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SOUNDS GENERATED BY A FIXED OFFSHORE OIL AND GAS PLATFORM DURING PRODUCTION PERIODS

N. Pérez-Gimeno[1*] **J.L. Cueto-Ancela** [1] **E. Nava-Baro** [2]

[1] Acoustic Engineering Laboratory of the University Institute of Marine Research (INMAR), University of Cadiz, Puerto Real, Spain.

[2] Department of Communications Engineering, University of Malaga, Malaga, Spain.

ABSTRACT

Noise emissions from oil and gas platforms, particularly fixed ones, remain underexplored compared to their mobile and semi-submersible counterparts. Existing research provides a limited view of the sound characterization of fixed platforms. This paper presents the results of the noise measurement campaign and how the collected data feeds an automated sound pattern detection model. The ultimate goal is to provide new insights into the underwater soundscape.

In collaboration with RIPSA (Repsol Investigaciones Petrolíferas S.A.), an acoustic measurement campaign was carried out in Mediterranean waters. Three hydrophone recorders (PAM) were deployed within a 500-meter radius of a fixed oil and gas platform. One week of collected data was analyzed, resulting in a comprehensive classification of acoustic events to generate training and testing datasets. Using a machine learning approach, a classification model based on the K-Nearest Neighbors (KNN) algorithm was developed. This was used to identify and categorize the acoustic events associated with platform activities.

This study shows how this combined approach is an effective tool for characterizing the underwater sources that form part of the soundscape of a fixed offshore oil and gas platform during its production phase.

Keywords: *underwater soundscape, anthropogenic noise, machine learning.*

[*] ***Corresponding author***: neus.perez@uca.es.

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1. INTRODUCTION

In recent years, interest in understanding the underwater acoustic impact of offshore oil and gas operations has grown, yet fixed production platforms remain relatively understudied compared to their mobile and semi-submersible counterparts. Despite their global prevalence, fixed platforms have received limited attention in scientific literature, which predominantly focuses on mobile rigs or on impacts to marine fauna near offshore infrastructure ([1-4]).

Understanding the nature of underwater noise is critical, as anthropogenic sound can influence marine species' behavior, physiology, and even survival ([5-7]). The characterization of acoustic sources, particularly in terms of frequency content, amplitude, and temporal patterns, enables researchers to assess the ecological implications of these sound emissions. Third-octave band levels (TOL), for example, are especially relevant for studying impacts on cetaceans and other marine mammals due to their alignment with auditory sensitivity ranges ([8]). Comprehensive acoustic characterization not only informs ecological risk assessments but also provides essential inputs for sound propagation modeling, regulatory compliance, and the design of mitigation strategies ([9-11]).

To contribute to this growing field, the present study focuses on developing an automated sound pattern detection model for a fixed oil platform in the Mediterranean Sea.

2. MATERIAL AND METHODS

As part of the RIPSA project, a year-long acoustic monitoring campaign was conducted near an offshore fixed hydrocarbon production platform located approximately 50 km from the Mediterranean coast[1].

2.1 Case of study: Offshore gas & oil fixed platform

The study was conducted on a fixed "jacket-type" offshore oil and gas platform, with its lower deck positioned approximately 25 meters above sea level. Oil was extracted from both platform-based and subsea satellite wells, processed onboard, and transported to shore through a network of umbilicals, flowlines, and risers (see Figure 1). During the measurement campaign, the platform was continuously supported by multi-supply vessels. To support the analysis of acoustic data, relevant non-acoustic information—such as production rates of active wells and environmental conditions—was also collected to contextualize platform operations.

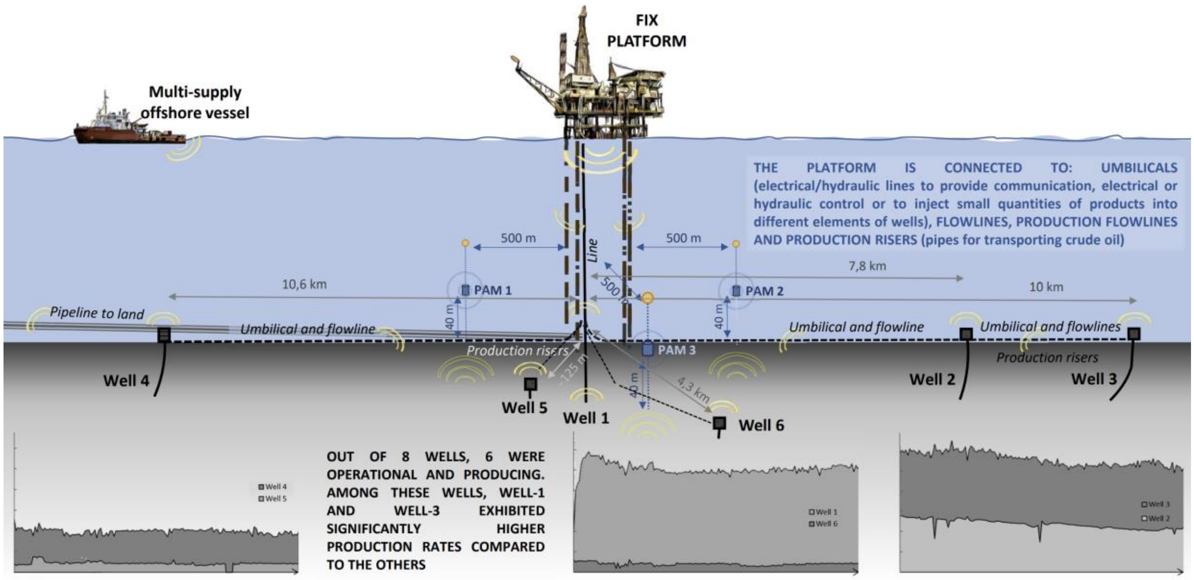

Figure 1. Diagram of the acoustic measurement campaign and schematic of the location of production platform elements, showing the temporal evolution of the study period of the production of 6 wells

2.2 Acoustic data acquisition: Fieldwork

The acoustic monitoring campaign spanned from October 1, 2016, to October 17, 2017, though the analysis presented focuses on the first five months—until February 24, 2017—resulting in 1,286.5 hours of recordings. Three Passive Acoustic Monitoring (PAM) systems were deployed 500 meters from the platform, forming an equilateral triangle at about 40 meters above the seabed. The systems operated on a 3-minute recording cycle every 22 minutes, achieving a 14% duty cycle—above the 10% typically recommended for such studies [12]. Recordings were made using two SM2M and one SM3M units, capturing sound at a 96 kHz sampling rate and 16-bit resolution.

All devices were equipped with omnidirectional hydrophones (−165 dB re V/Pa sensitivity) and a 2 Hz to 48 kHz system bandwidth.

2.3 Acoustic data processing and pattern detection

Acoustic data were processed using MATLAB to calculate mean broadband sound pressure levels (SPLs) and third-octave levels (TOLs), averaged over 1-second, 1-minute, and 3-minute intervals, as well as daily means (SPL_{24h} and TOL_{24h}).

To characterize sound patterns linked to platform activity, recordings were segmented into 1-minute intervals. A meticulous manual review was conducted by listening to and analyzing the 1-minute segments from recordings made

[1] For confidentiality reasons, it is not permitted to identify or locate the platform studied

during the first week of October 2016 to identify specific sound patterns (categories).

A total of 1,965 one-minute recordings were classified in eight distinct sound categories, representing acoustic events associated with platform activity. These categories are summarized in Table 1.

Table 1. Summary of pre-classified 1-minute recordings used as training and test data.

Category	Nº 1-minute records
0 - No pattern_ generic activity	233
1 - Pulses	47
2 - Marked cycles	132
3 - Continuous & 3.15kHz- high levels	707
4 - Continuous & 3.15kH- low levels	255
5 - Blasts	75
6 - Machinery continuous	517
7 - Works_ sirens and knocks	41

A machine learning approach was implemented through the development of a classification model based on the K-Nearest Neighbors (KNN) algorithm. Using the dataset of pre-classified 1-minute recordings, which was divided into training and test subsets.

The recordings were characterized by 34 parameters: third-octave bands (40 Hz to 12,589 Hz), SPL_max, SPL_peak, Percentile_1%, Percentile_99%, SPL_mean, and SPL_std Once trained, achieving satisfactory accuracy, the model was applied to the remaining unclassified recordings.

2.4 Underwater Soundscape: Daily acoustic patterns

To describe the underwater soundscape surrounding the fixed platform, each classified acoustic event was analyzed in terms of its daily occurrence. The number of events per category was quantified and organized into 24-hour intervals, allowing for the visualization of temporal patterns across the monitoring period. This method provided a detailed representation of how frequently specific types of anthropogenic sounds occurred, offering insights into the acoustic dynamics of the area influenced by platform operations.

3. RESULTS

The SPL_{24h} (dB re 1 µPa) and TOL (dB re 1 µPa/Hz) were estimated. Figure 2 illustrates the hourly averaged SPLs (in linear scale) measured at each of the three PAM locations—PAM1, PAM2, and PAM3— between October 1, 2016, to February 24, 2017.

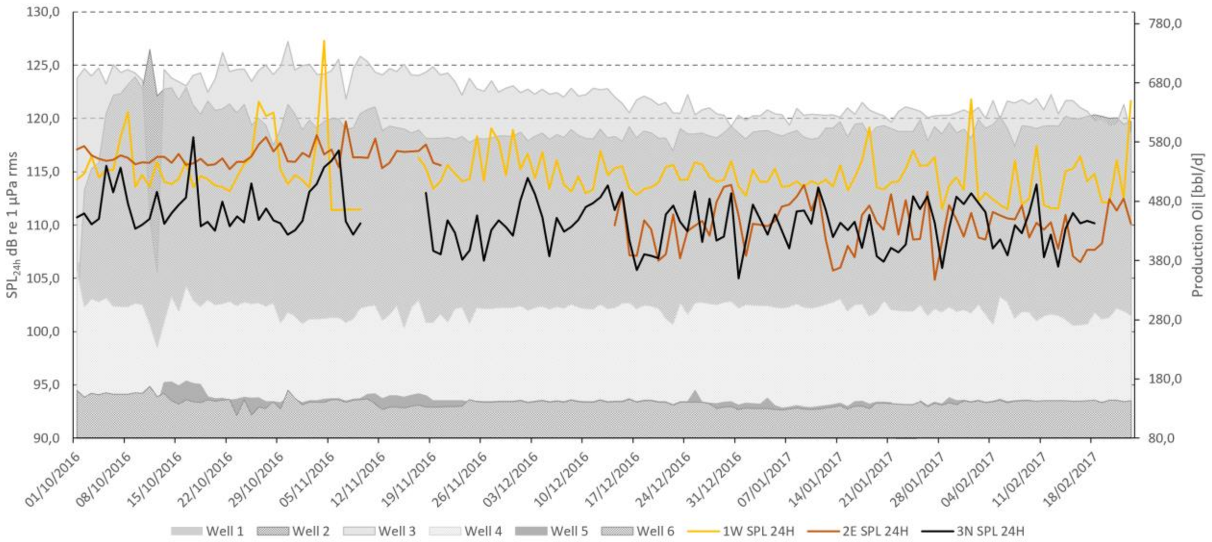

Figure 2. SPL_{24h} (October 1, 2016 to February 24 2017 UTC) from the three measurements points during platform production. The gray shades correspond to the production of six oil wells during the data collection.

The mean broadband level of the three measurement points ranged between 110 and 115 dB re 1 µPa. The gray shading areas in the figure indicate the production rates of the six active oil wells during the data collection period. Notice that Wells 1, 2, and 3 consistently have higher production than Wells 4, 5, and 6.

3.1 Detection of sound patterns of an operational offshore gas & oil fixed platform

The trained K-Nearest Neighbors (KNN) model was used to process a total of 75,219 unclassified one-minute recordings, representing the remaining dataset collected between October 2016 and February 2017. The results obtained are summarized below.

Table 2. Categorization of the different sound patterns in the recordings from October 2016 to February 2017 for the three points.

Category	Nº 1-minute records PAM1		Nº 1-minute records PAM2		Nº 1-minute records PAM3	
0 - No pattern	3239	12,4%	8828	38,3%	1706	6,8%
1 - Pulses	1100	4,2%	470	2,0%	2171	8,7%
2 - Marked cycles	568	2,2%	208	0,9%	232	0,9%
3 - Continuous & 3.15kHz- high	9822	37,5%	4931	21,4%	448	1,8%
4 - Continuous & 3.15kH- low	2152	8,2%	2914	12,6%	242	1,0%
5 - Blasts	819	3,1%	624	2,7%	1840	7,4%
6 - Machinery continuous	7751	29,6%	4058	17,6%	2171	8,7%
7 - Works_ sirens and knocks	699	2,7%	342	1,5%	16095	64,5%
No id	76	0,3%	685	3,0%	43	0,2%
Total processed	26226		23060		24948	

Table 2 presents the results of the K-Nearest Neighbors (KNN) model used to classify one-minute acoustic recordings collected at three measurement points (PAM1, PAM2, and PAM3).

3.2 Underwater Soundscape: Daily acoustic patterns of an operational offshore gas & oil fixed platform

The underwater soundscape of the fixed offshore oil platform during five months of operation (October 2016 to February 2017) is illustrated in Figures 3 to 5. Each acoustic event is color-coded to distinguish between sound categories, providing a clear visualization of their temporal variability and the relative dominance of specific sound types throughout the monitoring period.

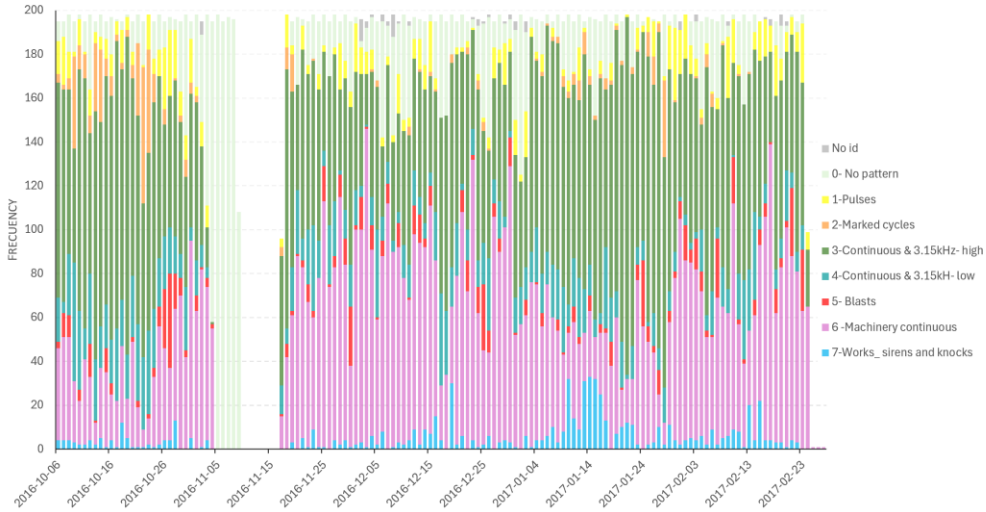

Figure 3. Daily contribution of each sound category over five months (October 2016 to February 2017) at point at PAM 1.

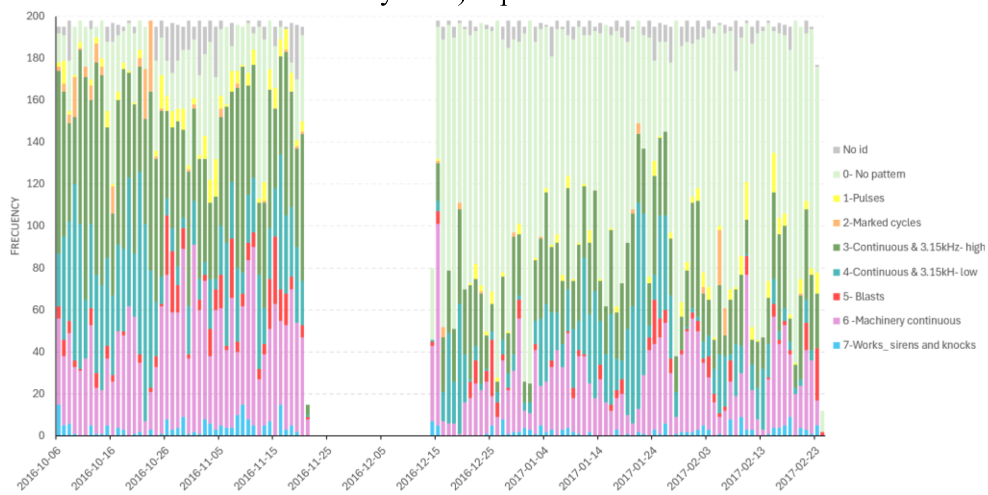

Figure 4. Daily contribution of each sound category over five months (October 2016 to February 2017) at point at PAM 2.

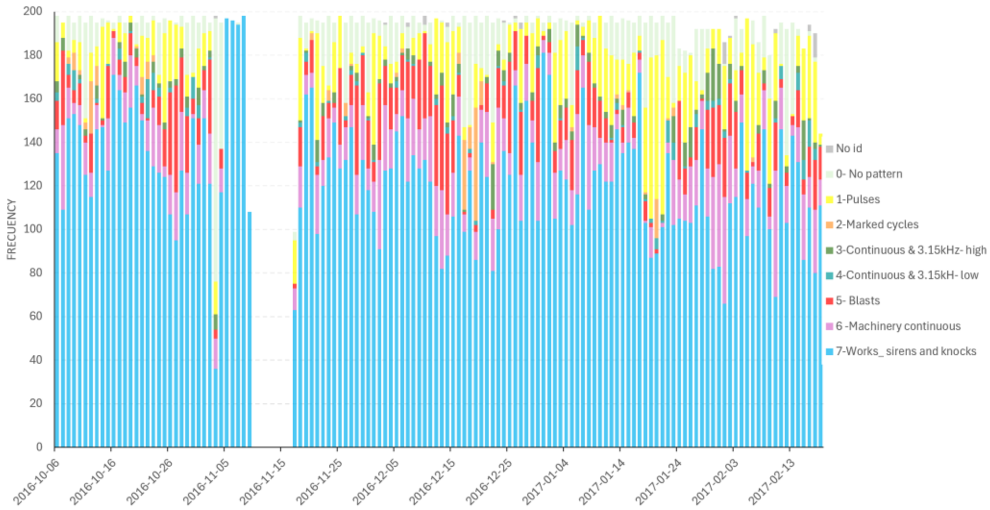

Figure 5. Daily contribution of each sound category over five months (October 2016 to February 2017) at point at PAM 3.

The results shown in the figures provide insights into the temporal variability of sound categories, highlighting long-duration events that persist over multiple days.

4. DISCUSSION

The acoustic data collected over five months provide clear evidence of the platform's operational impact on the surrounding underwater soundscape.

The operational configuration of the fixed offshore oil and gas platform—including its connections to multiple seabed extraction points via an extensive pipeline network— plays a significant role in shaping the underwater acoustic environment.

4.1 Underwater Soundscape: Daily acoustic patterns of an operational offshore gas & oil fixed platform

The systematic classification and analysis of 75,219 one-minute acoustic recordings revealed a complex and spatially heterogeneous underwater soundscape influenced by the operational dynamics of the fixed offshore platform. The distribution of sound event categories varied significantly across the three hydrophone monitoring points.

PAM1 and PAM2 showed a high prevalence of Category 3 ("Continuous & 3.15 kHz – high levels") events—37.5% and 21.4% of recordings, respectively—as well as Category 6 ("Continuous machinery"), which accounted for 29.6% at PAM1 and 17.6% at PAM2. In contrast, PAM3 exhibited a distinct acoustic profile, heavily dominated by Category 7 ("Works, sirens, and knocks"), which comprised 64.5% of its recordings.

The spatial and temporal differences observed across PAM1, PAM2, and PAM3 could be linked to their relative proximity to different wells and infrastructure elements. For example, PAM2 is nearer to Wells 2 and 3, PAM1 is closer to Wells 4 and 5, and PAM3 is relatively proximal to the pipeline corridor to shore and areas where support vessels operate (see Figure 1).

Daily visualization of sound categories revealed persistent acoustic patterns, particularly in Categories 3 and 6 at PAM1 and PAM2, suggesting continuous operational activity. Although Category 5 ("Blasts") appeared less frequently—3.1% at PAM1, 2.7% at PAM2, and 7.4% at PAM3—it was associated with elevated sound pressure levels, occasionally peaking at 152 dB re 1 µPa, well above the mean broadband levels.

These results demonstrate the effectiveness of automated classification models like KNN for processing large datasets and underline the value of combining acoustic monitoring with detailed non-acoustic metadata to improve source attribution and interpretation of soundscapes in complex offshore environments.

Given the limited information available in scientific literature regarding the noise emissions from fixed offshore oil platform [3], and considering the global expansion of such activities, acoustic characterization of these platforms becomes essential. Understanding the acoustic impact of these platforms is therefore of global relevance, especially regarding potential effects on marine fauna and ecosystems [13-14].

5. CONCLUSIONS

This study provides evidence that oil and gas platforms contribute to oceanic noise pollution by producing sound over a broad range of frequencies—including all frequencies in our measured acoustic range (0 to 48 kHz). The findings reveal mean broadband level in the study area ranged between 110 and 115 dB re 1 µPa and highlight the complexity of the underwater acoustic environment surrounding operational offshore platforms.

Using an extensive dataset of over 75,000 one-minute recordings, analyzed through an automated KNN-based classification model, the results demonstrate significant spatial and temporal variability in the underwater soundscape influenced by the platform's operational dynamics.

The dominant presence of continuous tonal signals and machinery-related noise at PAM1 and PAM2, along with the unique acoustic profile at PAM3 highlights the importance of hydrophone placement relative to infrastructure elements such as wells, pipelines, and vessel activity. These findings emphasize the relevance of both stationary and mobile sources in shaping the acoustic environment.

The use of a machine learning-based classification approach (KNN model) allowed for efficient and consistent identification of sound events within extensive datasets. This enabled a reconstruction of the underwater soundscape, revealing how noise levels vary spatially and temporally in relation to platform operations. While the exact contributions of individual noise sources, such as pipelines or wellheads, remain unclear, the study emphasizes the critical need for long-term acoustic monitoring to deepen our understanding of anthropogenic impacts on marine acoustic environments.

Given the global expansion of offshore oil and gas infrastructure—and the limited data available on fixed platforms—this type of acoustic profiling is essential for assessing environmental impacts and informing mitigation strategies.

6. ACKNOWLEDGMENTS

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