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Source identification from unperceived low-frequency noise emissions at a Madrid home

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A R T I C L E I N F O

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A B S T R A C T

People may be exposed to energy sources that they cannot perceive with their senses, but which may be harmful to their organism, and therefore, individuals cannot avoid them. One of these energy sources is the sound, particularly sound out of the hearing range (20–20000 Hz). Although the sounds are imperceptible for frequencies below 200 Hz unless they have high intensities. Sound with frequencies below 200 Hz is called "low frequency sound".

This study focuses on low frequency sound generated by artificial sources, and specially in sound located in urban areas. Specifically in the measurement and detection of low frequency sources from the perspective of individuals who are manifesting the symptoms associated with their exposure.

To this end, a household of Madrid with individuals who have symptoms is taken as sample. This home did not have large potential sources of low-frequency sounds near its location, such as streets with high intensity of traffic or the subway in order to better contrast other possible sources that are not so obvious.

The results show high levels of sound emission at the lowest frequency range (20–200 Hz). These results also show that filters should not be applied to remove non-audible frequency spectrums, such as A type, because it omits sounds in urban areas that could affect people.

Data treatment incorporates analysis methods based on machine learning which allow differentiate between sources without measuring on them. Finally, further developments must incorporate measurements bellow 20 Hz and will increase the numbers of households sampled.

1. Introduction

The study was carried out due to indications of symptoms similar to those described in previous articles by some individuals who contacted us via e-mail, because they had these symptoms (see Tables 1 and 2).

Low frequency sounds are sound waves below 200 Hz. They can only be perceived by a part of the population, and only from a minimum threshold intensity (usually high) which depends on factors such as age and exposure to other sound [1].

Human hearing frequency thresholds are located between 20 and 20000 Hz. Sound waves with frequencies bellow 20 Hz are called "infrasound" (sometimes certain individuals can perceived these frequencies, but only at very high intensities [2]).

These low frequency sound waves are naturally generated by phenomena such as earthquakes, volcanoes, and storms [3–5], as well as human activities such as traffic, industry, and music [6]. There is an incipient knowledge from the scientific world about the effects of the absorption of infrasonic and ultrasonic acoustic waves on human health [7,8].

There are many articles about low frequency sounds, and they can be divided into the following categories: procedures and instrumentation for measuring low frequency sounds [9,10]; measurement and analysis of low frequency sounds from laboratory, natural or human activity sources [11–13]; exposure to these sounds and their effects on health [14,15]; and study of materials that allow this type of sounds to be absorbed [16].

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Table 1
Sound level meter characteristics.

Noise Monitoring Station SVANTEK SV307		
https://acsoft.co.uk/product/sv-307-class-1-noise-monitoring-station/		
Standards	Class 1: IEC 61672–1:2013, Class 1: IEC 61260–1:2014	
Weighting Filters	A, B, C, Z, LF	
RMS Detector	Digital True RMS detector with Peak detection, resolution 0.1 dB Time constants: Slow, Fast, Impulse	
Microphone	Patented1 MEMS design microphone ST 30A in 1/2″ housing	
Preamplifier	Integrated	
Linear Operating Range	30 dBA RMS ÷ 128 dBA Peak (in accordance to IEC 61672)	
Dynamic Measurement Range	23 dBA RMS ÷ 128 dBA Peak (typical from noise floor to the maximum level)	
Internal Noise Level	less than 23 dBA RMS	
Frequency Range	20 Hz ÷ 20 kHz	
Meter Mode Results	Elapsed time, Lxy, Lxeq (LEQ), Lxpeak (PEAK), Lxymax (MAX), Lxymin (MIN), LxyE (SEL), 2 x LR (ROLLING LEQ),10 x LN (LEQ STATISTICS), Lden, LEPd, Ltm3, Ltm5, GPS coordinates Simultaneous measurement in three profiles with independent set of filters (x) and detectors (y)	
Statistics	Ln (L1-L99), complete histogram in meter mode and 1/1 & 1/3 octave analysis Simultaneous measurement in three profiles with independent set of filters and detectors	
1/1 Octave Analysis2 (optional)	Real-time analysis meeting class 1 requirements of IEC 61260 (31,5 Hz ÷ 16 kHz)	
1/3 Octave Analysis2 (optional)	Real-time analysis meeting class 1 requirements of IEC 61260 (20 Hz ÷ 20 kHz)	
Data Logger	Logging of summary results (SR) and spectra data with interval step down to 1 s and time history (TH) of selected parameters with shorter interval step down to 100 ms.	
Audio Recording2 (optional)	Time domain records to wav file format on demand with selectable bandwidth and recording period	
Ingress Protection Rating	IP 65	
Inputs Power supply	LEMO 4-pin, extended I/O port LEMO 5-pin	
Remote System Check	Real-time system check1 and Built-in sound source producing level of 100 dB at 1 kHz	
Memory	Micro SD card 16 GB (removable)	
Display & Keyboard	OLED colour display 128 × 160 px and 10 push-button keyboard	
Communication Interfaces	USB, 4G modem	
GPS	for time synchronization and localization	
Power Supply	Li-Ion rechargeable battery (non-removable)	
	Operation time on battery (7.2 V/10 Ah)	
	Modem off	up to 6 days
	Modem on	up to 5 days3
	Solar Panel (not included)	MPPT voltage 17.0 V ÷ 20.0 V
	AC power supply (included)	Input 100 ÷ 240 VAC, output +15 VDC 2.5 A, IP 67 housing
	External DC source (not included)	voltage range 10.5 V ÷ 24 V e.g. 12 V or 24 V accumulator
Environmental Conditions	Temperature	from −20 °C to 50 °C
	Humidity	up to 95 % RH
Dimensions	680 mm length; 80 mm diameter excluding windscreen (windscreen diameter 130 mm)	
Weight	Approx. 1.8 kg	

There are also many studies that analyze these sounds in urban areas [6,12,14,15,17–33] and some of them also show their association with certain symptoms [5,23,27,30,32,33].

The main motivation of this study is the detection of low-frequency noise sources through the analysis of noises in homes whose residents present possible symptoms associated with their exposure (dizziness, nausea, insomnia ….).

This approach reverses the usual search order for sampling used in recent studies. The most common approach is based on performing measurements at locations close to known low-frequency sound sources [11–13,17,18,20–28,30,34–40]. In other studies, tests are also carried out under controlled laboratory conditions [14,15], measuring the possible impact of these emission sources on individuals. Sampling based on locations close to the best-known sources makes it possible to eliminate most of the rest of the factors, as it focuses its analysis on the "emitting source" factor, but it can rule out other possible sources not previously considered.

However, the approach envisaged in this study would avoid a priori ruling out other sources, although it represents a great challenge, since possibly the symptoms associated with the individuals analyzed may also be due to other factors unrelated to this type of sounds, or even present physiological factors that favor the appearance of these symptoms.

This study contributes mainly in two ways:

- It makes a "downstream" study, focusing for sampling on the possible symptoms associated with exposure, and besides it allows prolonged exposure to this type of sounds to be assessed. Sources are not determined or identified a priori.
- Provides the knowledge associated with "machine learning" for the assessment of possible sources, especially through dimensional reduction tools which allow to identify the number of sources quickly and accurately.
- Likewise, it allows us to assess whether the application of recommended filters, for instance type A filters, which are mainly focused on perception of audible and annoyance sounds, they may be omitting the presence of other imperceptible sounds which affect people who are exposed to them.

Therefore, the goals derived from this study:

- Determination of the sources causing low frequency sounds based on sampling population through the symptoms associated with their exposure.
- Data analysis through dimensional reduction, both from a linear and non-linear point of view in the context of stationary sources during the nighttime period.

This work significantly contributes a set of tools widely used in other disciplines for the analysis of the sound measurements carried out. It also allows expanding the spectrum of possible sources of low-frequency sound emissions.

Most of the articles focus on measurements of low-frequency sounds in locations close to very important emission sources such as wind turbines [18,23,25,27,28]. Other studies analyze the doses received by workers in certain industries, as well as the associated effects of this exposure on health [41–44].

Studies have also been carried out in homes to measure low-frequency sounds, and based on the results obtained, determine possible sources such as traffic [14,29,30,32,45]. These household studies are based on random sampling, while, in the approach carried out in this study, the individuals in the sample are selected based on the presence of symptoms mentioned in many previous articles [9,20,22,24,31,34–39,46–48]. Furthermore, it is not only limited to a different sampling method, but also modifies the analysis of its results by applying machine learning tools to determine possible emission sources.

The main advantages are the following:

- It associates symptoms with low frequency sound sources. In many cases there are no symptoms, even if low frequency sources are present, possibly due to differential physiological issues between

individuals. Search for effects for subsequent determination of causes instead of search for causes for subsequent evaluation of effects. This approach requires studies of other possible non-acoustic factors to rule them out.
- The study spectrum is expanded by introducing new possible sources other than traffic, wind turbines, etc.
- Establishes a pattern for dimensionless reduction. Neural networks have weights which are the parameters that define the system of nonlinear simultaneous equations, and that, therefore, allow an explanation of the adjustment made to the model.
- It associates long-term effects derived from the symptoms described with low-frequency sound sources with prolonged and continued exposure over time. Avoids nocebo effect associated with other types of measurements.

The approach taken to reach these objectives are the following:

- Set sample in the study population who suffer usual symptoms associated to low frequency sound exposure, and in areas where a clear source of low frequency emissions does not appear.
- Once the sample is determined, other factors such as low environmental noise will be considered, and its proximity or not to sources documented by scientific literature will be valued.
- Installation and measurement of sound at the home. A broad experience specialized company in the noise measurement according to current standards and laws will make measurements.
- Measurement of sound emissions at the site on the days of least activity in neighboring homes to avoid interference and guarantee quasi-stationary sources over time.
- If measurements show that exists significant sound intensities at the lowest frequencies, individuals which live at this home will carry out a medical check in the auditory system, because in some cases, these symptoms could explain from a physiological point of view. Besides, it will be measured other factor such as electromagnetic radiation.
- Final analysis of data results obtained in measurements, applying machine learning tools that allow an estimate of possible sources.

The following schema shows different steps to reach these objectives:

The first two stages exclusively characterize the study. In the rest of the stages, we will advance in the methodology to carry them out, and we will end with an analysis of the results and their conclusions.

Therefore, it is shown below:

- Methodology and criteria for choosing the sample home.
- Final location of the sample
- Measurement methodology and selection criteria for measuring equipment.
- Technical sheet of equipment used.
- Test characteristics
- Data Analysis Methodology
- Data preparation and analysis
- Discussion
- Conclusions

2. Methodology

2.1. Methodology and criteria for choosing the sample home

We will select among the houses whose residents present symptoms described in the articles mentioned above [5,23,27,30,32,33]: dizziness, nausea, and insomnia. At least two members of the household must have experienced these symptoms for a period of more than a year.

The study population includes all the homes inhabited by people who contacted this institution expressing the symptoms described above. Most of these people have been contacted thanks to the different publications on infrasound and low-frequency sounds that this university has previously made [5,7,8,49–51].

The final selection of the home will not be random due to population size and will depend on the following factors:

- There is no presence of large emission sources less than 150 m away if the population density is greater than 350 inhabitants per hm2, or 500 m if the population density is less than 350 inhabitants per hm2.
- Preliminary assessment that shows apparent absence of physiological factors in people that may cause these symptoms.
- Preliminary assessment that shows the apparent absence of other external factors (for example: electromagnetic fields) that could generate symptoms like those described above.
- City of more than a million inhabitants close to San Pablo CEU University (high population density)
- It is recommendable that the main emission sources remain at a medium level of activity, and neighborhood activity will be small. The best day for measurements will be verified through preliminary inspection (avoid the presence of intermittent sources).
- The location of the measuring equipment will be in the bedroom where the residents rest.

2.2. Final location of the sample

The measurements were carried out in a home that had the following characteristics:

- Madrid, location close to the center about 1.7 km from Puerta del Sol in the northwest area of Madrid.

Table 2

Main exploratory analysis estimators of the pressure variable expressed in dB. Entropy indicator shows that data without a filter (total Z) provides more relevant information than data with a filter (total A and C).

Estimator[a]	20 Hz	200 Hz	2000 Hz	20,000 Hz	Total A	Total C	Total Z
Mean	47.6	32.5	16.4	21.3	34.2	55.9	62.0
Median	36.7	18.6	11.8	21.2	20.4	40.2	55.2
Standard Deviation	67.6	52.4	30.6	21.6	51.8	74.9	77.5
Robust Deviation	13.5	8.1	−27.9	−25.6	2.7	15.7	29.7
Coefficient_Variab	10.0	9.9	5.1	1.0	7.6	8.9	5.9
Robust_Coef_Variab	0.1	0.3	0.0	0.0	0.1	0.1	0.1
Asymmetry	26.5	25.4	38.1	154.4	21.1	14.1	15.2
Kurtosis	1221.1	865.5	2145.0	27,234.4	653.5	245.6	316.9
Huber_Mean	36.7	18.9	11.8	21.1	20.7	40.3	55.2
Huber_Dev	13.5	8.7	−27.7	−25.0	4.2	16.0	29.6
Tukey_Mean	36.7	18.4	11.8	21.1	20.2	40.2	55.2
Tukey_Dev	13.5	7.7	−28.6	−25.5	1.6	15.5	29.7
Shannon Entropy	0.12	0.18	0.15	0.01	0.24	0.17	0.16

Note: Negative values may exist in the precision estimators due to conversion to dB could be below 20 μPa.

[a] Statistics calculated with the P variable expressed in Pa and transformed once calculated to dB.

- Distance to main possible emission sources (subway tunnel and high traffic density street that passes above): 205 m.
- Housing without access to an outside street. Presents audible sounds of very low intensity at night.
- Traffic density at night (11:00 p.m. to 6:00 a.m.) less than 1 vehicle per minute. Predominant vehicle type: Passenger cars
- Height from sea level: 669.93 m. The measurements were carried out on the sixth floor of the building.
- Population density: >350 inhabitants per hm2
- Community heating located in the basement of the building.

2.3. Measurement methodology and selection criteria for measuring equipment

The measurement methodology will be governed by the following points:

- Test duration: 3 days
- Periods: 3 (day/afternoon/night)
- Residents will remain outside their home during the tests (avoid sounds generated by the tenants themselves)
- The tests will be carried out during the weekend (avoid intermittent sound sources from neighbors during the nighttime)
- A company specialized in noise measurement with broad experience in the chosen city will be in charge of carrying out the measurements.
- The measurement procedures will be those indicated in Annex I of the Ordinance for the Protection of the Atmosphere against Acoustic and Thermal Pollution of Madrid (this ordinance is limited to noise and applies filter A in its calculations, so it should not be applied to the measured results, since it eliminates low frequencies)
- Measurements will be carried out with the doors and windows closed in the bedroom.
- The instrumentation will be located at least:
  o 1.20 m from the floor, ceilings, and walls
  o 1.50 m from any door or window

Regarding the measurement equipment, the following criteria will be applied:

- Minimum operating range: 20–500 Hz
- Minimum resolution for intensity calculation: 0.2 dB
- Minimum intensity measurement range: 20–130 dB
- Possibility of obtaining frequency and intensity profiles at 1/3 octave in the operation range
- Before the tests, an acoustic check of the measurement chain must be carried out. Sound level meter does not differ from the pattern generated by the calibrator by ± 0.3 dB. Under no circumstances may the operator modify the legal settings indicated in Order ITC/2845/2007.
- The data resulting from the measurements must be stored in time intervals with a maximum duration of 5s, and in formats accessible from the main data analysis tools.

2.4. Technical sheet of equipment

The following tables shows technical data about instrumentation which was used during test:

2.5. Test characteristics

The tests were carried out on the weekend because the activity in the adjacent homes was considerably reduced, but activities of nearby businesses were not. Household members were not present during testing.

A company accredited by ENAC, with extensive experience in noise measurements in the city of Madrid, was contracted to take the measurements.

The duration of testing was 72 h (3 consecutive days). Different samples were taken during three time periods (day/evening/night) to prove that the levels shown in the tests were reproducible independently of the day and time period chosen in each test.

The measurement procedure indicated in section 1 of Annex III of the Ordinance for the Protection of the Atmosphere against Noise and Heat Pollution of the Madrid City Council [52] in force as of November 2021 was applied.

Measurements were taken in a 1/3 octave frequency spectrum at 5-s intervals.

Indoor measurements were always taken with the windows and doors closed.

The following possible sources have been detected:

- Two supermarkets with industrial heat and cold machines at distances between 20 and 50 m
- Fruit shop with industrial heat and cold machines at distance of 20 m
- Secondary road traffic during rush hour (both peak and valley) 25 m away
- Domestic cooling and heating equipment in the building where the home is located or in the adjacent buildings, although during the tests they remained mostly disconnected.
- Community gas boiler in the basement of the building

2.6. Data Analysis Methodology

The following figure shows a scheme of the methodology:

When test finish, data will download and prepare, a preliminary analysis of the data will perform for each 1/3 octave frequency, treating it as a time series or as a data set with no time dependence (single stationary source hypothesis).

Concerning the sources of noise generators, we began with a causal hypothesis. Therefore, the existing relationship between the different frequencies will have common origins and their dependence in time will depend on the operation of these possible sources. There shall be no other unanticipated time-varying factors affecting the frequency spectrum (for example, with temperatures that affect sound transmission as well as industrial heating and cooling machines, it will be a causal factor that is not included for one and will be included for the other, etc.).

Two types of variables are considered for the determination of the different indicators:

- Pressure variable (P) measured in Pa of the sound wave, as well as pressure variables for each frequency i (P_i)
- Intensity variable measured in dB, which is obtained by the following pressure variable formula:

$$I = 10 \cdot \log_{10}\left(\frac{P}{P_0}\right)^2$$

Being $P_0 = 20 \times 10^{-5}$ Pa

- Calling "f" as function $f : \mathbb{R} \longrightarrow \mathbb{R}$:

$$I = f(P) = 10 \cdot \log_{10}\left(\frac{P}{P_0}\right)^2$$

In case of time series analysis, the traditional approach will be used:

- Data Analyst will only considerer stable time periods. In this case, it is almost sure nighttime.
- Determine stationarity or not of the time series with respect to its moments. This process will be iterative with respect to outcomes of subsequent steps (for instance: periodogram analysis).
- Determine simple, partial autocorrelations, and cross correlations between variables. Check if they have low or high values. If

correlations are close to zero in all types, the hypothesis of non-time dependent variables is accepted, and we will not continue with time series analysis.

- Make the periodogram of the intensities (it represents the power spectral density and is equivalent to the Fourier transform of simple autocorrelation). Periodogram must be a consistent estimator of the sample spectrum. Therefore, time series will be previously refined and smoothed with the most common windows (rectangular, Bartlett, Daniell, Welch, Blackmann-Tukey …).
- After periodogram, two cases will be considered, one with a simple filter and the other without a filter. The theoretical basis of the filter is the same as that of the kernel and convolution in machine learning.
- The model is identified with the results of the partial and simple autocorrelation graphs (Box-Jenkins, SARIMA, etc.), as well as with the cross correlations (in case of transfer models).
- Finally, models will be estimated and adjusted, and their residues analyzed through hypotheses contrasts (diagnosis). It is likely with this information to know a bit about the performance of the control system of machinery generates low frequency sounds. For instance: a wavelength of 25 s could be the action period of the machine control system.

If a non-time-dependent analysis can be performed, the KDD (Knowledge Discovery Databases) procedure would be used:

Selection- > exploration- > cleaning - > transformation - > analysis or data mining - > evaluation (assessment likely sources) - > dissemination (this article).

The purpose of this analysis is to determine the main sources that generate low frequency sounds.

In data mining procedures, dimensional reduction methods would be fundamentally used, because we want to differentiate among sources, highlighting:

- Main components (linear)
- Factorial (linear)
- Neural networks (non-linear)

Linear analysis would undoubtedly allow us to adjust the nonlinear model (neural network or system of nonlinear simultaneous equations) in a more logical and simple way.

3. Results

As mentioned above, the main objectives are the following:

- Determination of the sources causing low frequency sounds based on sampling population through the symptoms associated with their exposure.
- Data analysis through dimensional reduction, both from a linear and non-linear point of view in the context of stationary sources during the nighttime period.

Both objectives converge in this section, because Data analysis will allow at least differentiate among various likely sources, although without determining the exact location of themselves.

Before exploratory analysis, it was made possible to plot some important graphs which provide key information for subsequent analysis (see Fig. 1).

The following figure (Fig. 3fig2) shows the relationship between the intensity obtained at each instant of time for each 1/3 octave frequency measured, and its objective is to determine the presence or absence of low frequency sounds in a visual way. These color maps allow highlighting the existence of high intensities at low frequencies (see Fig. 2).

Time is observed on the abscissa axis and frequency appears on the ordinate axis. The color marks the greater or lesser intensity according to the color bar on the right. Areas with higher intensity colors always appear at lower frequencies.

The interpretation of color maps shows that there are low-frequency noises in this home with especially high levels at the lowest frequencies on the spectrum, exceeding 50 dB at frequencies below 50 Hz (colors with the highest intensity are at the bottom of the map). 20 Hz frequency is likely to accumulate frequency intensities below the range of the equipment.

The following graph (Fig. 4) shows the development over time of the intensity whether or not applying a type A filter to the intensity, which reduces intensity of lowest frequencies.

This time series diagram shows a difference of around 20 dB when we apply type A filter or not. If we focus this type of diagram on each night

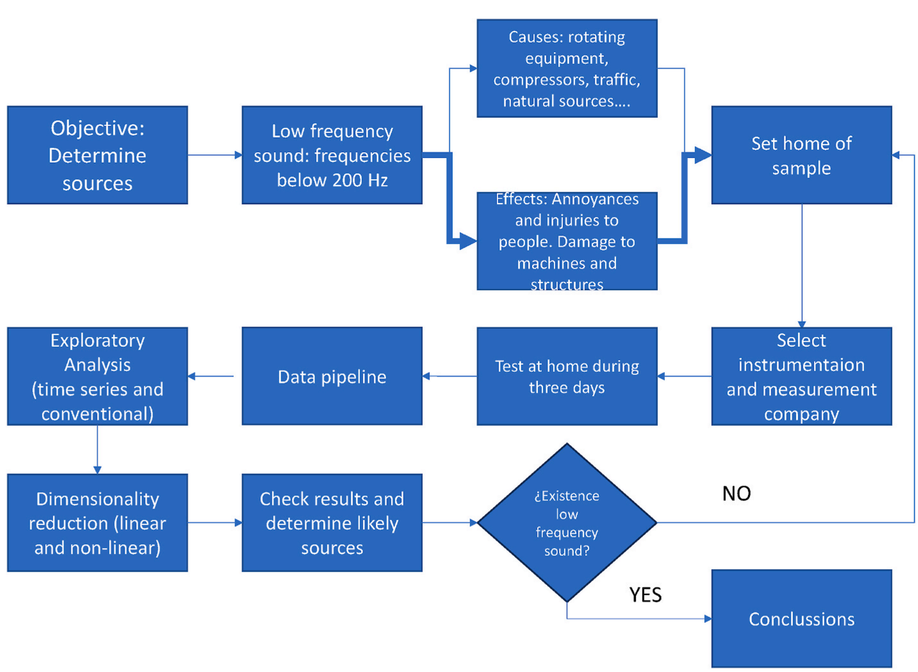

Fig. 1. Study implementation scheme.

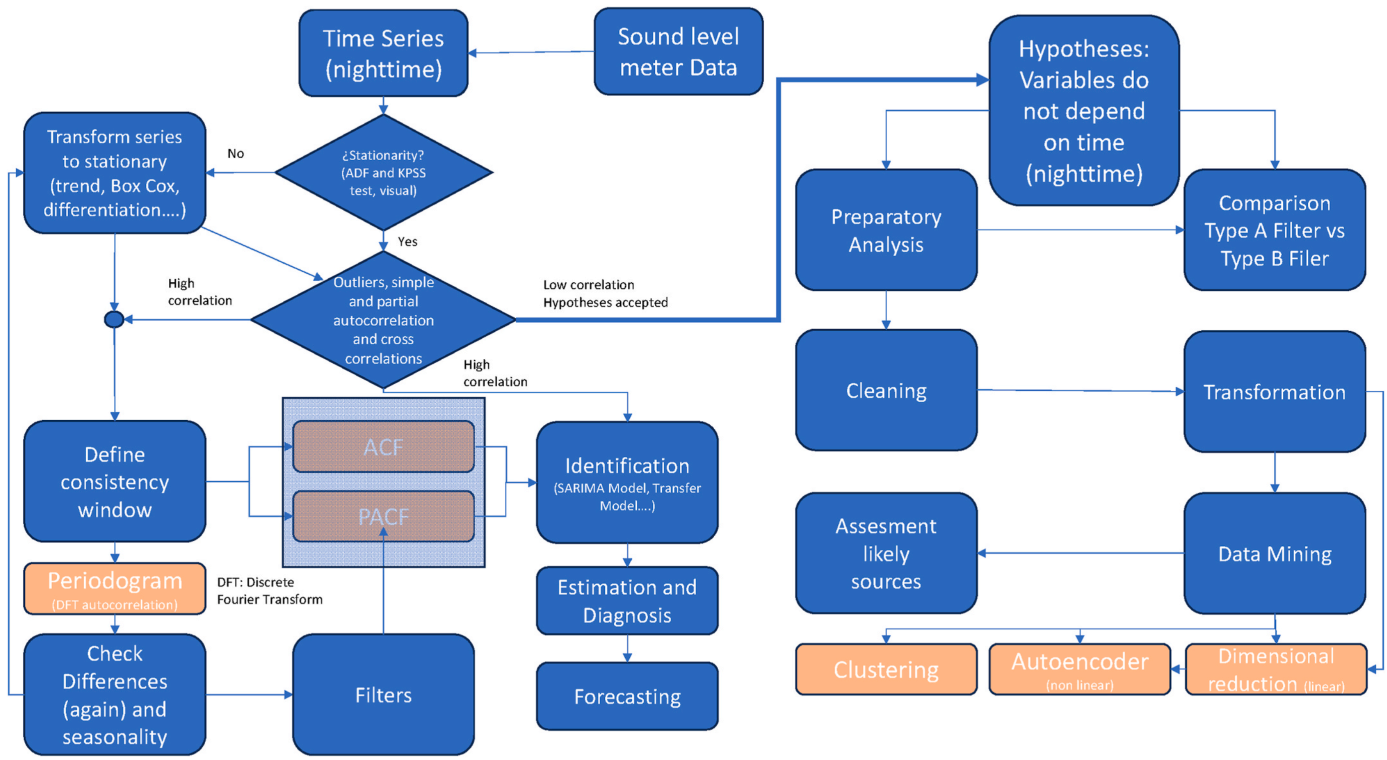

Fig. 2. Data analysis methodology scheme.

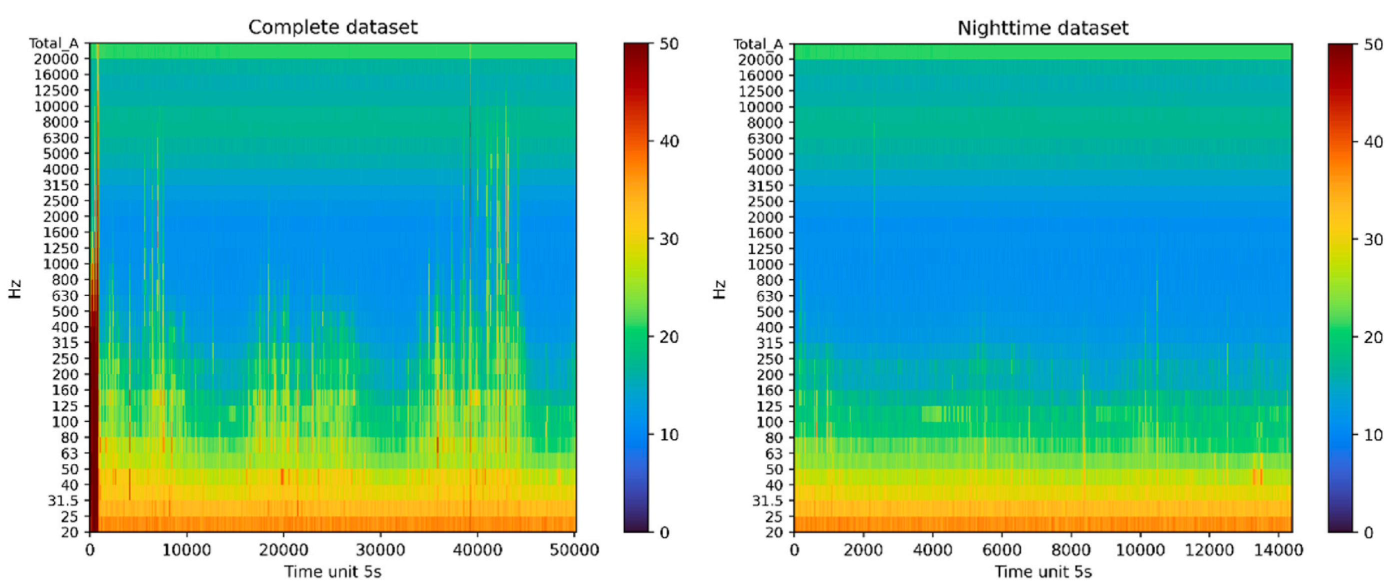

Fig. 3. Time– frequency-intensity color map. This figure corresponds to preliminary data analysis. These maps show time evolution of sound frequencies and intensity. Left map considers the complete sampling set. Right map only considers samples taken between 00:00 and 07:00 h. Color represents sound intensity. Colors closest to red will be the most intense. Lowest frequencies have the most intense colors. This sound has important intensities at low frequencies. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

at different frequencies without applying any type of filter, we obtain the following graphs (Fig. 5):

Fig. 5 shows high intensities at lower frequencies. These results stand out even in the nighttime period. Therefore, visual inspection at low frequencies suggests that the optimal study interval in terms of stability is found during the night from 00:00 to 07:00. This could also be determined by clustering techniques without hierarchies (k-means and mini-batch k-means, Kohonen networks), although in this case, they did not yield the expected results.

Exploratory analysis follows preliminary visual analysis. The exploratory analysis of the data allows us to analyze individually every variable, as well as their relationships: In this case, the variables are time series, and, therefore, it is also necessary to see the relationships of the variable at an instant of time with its previous moments, as well as the relationships between variables at different times. Our objective is to detect whether errors may have arisen due to an incorrect original design, measurement errors or sources with specific actions that have caused a distortion. It also allows an initial assessment of the variables,

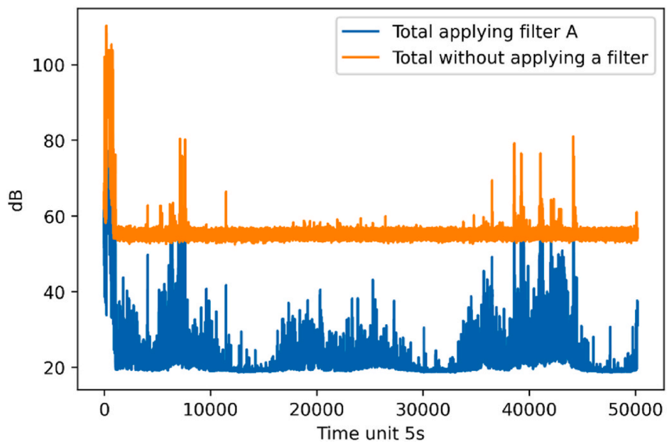

Fig. 4. Total sound intensity time series (with or without A filter). This figure is included in the preliminary data analysis. This line plot compares time evolution of total intensity with or without applying “A filter”. “A filter” reduces intensity on lowest frequencies because they are not audible for humans. It is the filter which recommends most standards (for instance: ISO). Plot shows a difference of 20 dB between applying filter or not applying filter. Time evolution without filter has more stability than with filter.

very useful to be able to assemble the learning model.

A clear distinction must be made between a signal analysis and its possible transformations using tools such as the Fourier transform, and a statistical analysis, which determines a periodogram of the intensities over time for a given frequency, being in its formulation very similar to the Fourier transform but taking into consideration exclusively the intensities at a given frequency. The latter is usually more related to control actions in the sources of sound emission.

The exploratory analysis will include two studies:

- Variables do not show time dependence.
- Variables show dependence on time.

The initial consideration is that variables do not depend on time during nighttime since control system of these machines (sources) induce a stable operation when there is no activity in the premises. In addition, other possible more intermittent sources will present intensities at frequencies much higher than those under study. However, it is necessary to verify that this hypothesis is true, hence an exploratory analysis of the time series is also carried out.

The analysis considering non-dependence in time must focus on moments, robust indicators, and Shannon entropy, because entropy allows us to see the value of the information contained in that series. In our case, entropy measures the presence of outliers, since these outliers provide a large amount of information, and, therefore, lower entropy. Even so, on this last point, no important results were obtained, but yes when we compare entropy among different types of filters (A, B, Z = no filter), where the entropy decreases when less restrictive filters are applied. The other measures focus on the shape of the distribution, and the correlation graphs between variables for the same instant of time.

Pressure and intensity are study variables, because are data collected by sound level meter. The estimation of P and I was performed as follows (In this way we guarantee that it is unbiased and consistent under the hypothesis of simple random sampling):

$$\widehat{\mathrm{P}}(\mathrm{Pa}) = \widehat{E(P)} = \frac{\sum_{i=1}^{N} \mathrm{P_i}\ (\mathrm{Pa})}{\mathrm{N}} \qquad \text{eq.1}$$

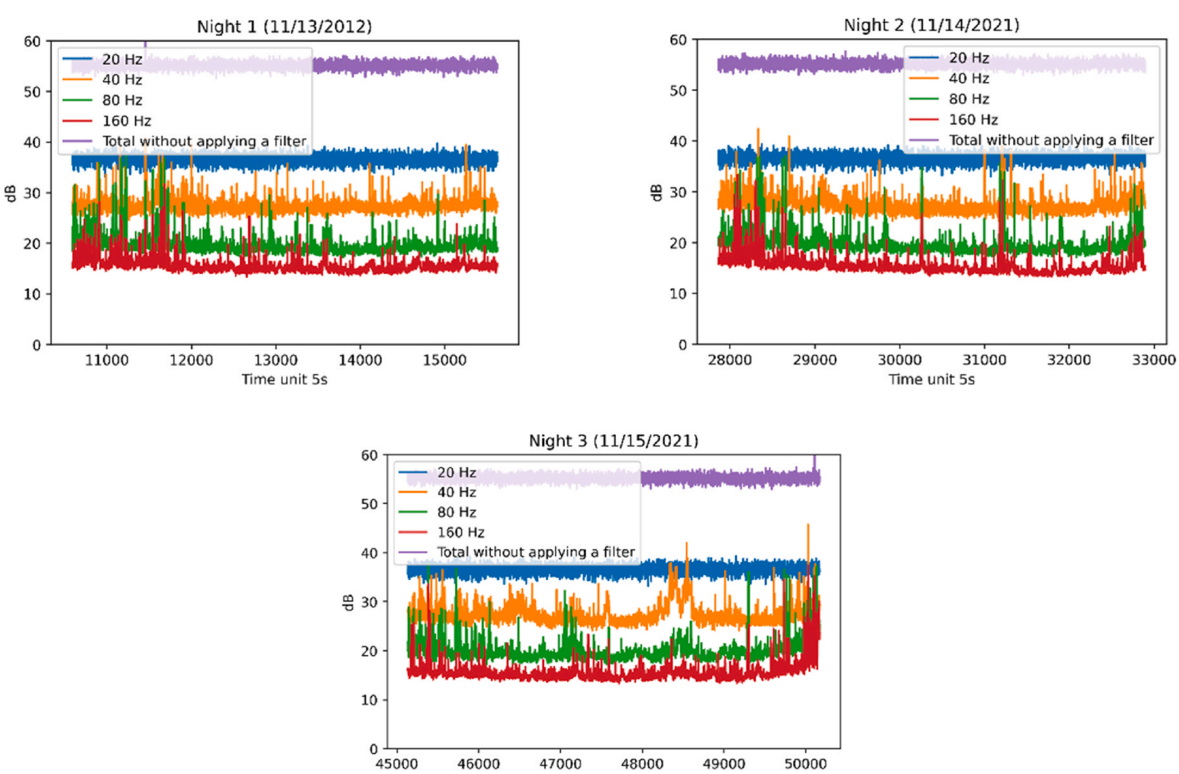

Fig. 5. Total and low frequency intensity time series (nighttime tests). These line plots were carried out in the preliminary analysis. There are three plots for each of the nights sampled. Plots compare time evolution of intensity at different low frequencies with total intensity. The lowest frequency (20 Hz) is the one that provides the greatest sound intensity.

$$\widehat{\mathrm{I}}(\mathrm{dB}) = \mathrm{f}(\widehat{\mathrm{E}(\mathrm{P})}) = 10\log_{10}\left(\frac{\frac{\sum_{i=1}^{N} \mathrm{P_i}\ (\mathrm{Pa})}{\mathrm{N}}}{2\cdot 10^{-5}}\right)^2 \qquad \text{eq.2}$$

The pressure and intensity could also be estimated based on the variables shown below. This approach does not consider linear changes in units, and is therefore erroneous from an acoustic point of view, although it is useful in statistical terms.

$$\widehat{\mathrm{P}}(\mathrm{dB}) = \widehat{\mathrm{I}} = E(\widehat{f(P)}) = \frac{\sum_{i=1}^{N} \mathrm{I_i}(\mathrm{dB})}{\mathrm{N}} \qquad \text{eq.3}$$

$$\widehat{\mathrm{P}}(\mathrm{Pa}) = f^{-1}(\widehat{E(I)}) = \mathrm{P_0}(\mathrm{Pa})\cdot 10^{\frac{\sum_{i=1}^{N} \mathrm{I_i}(\mathrm{dB})}{\mathrm{N}}} \qquad \text{eq.4}$$

The direct estimator of intensity ($\widehat{\mathrm{P}}(\mathrm{dB}) = \widehat{\mathrm{I}} = \mathrm{E}(\widehat{\mathrm{f}(\mathrm{P})}) = \frac{\sum_{i=1}^{N} \mathrm{I_i}(\mathrm{dB})}{\mathrm{N}}$ eq. 3) can be used for the estimation of the mean and its variance.

The following table shows the estimators of the exploratory analysis of the I variable ($\widehat{\mathrm{I}}(\mathrm{dB}) = \mathrm{f}(\widehat{\mathrm{E}(\mathrm{P})}) = 10\log_{10}\left(\frac{\frac{\sum_{i=1}^{N} \mathrm{P_i}\ (\mathrm{Pa})}{\mathrm{N}}}{2\cdot 10^{-5}}\right)^2$ eq. 2):

The table shows that the application of the type A filter causes important variations in the main indicators with respect to the rest of the filters. Furthermore, the entropy clearly indicates that there is a considerable loss of information (entropy increase) when applying the

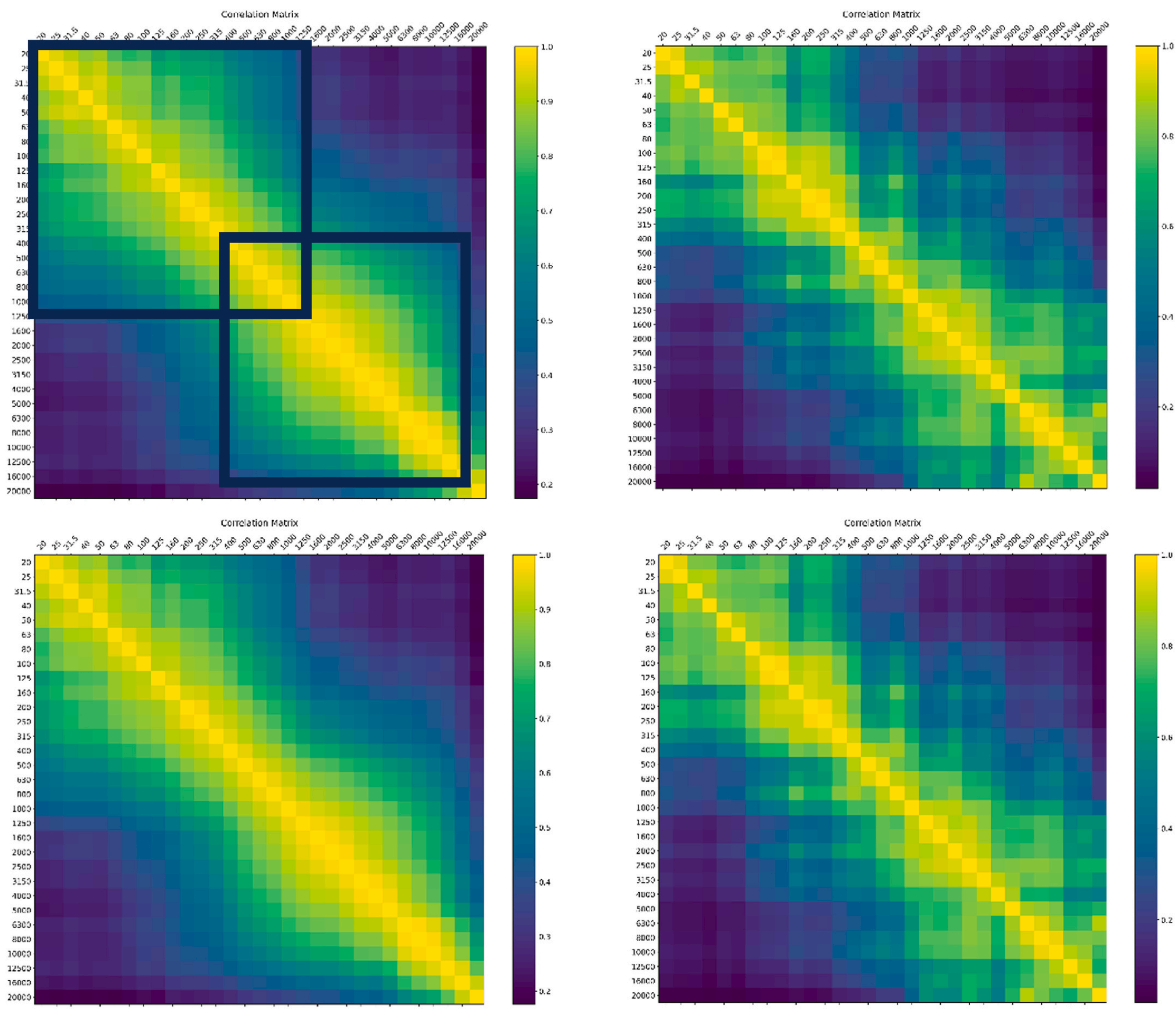

Fig. 6. Correlation matrix color map. These color maps are included in the exploratory data analysis. Every color map compares frequencies using the correlation coefficient. There are four color maps. Top maps correspond to sound intensity with or without outliers. Bottom maps include comparison of sound pressure with or without outliers. Color shows absolute value of correlation coefficient. Yellow represents correlation coefficient close to one. Yellow colors are grouped around matrix diagonal, and each map seems to show two differentiated areas more related to each other. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

type A filter with respect to no filters applied.

In order to find relations among frequencies, we calculate Pearson correlation matrices for different variables (frequencies). Previously, data without outliers have been obtained (substitution outlier by median), and these data will be compared with the original data (contain outliers). The main results are shown in the following graphs (Fig. 6). First graphs two shows intensity correlation (without and with outliers). Last two graphs show intensity correlation (without and with outliers).

The differences between the matrices with or without outliers are practically null, but two possible differentiated zones are already shown, which could correspond to two different possible sources. When performing the hypothesis test (H_0: $\rho = 0$), the p-value in the pressure variable and the intensity variable shows that there are significant correlations between the different frequencies.

This reinforces the hypothesis of different sources over time, although it does not certify whether these sources vary their emissions and sound frequencies over time. "Source causality" means that there is a correlation between frequencies. One of these possible sources would happen at frequencies below 200 Hz. The following figure (Fig. 7) shows a diagram with this "source causality", indicating sound is a result of mixing different active sources:

This diagram shows that the generating sources may or may not be operational at a certain time interval. Therefore, you can hypothesize statistical differentiation of active sources, since each source probably has a different "timbre" (frequency spectrum), and although the spectrum generated by each source can vary over time, as well as the conditions of wave propagation, these changes could even favor their separation using statistical algorithms.

There are also different graphic methods used in exploratory analysis to identify the nature of the study variables and facilitate their classification. Fig. 8 shows Q-Q plots at different frequencies during the nighttime, which allow us to observe for this case the difference between a normal distribution function and the empirical distribution of the sample. This method can also determine the existence of outliers in many cases through the difference that appears at the ends of the plot. Fig. 8 shows a difference close to zero at the lowest frequency, and important deviations at the highest frequencies likely due to the presence of outliers.

Another visual exploratory method used in the analysis to differentiate and classify variables was Box and Whisker plots. This method can summarize the main robust estimators in a few figures and assess the asymmetry and outliers of a variable. Fig. 9 is a box and whisker plot that shows similar outcomes to Fig. 8 for the variables during nighttime with strong symmetry and few outliers at the lowest frequencies, and important asymmetries and outliers at higher frequencies.

Concerning time data analysis (dependence on time), it focuses on frequencies estimating simple and partial autocorrelation, and crossed correlation among frequencies (between variables at different moments of time), and it is observed at low frequencies that there is practically no correlation with previous moments of time at night (with itself or with another variables), so time series is basically a fixed value plus a pure random variable.

Figs. 10 and 11 show color map with the cross-correlation matrix. Color indicates correlation of the sound intensity between frequency at 20 Hz and another frequency with a time lag. Color bar on the right quantifies the correlation value, and the axes the compared frequencies (for instance: position in row "i" and column "j" means cross-correlation between 20 Hz and frequency in j with a temporal delay of j-i in absolute value time intervals).

These figures compare between data considering only night samples and the complete data set of periods (day, afternoon, and night). Fig. 10 indicates that intensity at 20 Hz behaves as white noise for all effects during nighttime. A similar behavior is observed at all 1/3 octave frequencies when we analyze their cross-correlation matrices. However, Fig. 11 (complete data set) shows significant correlations appear at low frequencies compared to when exclusively considering the nighttime period.

One of the most used tools in the analysis of time series are autocorrelation plots. Autocorrelation plots allow us to determine the influence of time on a variable, although they do not allow us to determine the influence of other variables over time. Figs. 12 and 13 show the total and partial autocorrelation functions at 20 Hz. The difference between these two figures is due to the sampling data considered. Fig. 12 shows exclusively the night periods and Fig. 13 the entire sample at 20 Hz. It can be seen in Fig. 12 that for all purposes it behaves like white noise while Fig. 13 presents a more complex behavior. A similar behavior it is observed at other low frequencies.

Fig. 12 shows sound pressure time series behave like a model with a fixed value plus random noise. Consequently, it is a good approach for nighttime periods to consider that these series do not depend on time.

The most plausible hypothesis for this behavior is that the machines that generate very low frequencies are different from those that generate audible frequencies. However, this separation with machine learning methods is not easy, because similar behaviors present small differences in data. It is likely that machine learning methods work better considering all periods (day/afternoon/night) than considering only nighttime

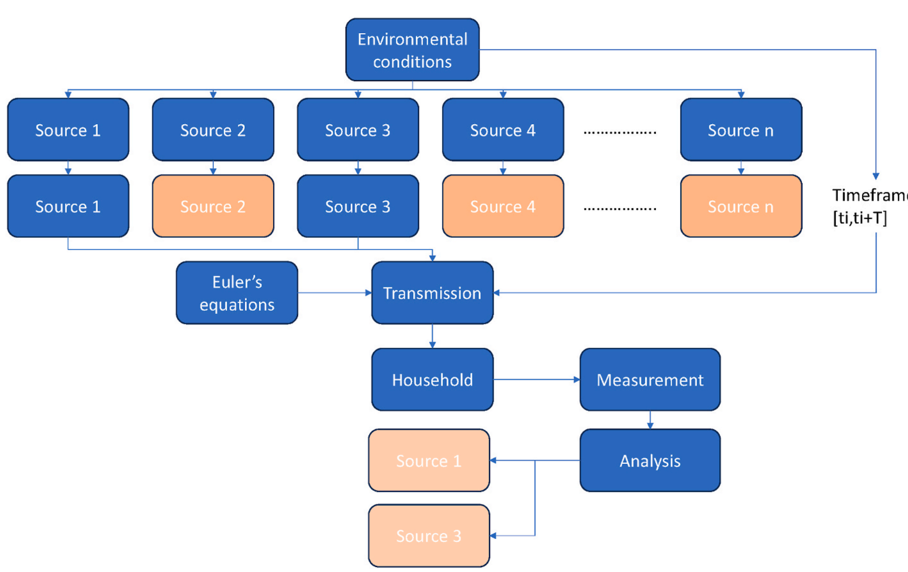

Fig. 7. Causality diagram of sources and the receiver. Example diagram which shows the hypothesis for splitting sound sources.

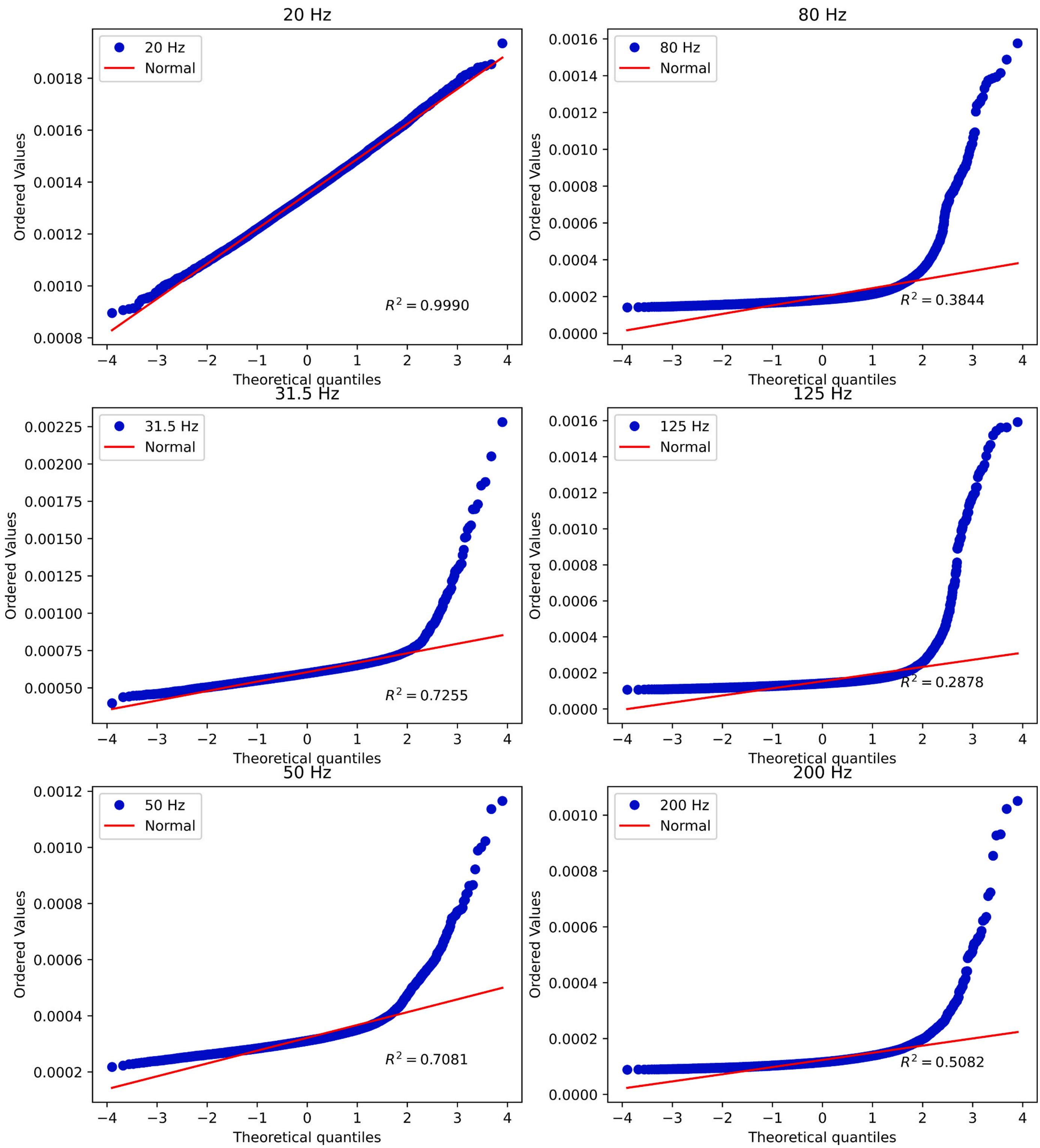

Fig. 8. QQ-Plots (P value) during nighttime. This plot is in the exploratory analysis and compare a theorical distribution function (straight line) with sampling pressure value (blue points). There are six plots for each low frequency. The difference between straight lines and blue points indicates that sampling population is close to theoretical distribution (gaussian) and likely the presence of outliers. Plots at low frequency are much closer than plots at higher frequency. It is likely due to outliers or different combined sources. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

period.

It is also surprising the null influence of the weather during the nighttime period, which favors a more conventional analysis rather than a time series analysis.

As we can see when we compare robust pressure and intensity estimators with mean and variance estimators, the best performance is obtained with robust estimators, because they are not affected by the type of variable (pressure or intensity). Consequently, we could convert outliers by using robust estimators, in particular with median estimator. If we compare the joint distributions of two variables before and after

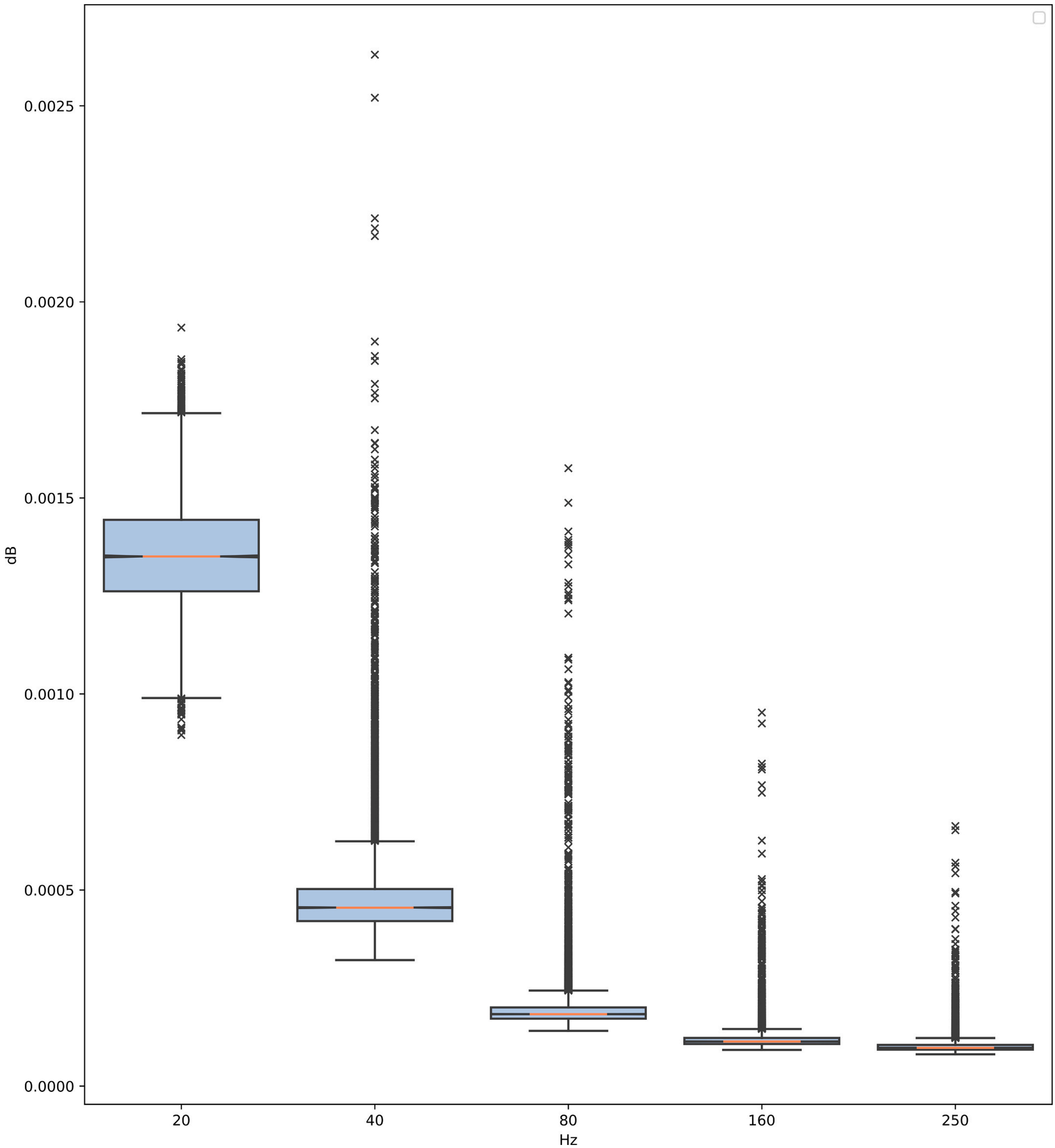

Fig. 9. Box and whisker plot (P value) during nighttime. Figure corresponds to exploratory analysis and represents visually the structure and robust estimators of the pressure variable. Box shows that at low frequencies, sampling distribution is symmetric and with a few outliers. Outliers are represented by points above or below the horizontal lines, which they are normally maximum or minimum (length of 1.5 times the Interquartile range from the Q1 or Q3 location). Outliers increase when frequency rise It seems it would be better to consider low frequencies.

converting their outliers, we observe that the distribution becomes more regular and symmetric when we change these outliers. In any case, the percentage of outliers for each frequency is always less than 10%, so the substitution is likely right. The following figure (Fig. 14) shows the results before and after transforming the outliers. Graph includes level lines in the scatter plots, below diagonal and one variable distributions in the diagonal (variable with itself).

So far, we have seen the main results in the night period, because it was the most stable period. However, there are many more interactions when all the data is considered. It is observed that the data in all time periods are not altered in intensity at lower frequencies. Therefore, it is easier to make transformations and separate them. Simply check the

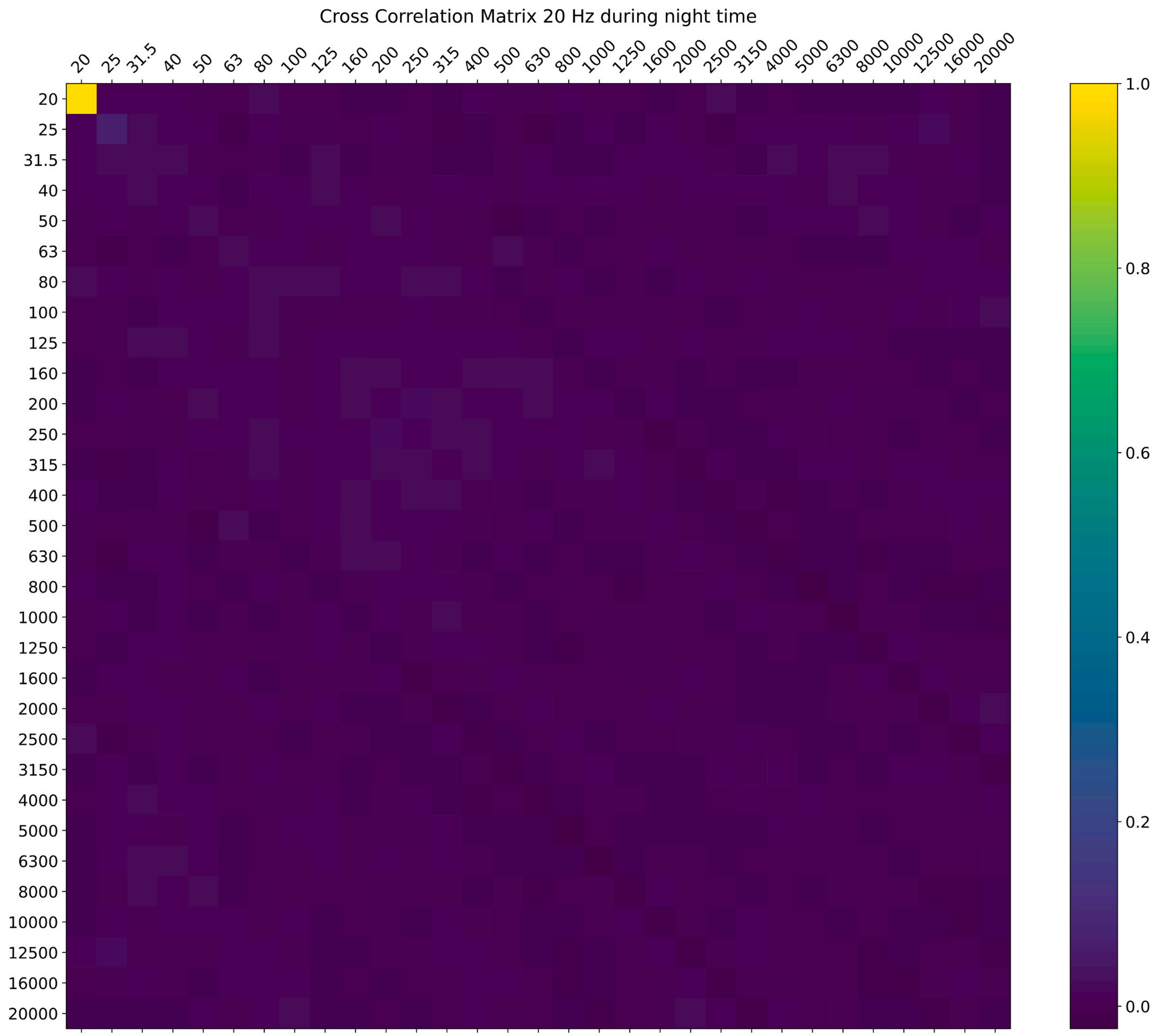

Fig. 10. Cross-correlations matrix at 20 Hz during nighttime. This figure is included in the time analysis and is a color map. Cross correlation is calculated from data at 20 Hz and data at higher frequencies with a time lag. Color shows intensity. The maximum correlation is yellow, and the minimum correlation is purple. Above diagonal, an element in a row with number "i" and column with "j" shows correlation between 20 Hz data without lag time and frequency located in "j" with a time delay of "j-i" time periods (5s/period) in absolute value. Figure indicates that 20 Hz does not correlate with another higher frequencies at night. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Barlett sphericity test and the Kaiser-Meyer-Olkin test, we observe that it would be better to use all periods. If we check time series considering all periods, the simple autocorrelation plots show a very slow decline in the data set, which may also be due to the existence of unit roots, but this does not affect to our machines learning methods.

If we reduce the frequency variables to a smaller number of variables, using traditional machine learning methods, it is likely that these variables can represent groupings of frequency spectrum of a sound source. These methods are called "reduction dimensionality methods". The most common reduction dimensional methods are the following:

- Main components (linear)
- Factorial (linear)
- Neural networks (non-linear)

Therefore, the dimensional reduction is then carried out with well-known machine learning methods such as the main components of factor and rotation factor. In these cases, the best approach is usually a rotation factor analysis.

The Fig. 15 clearly shows a possible source in the second factor as it presents very high absolute values for low frequencies. In addition, commonality explains more than 80% with only three factors. If a dimensional reduction is performed with values in the KMO test that discourage it, there are no high commonalities, and it is impossible to pinpoint factors.

Finally, an autoencoder was used to evaluate a system of nonlinear simultaneous equations, represented through a neural network with hyperbolic tangent activation functions (derived from the minmax standardization of the pressure variable). Just as convolution (kernel or filter) allows for identifying visual objects, it also helps to decisively

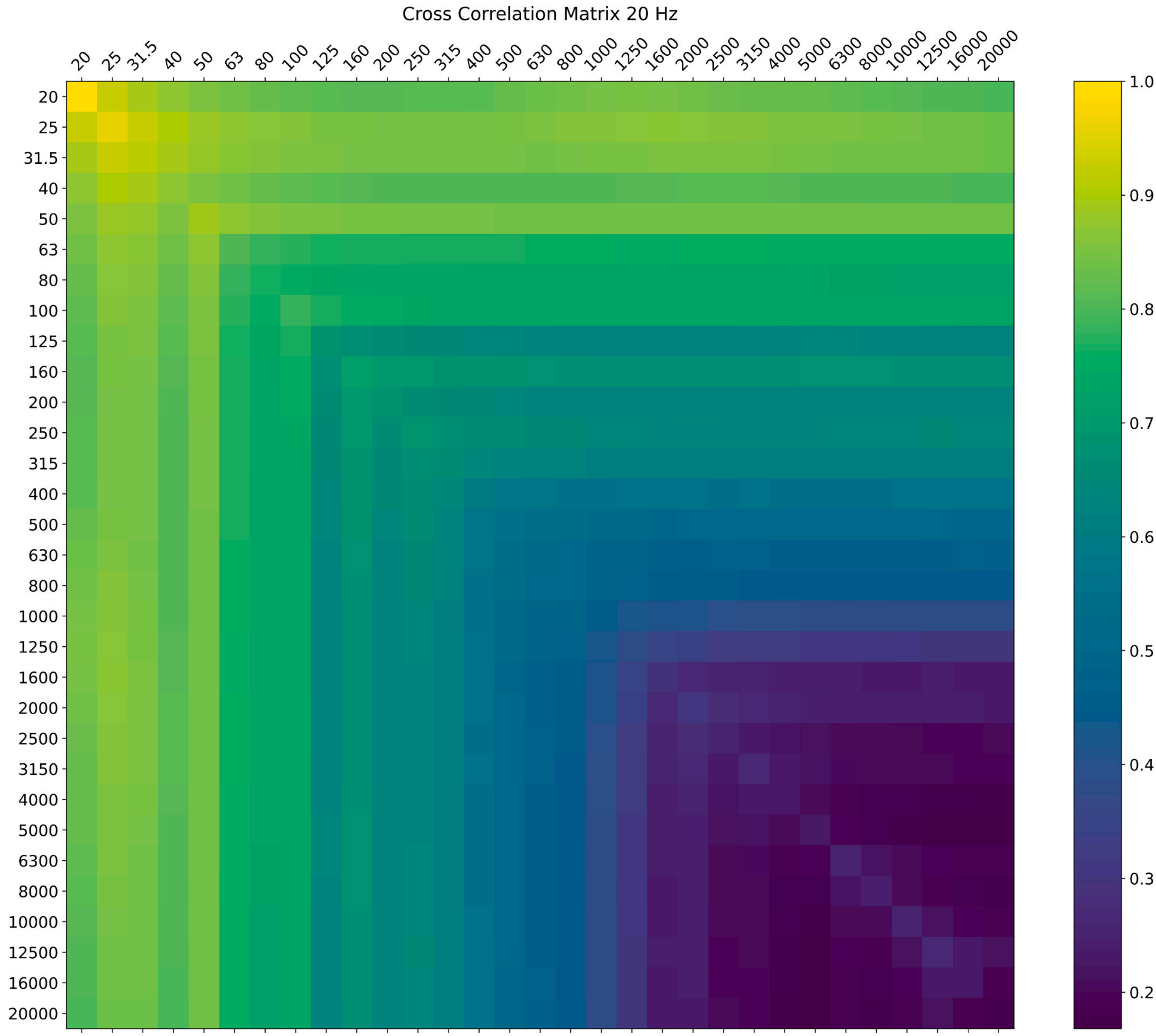

Fig. 11. Cross-correlation matrix at 20 Hz over all sampling periods (day, afternoon, and night). This figure represents the same than Fig. 10. The only difference between both figures is in sampling data which is taken. While Fig. 10 only considered data at night, this figure considers the whole sampling data. due to the presence of other sources at day. Figure shows correlations with higher frequencies with or without applying time lags with respect 20 Hz frequency. More sound sources seem to be involved during daytime periods.

identify new timbres or sources. After testing several topologies, the closest was obtained with a convolutional layer composed of ten neurons and an output that addresses to a dense layer with five neurons and ends in another layer that reverses the convolution. A set of 10,000 samples is used for the adjusted test model and the results are shown in the following figure (Fig. 16):

4. Discussion

The results obtained show that the hypothesis of non-time dependence is correct during nighttime, but not in the daytime periods, since a multitude of new sources appear. Besides, Figures shows that low-frequency urban sources are usually scarce compared to the rest of the sound sources, and can be separated from the rest, because outliers and the lowest entropies seem to be found in the truly audible frequencies (above 200 Hz).

An important discussion is related to the use or not of filters to remove practically inaudible frequency spectrums. The results show that the use of filters greatly distorts the data, reducing the value of the information they provide (entropy). Besides, this remotion of frequencies reduces the total intensity calculated to very low values.

This inability to measure all acoustic frequencies makes it impossible to analyze the main frequencies below 50 Hz that a human body may be receiving, and therefore, it would not be possible to associate the negative effect of these doses on human body.

In this way, we have also investigated other likely types of sources (for instance: electromagnetic fields) whose absorption by the body could cause with symptoms similar to low frequency sounds. In any case, it is necessary to repeat measurements of these types of sources in other homes with people who show similar symptoms.

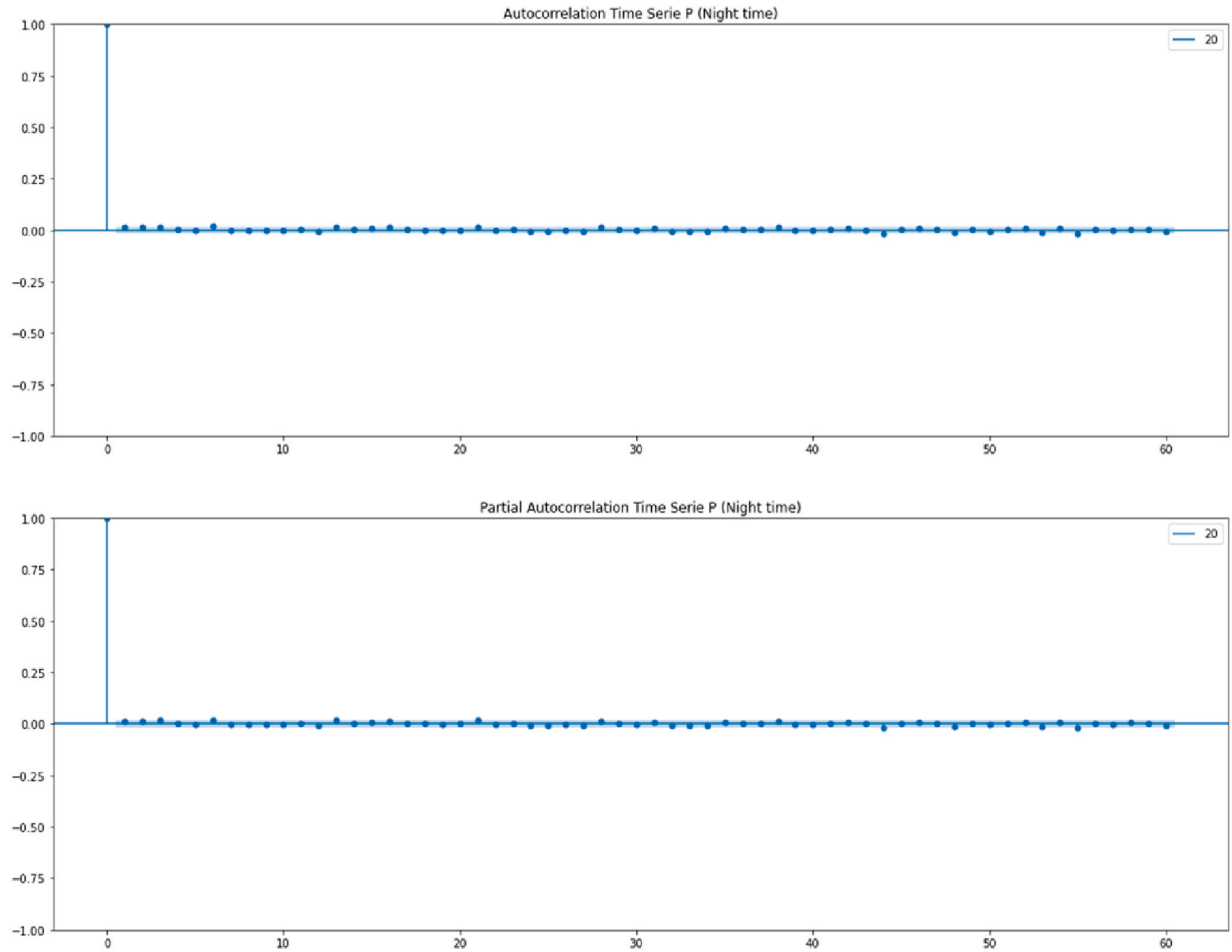

Fig. 12. Autocorrelation and partial autocorrelation plot of sound pressure at 20 Hz (nighttime). This plot is in time analysis and is separated in two graphs. Top graph considers autocorrelation and bottom graph partial autocorrelation. The role of this plot is to identify time series model, although they do not allow us to determine the influence of other variables over time. Partial autocorrelation differs from simple autocorrelation by removing the effects of lag times prior to time to be calculated. A model without values after 0 in both graphs represents white noise with respect to a mean value. It seems that the variations produced by the sound sources with respect to the average value are purely random, and, therefore, the sources that generate sound at 20 Hz work stationary during nighttime.

Likewise, the dimensional reduction methodologies allow limiting the number of low-frequency sources to a small number, explaining a large part of the behavior of the machines. In some cases, sources can have multiple machines within the same group called "source". The reason for considering measurements during nighttime is mainly due to the fact that control actions on the machines are much smaller and stationary as there are no significant variations with respect to the marked setpoint (low commercial activity).

Linear methodologies facilitate any subsequent adjustment of a non-linear model, and even allow us to show an accurate estimation of more likely sources. However, it is not yet possible to determine where is located the source.

The only sources which are running continuously in all homes and commercial establishments 24 h a day every day are refrigerators and freezers. The authors of this study plan to carry out a particular study on the frequency and NPS emitted by these devices.

There are standards for the measurement and analysis of sounds, such as ISO 9612 [46] and IEC 61400-11 [47], but these standards do not specifically cover the measurement of low-frequency sounds: "ISO 9612:2009 is not intended for assessment of masking of oral communication or assessment of infrasound, ultrasound and non-auditory effects of noise". Even the application of filter A is recommended on the origin data. The WHO Community Noise Guidelines indicate that we cannot yet establish a clear relationship between low-frequency sounds and damage to health yet, because new studies and longitudinal analysis over a longer time interval must be carried out.

However, recent studies [5,23,27,30,32,33] show that low frequency acoustic waves can cause damage to people's health. It could be interesting that public administrations take into account this health question and develop legislation and regulations which propose measurements without applying filters (avoid remove non-audible frequencies) and exposure limits as work as home. A principle of prudence should govern in order to avoid the potential risks that these low-frequency sound waves may represent for health.

5. Conclusions

The measurements show a sustained average acoustic intensity during the night period of around 50 dB between 20 and 25 Hz. The average acoustic intensity of all frequencies is greater than 60 dB.

As the sound level meter has a range between 20 and 20,000 Hz, it is not possible to check the sound pressure level below this frequency,

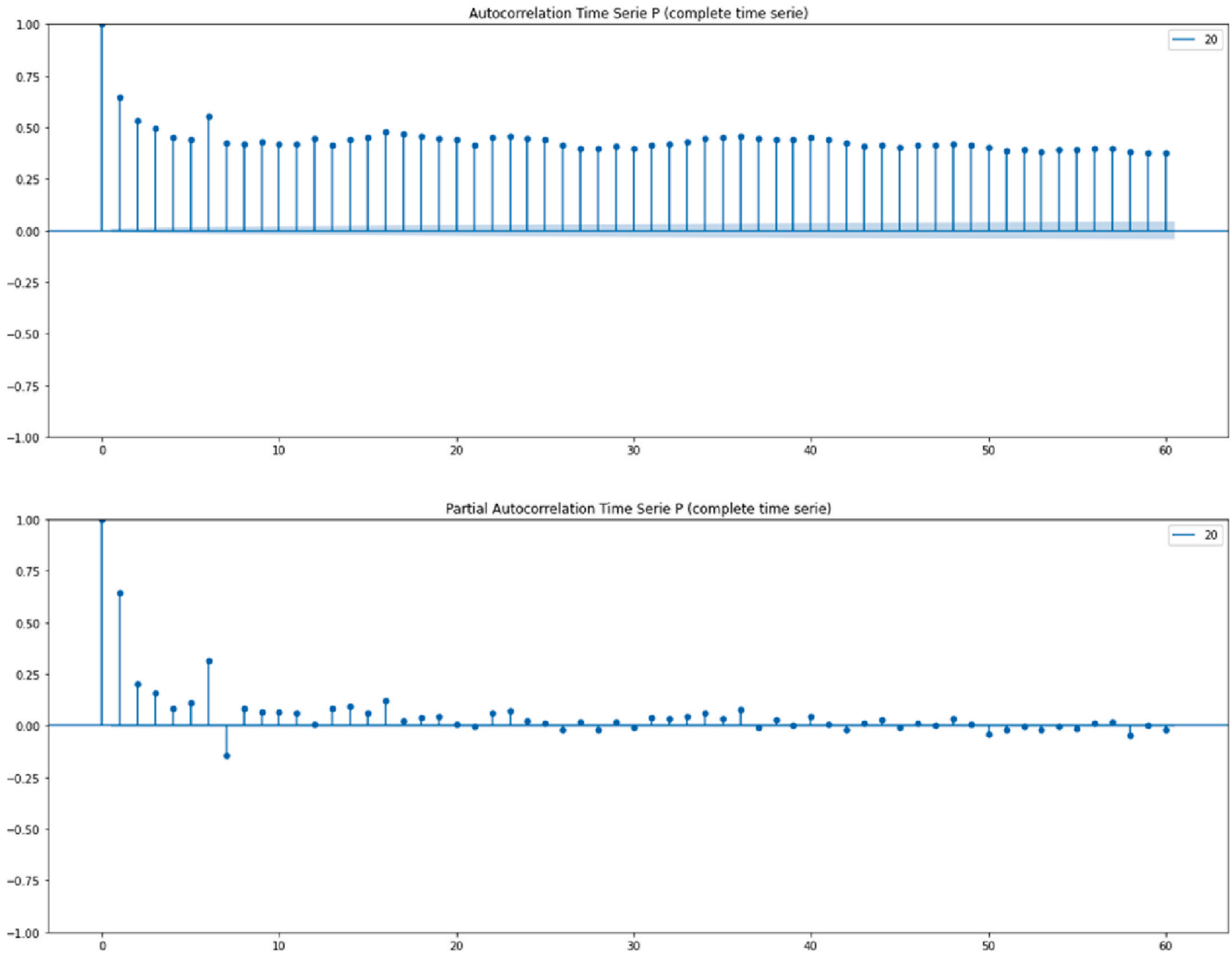

Fig. 13. Autocorrelation and partial autocorrelation plot of sound pressure at 20 Hz (entire sample). The only difference between Figs. 12 and 13 is the size of the sample. Fig. 13 considers the entire data set, including daytime periods and Fig. 12 only considers nighttime. In this case, pressure at 20 Hz is not white noise. It is very likely which new sound sources appear during daytime period, or another causes such as interaction with other frequencies, or sound sources, which worked stationary during nighttime, but they do not work stationary during daytime.

since part of the measured pressure may be infrasound.

Sound intensity time series for the lowest frequencies show stationarity over time, and with autocorrelations and cross-correlations close to zero, so the chosen study interval (nighttime) is correct. This stationarity is not kept in other periods of the day (morning and afternoon), due to the presence of a greater number of sources with intermittent performance.

Based on linear dimensional reduction data using factor analysis with rotations, the number of low-frequency sources is likely equal to one, although it is noted that one source may represent a set of nearby equipment. In any case, using rotation in factor analysis is essential to be able to specify the number.

Regarding nonlinear dimensional reduction, the previous linear dimensional reduction is useful for the design of the neural network, which will be of the "Autoencoder" type, because with the number of possible sources estimated previously, data analysts can start from the beginning with a scheme close to the final shape of the fitted neural network. However, this model does not easily allow us to obtain the sources that have low-frequency sound emissions.

Therefore, the proposed methodology is suitable for determining sources, including the choice of sampling points based on the associated symptoms.

Low frequencies could promote adverse effects even at frequencies lower than those contemplated in the study range (20–20000 Hz), so It should be taken into account that although the dB levels are below the possible limits indicated as harmful to health in the scientific literature, these harmful effects normally apply to specific exposures, but this lower limits may decrease in the case that they are exposures to low frequencies sustained over time.

Low frequency measurements should be made without filter A, since applying filters reduce the quality of the information, increasing its entropy, and besides completely omits the low frequency spectrum.

The authors of this work are aware that it is not possible with a single study to scientifically associate some people's symptoms with a possible energy absorption measured in only three days and with metrological limitations due to the limit of the equipment. It is necessary to carry out new measurements in homes to corroborate what is suspected from this study that the absorption of small and continuous doses of low frequencies may occur.

The subsequent tests that were carried out in the home to detect other factors that could cause the symptoms were negative, although since it was a single sample, it cannot be stated that there is a relationship between the symptoms that induced the sample and the existence of low noises. frequencies.

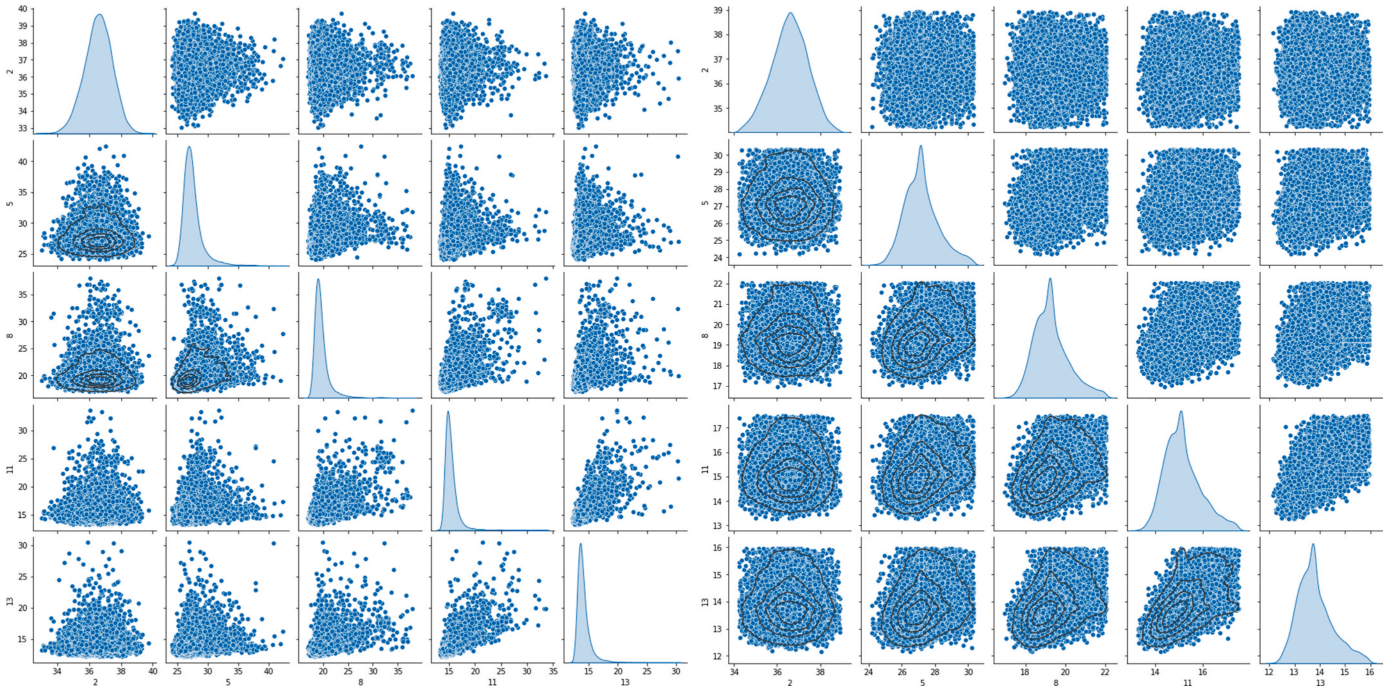

Fig. 14. Histograms and scatter plots between five low frequencies at night. This figure corresponds to exploratory data analysis. Each plot compares five different low frequencies and draws scatter plots when frequencies are different, or histograms when frequencies are equal. Scatter plot indicates for each sample the point obtained from the sound pressure of one of the frequencies on the X axis versus the sound pressure of the other frequency on the Y axis. Left plot shows case without removing outliers, and right plot shows case with substitution of outliers by median. In the case of replacing outliers, the shape of the distribution is more regular.

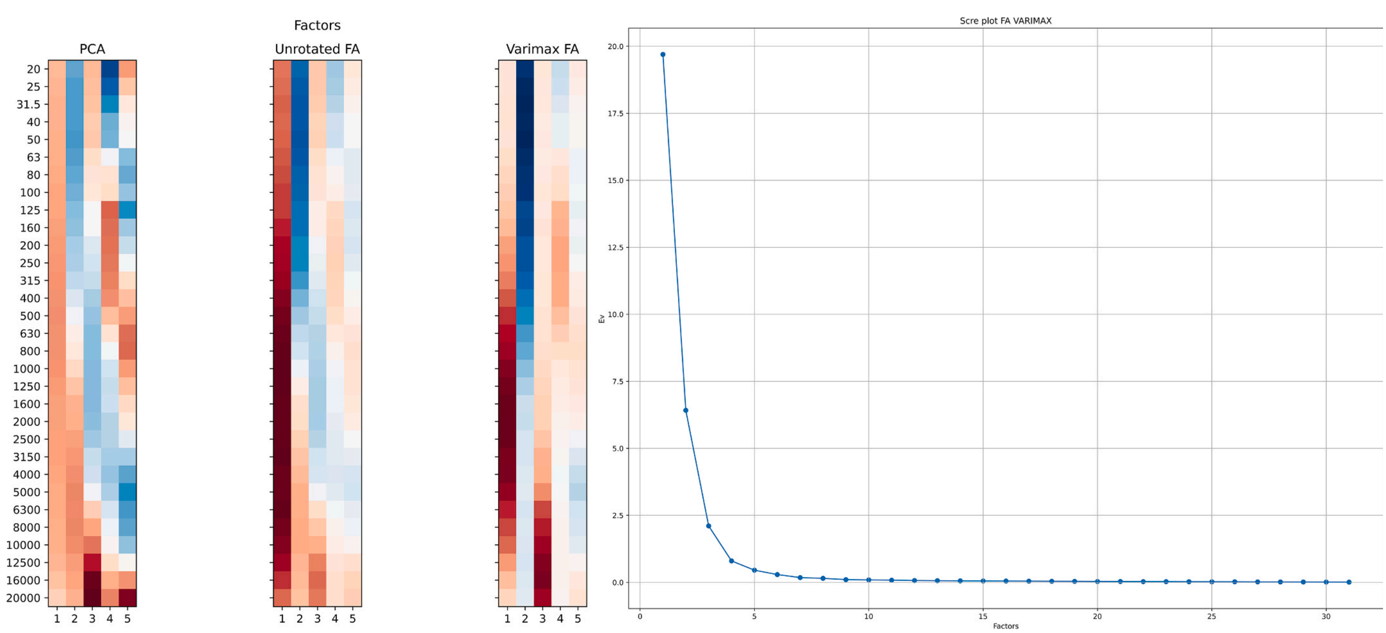

Fig. 15. Dimensional reduction factors color maps (PCA, Unrotated FA, VARIMAX FA) and sedimentation plot (entire sample). This figure shows the factor loadings which express the relationship between the original frequencies and the new factors. Figure contains three color maps corresponding to each of the linear dimensional reduction methods used (principal components, unrotated factorial, factorial with VARIMAX rotation), as well as a variance scree plot showing the contribution to the variance of each of the new factors for the VARIMAX factorial method. More intense colors indicate closer relationships of this factor with the frequencies where intense color appear. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

This study provides evidence of the existence of low-frequency sounds with high intensity even when most of the sources identified by scientific studies are not present nearby. Furthermore, these low-frequency sounds are almost inaudible to most of the population, so they do not allow individuals to perceive that they are receiving them, even though they may be harming them.

It also shows the need to avoid applying filters for the analysis or calculation of sound intensities, because the quality of the information would decrease, and most types of filters would exclude these non-audible frequencies. This invites to reform legislation, standards, and regulations to avoid excluding sound emissions that could harm people.

In addition, it changes the approach when selecting households of

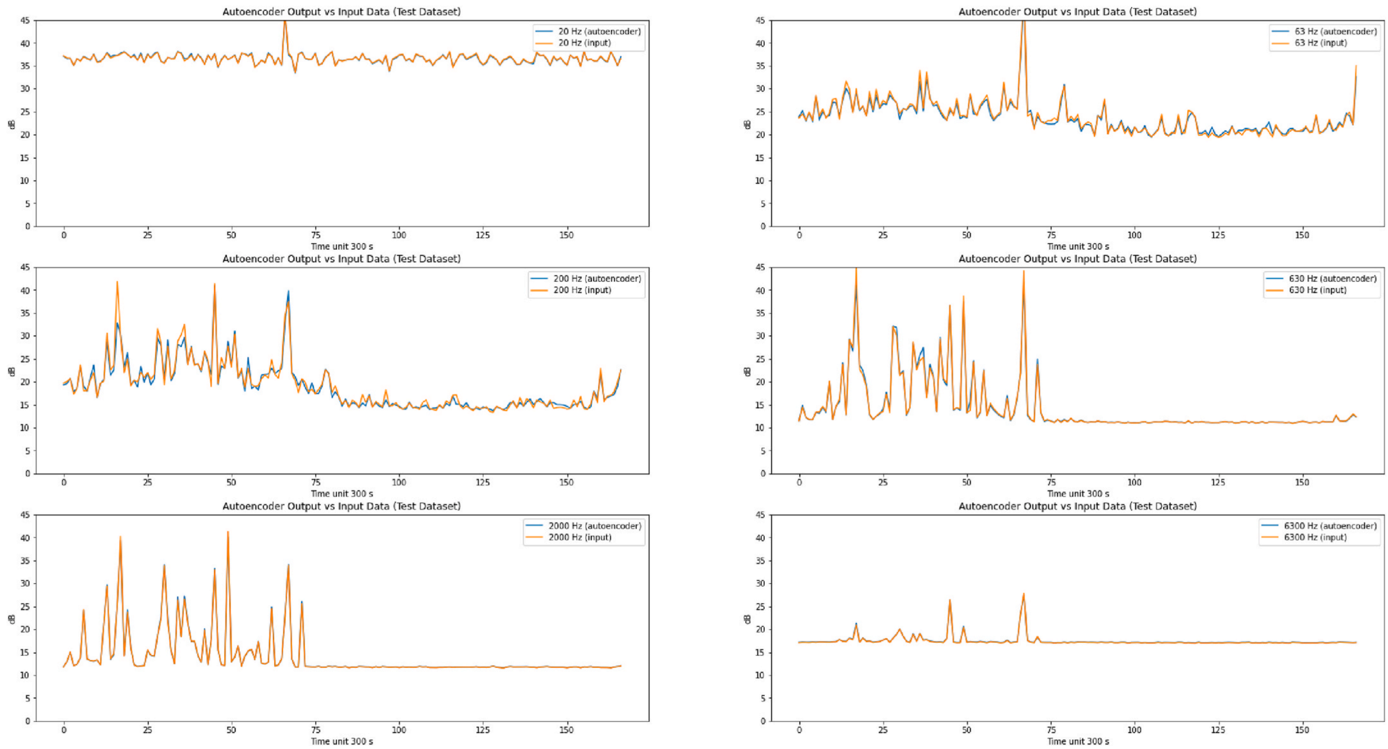

Fig. 16. Autoencoder output data compared to input data for the data set in the last 10,000 rows of the time series. The data are standardized.

the sample, since it focuses on possible adverse health effects instead of possible generating sources nearby.

Finally, the use of machine learning methodologies allows us to distinguish between sound sources, and even differentiate the frequencies generated by each source, although these methods would lose efficiency if the measurements are carried out in environments that do not guarantee stability, since the methodology It would be greatly complicated by the appearance of a number of atypical cases that are impossible to treat.

Future goals:

- Carry out more studies in other homes with inhabitants who present the symptoms mentioned in this article.
- Improve the methodology in non-linear models for the separation of sources by frequencies.
- Refine the models through verification tests with the turning off and on of the machines that make up the possible sources.
- Identify the exact location of sources with measurements at multiple points in the building.
- Perform laboratory tests with refrigeration equipment.

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CRediT authorship contribution statement

León José Azcárate: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David Baeza Moyano:** Writing – original draft, Visualization, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Gastón Sanglier Contreras:** Writing – original draft, Validation, Investigation, Formal analysis, Conceptualization. **Roberto Alonso González-Lezcano:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

[1] G. Leventhall, Low Frequency Noise. What we know, what we do not know, and what we would like to know, J. Low Freq. Noise Vib. Act. Control 28 (2) (2009) 79–104, https://doi.org/10.1260/0263-0923.28.2.79.
[2] G. Leventhall, What is infrasound? Prog. Biophys. Mol. Biol. 93 (1) (2007) 130–137, https://doi.org/10.1016/j.pbiomolbio.2006.07.006.
[3] C. Pilger, C. Schmidt, F. Streicher, S. Wuest, M. Bittner, Airglow observations of orographic, volcanic and meteorological infrasound signatures, J. Atmos. Sol. Terr. Phys. 104 (2013) 55–66, https://doi.org/10.1016/j.jastp.2013.08.00.
[4] J.B. Johnson, M. Ripepe, Volcano infrasound: a review, J. Volcanol. Geoth. Res. 206 (3–4) (2011) 61–69, https://doi.org/10.1016/j.jvolgeores.2011.06.006.
[5] D. Baeza Moyano, R.A. González Lezcano, Effects of infrasound on health: looking for improvements in housing conditions, Int. J. Occup. Saf. Ergon. 28 (2) (2022) 809–823, https://doi.org/10.1080/10803548.2020.1831787.
[6] G. Leventhall, Low frequency noise and annoyance, Noise Health 6 (23) (2004) 59–72.
[7] D.B. Moyano, D.A. Paraiso, R.A. González-Lezcano, Possible effects on health of ultrasound exposure, risk factors in the work environment and occupational safety

review. Healthcare (Switzerland), MDPI, 2022, March 1, https://doi.org/10.3390/healthcare10030423.
[8] M.B. Martínez, D.B. Moyano, R.A. González-Lezcano, Phacoemulsification: proposals for improvement in its application, Healthcare (Switzerland). MDPI (2021, November 1), https://doi.org/10.3390/healthcare9111603.
[9] J. Carpenter, M. Ögren, Infrasound in residential environments: a review of measurement techniques and results, Appl. Sci. 9 (8) (2019) 1715, https://doi.org/10.3390/app9081715.
[10] Y. Okamoto, T.-. Nguyen, H. Takahashi, Y. Takei, H. Okada, M. Ichiki, Highly sensitive low-frequency-detectable acoustic sensor using a piezoresistive cantilever for health monitoring applications, Sci. Rep. 13 (1) (2023), https://doi.org/10.1038/s41598-023-33568-3.
[11] K. Bolin, G. Bluhm, G. Eriksson, M.E. Nilsson, Infrasound emissions from wind turbines: measurements and sound quality analysis, J. Acoust. Soc. Am. 129 (6) (2011) 3727–3735, https://doi.org/10.1121/1.3585843.
[12] H. Møller, C.S. Pedersen, Infrasound measurements near wind turbines and in other environments, J. Low Freq. Noise Vib. Act. Control 25 (4) (2006) 237–265.
[13] F. Gu, T. Boczar, D. Zmarzły, M. Kozioł, Ł. Nagi, D. Wotzka, Z. Nadolny, Measurement of infrasound components contained in the noise emitted during a working wind turbine. https://doi.org/10.3390/en15020597, 2022.
[14] L. Yang, J. Kang, J. Gao, The effect of multiple noise sources on human performance and subjective responses, Appl. Acoust. 102 (2016) 14–22, https://doi.org/10.1016/j.apacoust.2015.10.021.
[15] X. Yang, Y. Gao, X. Ren, Influence of vibration on physiological and psychological states: a review. Journal of Low Frequency Noise, Vibration and Active Control 36 (1) (2017) 14–28, https://doi.org/10.1177/1461348417695985.
[16] L. Peng, P. Zhao, H. Cheng, Q. He, L. Du, Improved low-frequency sound absorption of porous silicone rubber resonance sheet with periodic cavities, J. Low Freq. Noise Vib. Act. Control (2022) 14613484211070356, https://doi.org/10.1177/14613484211070356.
[17] A.R. Hernández-Montoya, C.A. Ramos-Paja, M. Díaz-Méndez, J. Rangel-Magdaleno, Evaluación del ruido ambiental y la percepción comunitaria en torno a parques eólicos en México, Appl. Acoust. 162 (2020) 107148, https://doi.org/10.1016/j.apacoust.2019.107148.
[18] M. Pérez-Llorca, R. Montes-Soldado, A. Ordoñez-Fernández, Evaluación del impacto acústico de parques eólicos en el paisaje sonoro, J. Environ. Manag. 293 (2021) 112851, https://doi.org/10.1016/j.jenvman.2021.112851.
[19] M.B. Martínez, D.B. Moyano, R.A. González-Lezcano, Phacoemulsification: proposals for improvement in its application, Healthcare (Switzerland). MDPI (2021, November 1), https://doi.org/10.3390/healthcare9111603.
[20] S.A. Girard, S. Kamal, R. Debigaré, Infrasound levels in residential buildings near a wind farm, Environ. Res. 160 (2018) 292–303, https://doi.org/10.1016/j.envres.2017.09.013.
[21] A. Habib, J. Akhter, T. Hussain, H. Lee, Measurement and evaluation of infrasound and low-frequency noise in houses near a wind farm, J. Environ. Manag. 183 (2016) 499–508.
[22] M. Kotiranta-aho, A. Haapakangas, Investigación sobre la exposición a infrasonidos en viviendas cerca de turbinas eólicas en Finlandia, Revista de Investigación Ambiental 7 (2) (2017) 45–56.
[23] R.J. McCunney, K.A. Mundt, Low-frequency infrasound from wind turbines: exposure and health effects in residents living nearby – a review and meta-analysis of the scientific literature, Environ. Res. 168 (2019) 199–206, https://doi.org/10.1016/j.envres.2018.09.027.
[24] R.J. McCunney, R.E. Morley, A. Tovar, Assessment of infrasound exposure in homes near wind farms, J. Occup. Environ. Med. 59 (4) (2017) e30–e34, https://doi.org/10.1097/JOM.0000000000000967.
[25] E. Pedersen, K.P. Waye, Infrasound and low-frequency noise from wind turbines: exposure and health effects, Environ. Health Perspect. 115 (2) (2007) 167–171, https://doi.org/10.1289/ehp.9477.
[26] A.N. Salt, J.T. Lichtenhan, Infrasound from wind turbines – an overlooked health hazard, Bull. Sci. Technol. Soc. 34 (4) (2014) 130–137, https://doi.org/10.1177/0270467614542421.
[27] G.P. Van der Berg, E. Pedersen, J. Bouma, R. Bakker, Noise pollution from wind turbines: potential health effects assessed using noise maps and questionnaires in an urban and rural environment, Environ. Health 14 (1) (2015) 1–14, https://doi.org/10.1186/s12940-015-0048-2.
[28] V. Vijay, R. Balachandran, Infrasound from wind turbines: a review of scientific literature, Renew. Sustain. Energy Rev. 154 (2022) 111931, https://doi.org/10.1016/j.rser.2021.111931.
[29] M. Barceló, J. Escofet, Infrasound in the urban environment: a literature review, Environ. Int. 48 (2012) 114–128, https://doi.org/10.1016/j.envint.2012.07.006.
[30] B. Berglund, P. Hassmen, R.F. Job, Infrasound and low-frequency noise from wind turbines: exposure and health effects, Environ. Res. Lett. 14 (11) (2019) 113003, https://doi.org/10.1088/1748-9326/ab3eed.
[31] P.M. Bluyssen, E. Verheijen, D. Zhang, Low-frequency noise and infrasound in buildings: a review of measurements and standards, Buildings 11 (2) (2021) 51, https://doi.org/10.3390/buildings11020051.
[32] Y. Chen, Y. Lin, A comprehensive review of low frequency noise and its effects on human beings, Environ. Pollut. 269 (2021) 116160, https://doi.org/10.1016/j.envpol.2020.116160.
[33] A. Muzet, The impact of urban noise and infrasound on health, Noise Health 22 (104) (2020) 159–165, https://doi.org/10.4103/nah.NAH_69_19.
[34] J.A. Barcelos, P.H.T. Zannin, J.M. Ferreira, Infrasound in homes near highways, Arch. Acoust. Q. 45 (3) (2020) 431–439, https://doi.org/10.24425/aoa.2020.134475.
[35] K. Dawson, K. Robertson, M. Nilsson, Assessment of infrasound and low-frequency noise exposure in homes near a highway, Appl. Acoust. 180 (2021) 108119, https://doi.org/10.1016/j.apacoust.2021.108119.
[36] J.M. López, Infrasound in homes near high-voltage power lines, J. Environ. Health 10 (2) (2022) 45–55.
[37] M. González, Estudio sobre los niveles de infrasonido en viviendas cercanas a carreteras muy transitadas en España, Revista de Medio Ambiente 25 (2) (2019) 45–57, https://doi.org/10.1000/xyz123.
[38] A.S. Kraev, D.T. Adamson, Infrasound and low-frequency noise in homes near industrial facilities, Appl. Acoust. 180 (2021) 108115, https://doi.org/10.1016/j.apacoust.2021.108115.
[39] M. Pakalén, J. Keränen, V. Hongisto, J. Keski-Säntti, Infrasound and low-frequency noise in homes near gas turbines, J. Acoust. Soc. Am. 143 (2) (2018) 1054–1064, https://doi.org/10.1121/1.5026753.
[40] M. Sliwinska-Kowalska, P. Kotylo, Assessment of exposure to low frequency noise and infrasound among personnel working in a modern deep-encapsulated diesel engine room, Int. J. Occup. Med. Environ. Health 29 (5) (2016) 799–808, https://doi.org/10.13075/ijomeh.1896.00553.
[41] A.A. Adeyemi, C.O. Arum, O.O. Babalola, Environmental noise and vibration in the construction industry: a systematic review, J. Environ. Manag. 291 (2021) 112629, https://doi.org/10.1016/j.jenvman.2021.112629.
[42] E.R. Bauer, K.S. Norskog, B.W. Schmitz, Health risks associated with exposure to low-frequency noise and vibration in mining, J. Occup. Environ. Hyg. 13 (6) (2016) 447–456, https://doi.org/10.1080/15459624.2015.1133013.
[43] J. Bauer, M. Latzel, Assessment of low frequency noise and vibration in the workplace, Arch. Acoust. Q. 38 (4) (2013) 529–543, https://doi.org/10.2478/aoa-2013-0059.
[44] J. Krajewski, J. Podgórski, K. Makowska, M. Pawlaczyk-Łuszczyńska, Influence of exposure to low frequency noise and vibration on cardiovascular and hormonal parameters, Int. J. Occup. Med. Environ. Health 29 (5) (2016) 821–834, https://doi.org/10.13075/ijomeh.1896.00501.
[45] N. Mijalkovic, I.H. Flindell, S.A. Stansfeld, Low-frequency noise and infrasound in an urban setting, Environ. Res. Lett. 14 (9) (2019) 094008, https://doi.org/10.1088/1748-9326/ab2d55.
[46] R. Cipollone, P. Gabellini, M. D'Orazio, P. Conti, Low-frequency noise and infrasound in residential buildings: a pilot study, Appl. Sci. 10 (14) (2020) 4867, https://doi.org/10.3390/app10144867.
[47] V.F. Maceira, J.P. Rodríguez, I.G. Neira, Infrasound exposure in buildings: an overview of international standards and Guidelines, Arch. Acoust. Q. 44 (4) (2019) 545–556, https://doi.org/10.24425/aoa.2019.130019.
[48] H. Møller, C.S. Pedersen, Infrasound and low-frequency noise in residential environments: a review, Front. Public Health 8 (2020) 243.
[49] Determination of Occupational Noise Exposure - Engineering Method (ISO 9612: 2009).
[50] Wind turbines - Part 11: Acoustic Noise Measurement Techniques (IEC 61400-11: 2012).
[51] Environmental Noise Guidelines for the European Region, WHO, 2018. https://www.who.int/europe/publications/i/item/9789289053563.
[52] Ordenanza de Protección contra la Contaminación Acústica y Térmica. https://sede.madrid.es/sites/v/index.jsp?vgnextoid=0130511f3649e210VgnVCM2000000c205a0aRCRD&vgnextchannel=6b3d814231ede410VgnVCM1000000b205a0aRCRD, de 25 de febrero de 2011.