig.2

# **IV. CONCLUSIONS AND OUTLOOK**

The results of the experiments prove the high capabilities of the TESPAR method in signals classification tasks. We observed that the results for the ideal furnace - the Rijke-**Tube** show that all the different states of the burner can be discriminate from one another. The TESPAR A matrices are more powerful than TESPAR S matrices, in the classification process, but their use involves higher computational requirements. For the real furnace the results shows a 7% of misclassification of the system state when only the Euclidian distances were been employed to distinguish the different signal samples. By using more powerful classification tools the results will certainly be improved. In what the influence of filtering on the classification process is concerned, we consider that this procedure is not necessary in the case of these signals and these acquisition parameters.

These results encourage us to employ this method to supervise the burning system in order to find its states and to take appropriate decisions for keeping the burning process in the optimal state. We also consider that this method of acoustical analogy used in order to control the thermoacoustic instabilities in combustion, among the other methods (visual inspection of flame electrochemical gas analyzer), may provide more economical solution and a faster response.

In the next works, we intend to use these results to control the burning instabilities, based on the block diagram

of the combustion system in closed loop, presented in the figure below.



Figure 13. The block diagram for the combustion control using acoustical analogy

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