# PATTERN RECOGNITION FROM ACOUSTIC MEASUREMENTS ON PREDICTIVE MAINTENANCE SYSTEM OF A GAS TURBINE

# Walace de Souza Pacheco, M. Sc., walacepacheco@ufrj.br

Dr.-Ing. Fernando Augusto de Noronha Castro Pinto, fcpinto@ufrj.br

Federal University of Rio de Janeiro/Mechanical Engineering Department – Technology Center Block G R. G204, Rio de Janeiro, 21941-914, Brazil

Abstract. A considerable investigation effort related to predictive maintenance has grown in the last years. The need to optimize the maintenance effort has been increasing the interest in creating automated mechanisms of analysis when it comes to the condition of machines and equipment. Microphone-array-based methods are known as alternatives for noise source identification in machines. In this work, the monitoring of the changes in system conditions is based on the measured noise data starting from continuous signals produced by a microphone array. The "Beamforming" technique is used to visualize the directionality pattern of the noise emitted by a gas turbine. For the recognition of changes in the directionality patterns, in monitoring and diagnosis of the flaws in machines, the transformation algorithm Karhunen-Loève, also known as Proper Orthogonal Decomposition, will be used.

Keywords: Acoustics, Source Identification, Predictive Maintenance

# **1. INTRODUCTION**

The energy industry is demanding more and more power plant sites, requiring even greater maintenance efforts. The use of acoustic measurements is a promising way of complementing predictive maintenance systems (Tranter, 1990). The use of Beamforming analysis not only allows the standard diagnosis procedures to be implemented but also the spatial distribution of the sound sources can help the failure detection of the equipment. In order to ease the identification and storage of directionality patterns obtained from the Beamforming, this work uses the Karhunen-Loève Transform to aid the process of source location and the further study of eventual pattern changes.

### 2. BEAMFORMING

Beam-Forming is a method of mapping noise sources by assessing sound levels based upon the direction from which they originate. The implementation of the method is based on the delay-and-sum of the measured signals in each microphone. This can be accomplished either in the time or in the frequency domains (Brandstein and Ward 2001) (Christensen and Hald, 2004). A time delay is determined based on the the locations of the array sensors and the propagation direction of the sound. This time delay is converted into a frequency dependent phase delay in the case of the frequency domain implementation. One key assumption made is that the incident waves can be regarded as plane waves, conversely it is assumed that the array is placed in the far-field of the sources.

The idea behind the technique is that a coherent sound, in the form of a plane wave, coming from a specified direction and being received by different microphones will lead to similar signals that are delayed on time based on the different travel paths. If one considers that the other sources, which may be present and are spatially dispersed, will not be coherent with the main source, under study, the mean value of the different microphone signals, delayed accordingly to their spatial location and propagation direction, will reflect only the coherent signal coming from that chosen direction. The other signals being averaged close to zero.

Implementing this idea in the frequency domain can be expressed by Eq. (1):

$$B(\omega, \vec{r}) = \frac{1}{N} \sum_{n=1}^{N} P_n(\omega) \exp(-j\omega \frac{\Delta_n(\vec{X}_n, \vec{r})}{c}).$$
<sup>(1)</sup>

Where  $B(\omega, \vec{r})$  is the complex sound pressure amplitude, with frequency  $\omega$ , corresponding to incident waves from a direction defined by vector  $\vec{r}$ . The summation is done over all *N* microphones, individually indicated by subscript *n*, for all measured complex sound pressures  $P_n(\omega)$ . The different phase delays  $\frac{\Delta_n(\vec{X}_n, \vec{r})}{c}$  can be seen inside the exponential and depend also on the vector position  $\vec{X}_n$  of each microphone. The pure complex number is represented by *j* and *c* is the speed of sound. The phase delay is calculated from the different lengths of the incident wave paths  $\Delta_n(\vec{X}_n, \vec{r})$  from microphone to microphone, related to a common reference position on the array. If we put the coordinate origin in this reference these lengths are found as in Eq. (2) as the simple vector projection of  $\vec{X}_n$  into  $\vec{r}$ :

$$\Delta_n(\vec{X}_n, \vec{r}) = \vec{X}_n \cdot \vec{r}$$

Implementing these ideas with a generic description of the vectors  $\vec{X}_n$  allows one to construct a mapping of the incident wave amplitudes. In the case presented here a coordinate system will be used for the Beamforming with a vertical Y-axis with the Z-axis pointing towards the source. The direction on the horizontal plane is the azimuth angle

 $\phi$  and the elevation angle  $\theta$  represents the direction in the vertical plane. The graphic representation of |B|(-1, 2)|

 $|B(\omega, \phi, \theta)|$  will show the directions with more incident sound energy.

Beamforming allows a "*real-time*" analysis of the incident sound, since it can picture a snapshot of the waves reaching the array. Of course this snapshot is restricted by the amount of time necessary to acquire the samples needed for the FFT-algorithm being used.

Since the formulation is generic the actual form of the microphone array, i.e. their spatial distribution, is of minor concern. The sole requirement imposed, in form of a spatial aliasing condition, is that the distance between microphones should guarantee that there will be at least two of them per wavelength. Higher frequencies thus needing a closer spacing will need more microphones to correctly map the incident waves. Nevertheless an unstructured array with many sensors may allow a suitable choice of different microphone sets, depending on the frequency of interest, based on their spacing (Yunhong, 2005).

#### **3. KARHUNEN-LOÈVE**

The bi-dimensional data set obtained through the microphone signals may be further analysed by the application of the *Karhunen-Loève Transform*, also known as *Proper Orthogonal Decomposition*. Therefore the image signals, generated by the Beamforming algorithm, i.e. the sound pressure data are stored in a matrix  $\bar{Q}$ , which has each column corresponding to the directionality pattern, described with elevation and azimuth angles, related to the i<sup>th</sup> frequency bin of the FFT analysis done:

$$Q_{ij} = |(B_i(f_i, Elev, Azim))| \qquad (3)$$

Where *j* corresponds to an index of a pair of angles [*Elev*, *Azim*] and  $B_i$  is the response of the array to the i<sup>th</sup> frequency bin, according to Eq. (3). Here  $Q_{ij}$  from  $\overline{Q}$  corresponds to the SPL in this frequency bin  $f_i$  coming from the direction expressed by the set of angles related to the index *j*. In this work *i*=1.. $N_p$  and *j*=1.. $N_{ca}$ . The number of FFT bins and the number of chosen directions respectively. The conversion between *j* and the elevation and azimuth angles is shown in Fig. 1.



Figure 1. Spatial index *j* and angular directions of the incident wave.

Therefore we have a spatial dependency on j, the source orientation related to the array, and a frequency dependence on I, the strength of the source in the specified frequencies. The KL-Transform establishes a representation of this dependence as a set of frequency dependent base functions  $C_k(i)$  and spatial base functions (Feldmann et al.,2000) (Feldmann et al.,2002)  $D_k(j)$  related to the orientation *j*, according to Eq. (4):

$$Q_{ij} = \sum_{k=1}^{n} C_k(i) D_k(j) \quad .$$
(4)

One can control the quality of an order n approximation through the number o base function n used in the summation Eq. (4). Determination of  $C_k(i)$  and  $D_k(j)$  by the algorithm of the KL-Transform also determines an importance sorting of each of these base functions pairs for the representation of  $\bar{Q}$ . The algorithm starts from  $\bar{Q}$  calculating the covariance matrix  $\bar{M}$  with dimensions  $N_p \ge N_p$ , according to Eq. (5):

$$M_{ij} = \frac{\sum_{k=1}^{N_{ca}} Q_{ik} Q_{jk}}{N_{ca}} \qquad i = 1..N_p; j = 1..N_p$$
(5)

and determines the base functions through the solution of the standard eigenvalues problem of  $\overline{M}$  (6):

$$det \left( \bar{M} - \lambda \bar{I} \right) = 0 \quad . \tag{6}$$

Where  $\overline{I}$  is the identity matrix of corresponding dimension. The eigenvalues from Eq. (7) being real and positive sorted as  $\lambda_1 > \lambda_2 > \dots = \lambda_{k-1} > \lambda_k$  the quality *R* of an approximation, as in Eq. (4), with only *n* terms can be estimated in % as in Eq. (7) :

$$R = 100 \times \frac{\sum_{i=1}^{n} \lambda_{i}}{\sum_{k=1}^{N_{p}} \lambda_{k}} \quad .$$
(7)

The function  $C_k(i)$  being the eigenvector associated to the eigenvalue  $\lambda_k$  the spatial functions  $D_k(j)$  are calculated through the projection of the original data in  $\overline{Q}$  into the corresponding base function  $C_k(i)$ . These are an optimal base, in a least-square sense, to the approximation of the original data. Once the desired quality *R* being chosen the quantity *n* of necessary functions is also established, and the amount of data needed to store the results of the Beamforming analysis can be reduced by a factor expressed in Eq. (8):

$$F = 100 - 100 \times \frac{n \times (N_p + N_{ca})}{N_{ca} \times N_p} \quad .$$

$$\tag{8}$$

#### 4. INSTRUMENTATION

As shown in the Beamforming section one major drawback of method is the amount of microphones needed. Therefore, in order to keep the overall cost of the instrumentation at acceptable levels, electret microphones were built by the Laboratory of Acoustics&Vibration itself, which are calibrated in amplitude and phase through an impedance tube adapted for that purpose.

The signal conditioning is also specially developed for this application and fit in an air-tight casing to be used in potentially hazardous environments. A didactic equipment consisting of electric motor, mating gears, unbalance disks and rolling bearings, is also used to simulate a more complicated sound source in front of the array. Figure 2 shows the circular array with 12 microphones spaced by an angle of 30° at r=130mm and the equipment used for the experiment.

The signals were obtained inside a chamber in the laboratory with low background noise.





a) Didactic purpose machine

e b) Array circular with 12 microphones Figure 2. Equipment and array used for the experiment

a) Experimental setup

The signals of twelve microphones in the circular array, were acquired with a PXI-unit from National Instruments. The signal source for the sweep, the acquisition hardware and the amplifier can be seen in Fig. 3.





b) Acquisition hardware, signal generator, amplifier, power source and interface

Figure 3. Experimental setup with acquisition hardware.

The signals were measured and saved in the frequency domain. Processing and implementation of the Beamforming, were in Labview and the implementation the KL algorithm was done in MATLAB.

# 5. RESULTS

Results obtained by the application of the technique are shown here for two exemplar cases:

a) 2 loudspeakers in definite positions, used to verify the global results, and

b) a didactic equipment consisting of electric driven pair of geared shafts.

The following figures shows the two loudspeakers as pictured by a webcam in the coordinate origin of the array and the Beamforming images for two different frequencies, 3.1 kHz and 3.8 kHz. The lower right speaker is radiating at 3.1 kHz, while the upper left one at 3.8 kHz, mainly.

The quality of the approximation, depending on the order n of the approximation is seen in Fig. 5.

The base functions, calculated through the KL algorithm, are shown in Fig. 6, either as spectra, showing the frequency dependance, or directionality patterns, showing the spatial positioning of the sources related to the corresponding spectra.







b) Beamforming images

Figure 4. Two loudspeakers in definite positions and Beamforming images.



Figure 5. Percentage of information kept for the two loudspeakers case.



a) Frequency dependance



Figure 6. Base functions and spatial positioning of the sources related to the corresponding spectra for two loudspeakers case.

Finally one can rebuild the previous Beamforming patterns from an approximation using only three functions. The rebuilt patterns show good agreement with the original ones.



Figure 7. Reconstruction of the Beamforming patterns for two loudspeakers case.

Similarly the same analysis is done for the sound radiated by the more complex sound source exemplified by the didactic purpose machine, also shown from the webcam and the related spectrum.



a) Didactic purpose machine in definite positions b) Beamforming images Figure 8. Didactic purpose machine in definite positions and Beamforming images.

The directionality patterns from the original data are shown for three different frequency bins.

The following results were obtained by restricting the use of the algorithm to the frequency range, from 1.3 kHz to 4.3 kHz, where the array can achieve good results due to its geometry.



Figure 9. Percentage of information kept for the didactic purpose machine case.

The four more important functions, frequency and spatial, are shown in Fig. 10.



a) Frequency dependance

b) Directionality patterns

Figure 10. Base functions and spatial positioning of the sources related to the corresponding spectra for didactic purpose machine case.

Also the reconstruction of the Beamforming patterns can be accomplished with success from the first three functions.



Figure 11. Reconstruction of the Beamforming patterns for didactic purpose machine case.

# 6. CONCLUSIONS

The work shows the application of the Karhunen-Loève Transform to improve the analysis of directionality patterns from Beamforming.

The patterns obtained constitute an optimal base of functions in a least-square sense, that allows the further simplification of the source identification and location.

The time changes in this patterns can be related to changes in the operation of the equipment under monitoring. Identification of these may allow the identification of predictable failures during operation. This identification may also be well accomplished by a further application of the same algorithm to the pattern identification.

Further work include the application of the technique to a real gas turbine and the application of the KL-Transform to the failure prediction in the framework of its maintenance system.

The reduction on the amount of data to be stored, allowed by the use of an approximation only of order 3, will further simplify the database of the maintenance system.

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