TESIS DOCTORAL

ESCUELA INTERNACIONAL DE DOCTORADO

Programa de Doctorado Tecnologías de la Computación e Ingeniería Ambiental

Identificación y predicción de patrones de contaminación sonora en las Smart Cities mediante el uso de técnicas de Ciencia de Datos y tecnologías Big Data sobre datos acústicos

Autor:

Antonio Pita Lozano

Director:

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Murcia, mayo de 2023

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El Dr. D. Juan Miguel Navarro Ruiz como Director[1] de la Tesis Doctoral titulada "Identificación y predicción de patrones de contaminación sonora en las Smart Cities mediante el uso de técnicas de Ciencia de Datos y tecnologías Big Data sobre datos acústicos" realizada por D. Antonio Pita Lozano en el Programa de Doctorado Tecnmologías de las Computación e Ingeniería Ambiental, **autoriza su presentación a trámite** dado que reúne las condiciones necesarias para su defensa.

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[1] Si la Tesis está dirigida por más de un Director tienen que constar y firmar ambos.

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COMPENDIO DE PUBLICACIONES

Esta Tesis se presenta en la modalidad de compendio de publicaciones. Los artículos publicados y aceptados que componen la tesis son los siguientes:

- **Publicación 1:** Pita A, Rodriguez FJ, Navarro JM. Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data. *International Journal of Environmental Research and Public Health*. 2021; 18(16):8271. https://doi.org/10.3390/ijerph18168271

- **Publicación 2:** Pita A, Rodriguez FJ, Navarro JM. Analysis and Evaluation of Clustering Techniques Applied to Wireless Acoustics Sensor Network Data. *Applied Sciences*. 2022; 12(17):8550. https://doi.org/10.3390/app12178550

- **Publicación 3:** Navarro JM, Pita A. Machine Learning Prediction of the Long-Term Environmental Acoustic Pattern of a City Location Using Short-Term Sound Pressure Level Measurements. *Applied Sciences*. 2023; 13(3):1613. https://doi.org/10.3390/app13031613

RESUMEN

La gestión de la contaminación sonora en las ciudades es fundamental para mejorar el bienestar y la calidad de vida de los ciudadanos. La Directiva Europea 2002/49/CE establece un enfoque común para la evaluación y gestión del ruido ambiental, y para cumplir con este objetivo, los gobernantes de las ciudades están desarrollando estrategias de datos utilizando tecnologías de Internet de las cosas (IoT) y big data. Aunque las estadísticas básicas, como la media o la mediana, se utilizan para crear informes de rendimiento con los datos obtenidos en el mapa de ruido estratégico (SNM), el entorno acústico de un área es un fenómeno complejo que necesita ser caracterizado no solo por los niveles de ruido en el área, sino también por otras propiedades, como su comportamiento en diferentes períodos del día y su variación a largo plazo. Por lo tanto, el uso de técnicas de ciencia de datos podría ayudar a los consistorios a analizar los datos para aumentar el conocimiento sobre los entornos acústicos. En los últimos años, las grandes ciudades están desplegando redes de sensores acústicos inalámbricos (WASN) basadas en tecnologías IoT para realizar un monitoreo continuo de los parámetros acústicos ambientales en muchas ubicaciones. Estos datos pueden ser analizados y utilizados para actualizar los SNM y los planes de acción.

Esta tesis se enfoca en el uso de tecnologías big data y ciencia de datos para mejorar la gestión de la contaminación acústica en las ciudades. Se ha desarrollado una metodología de análisis de entornos acústicos urbanos utilizando técnicas de aprendizaje automático no supervisado para identificar y clasificar diferentes patrones de comportamiento acústicos en la ciudad. Además, se establecen

procedimientos basados en técnicas de aprendizaje federado que permiten la compartición del conocimiento de los datos sin necesidad de compartir los datos, mejorando así la identificación de patrones de comportamiento acústicos. También se evalúa la idoneidad de predecir el patrón acústico ambiental a largo plazo de una posición basada en información recopilada en un intervalo a corto plazo utilizando redes neuronales artificiales. En resumen, la tesis concluye que se pueden aplicar técnicas de ciencia de datos para identificar patrones complejos en la contaminación acústica y mejorar la gestión de esta.

ABSTRACT

The management of noise pollution in cities is essential for improving the well-being and quality of life of citizens. The European Directive 2002/49/EC establishes a common approach to the assessment and management of environmental noise, and to meet this objective, city authorities are developing data strategies using Internet of Things (IoT) and big data technologies. Although basic statistics such as mean or median are used to create performance reports with the data obtained in the strategic noise map, the acoustic environment of an area is a complex phenomenon that needs to be characterized not only by noise levels in the area, but also by other properties such as its behavior at different periods of the day and its long-term variation. Therefore, the use of data science techniques could help municipalities analyze data to increase knowledge about acoustic environments. In recent years, large cities have deployed wireless acoustic sensor networks (WASN) based on IoT technologies to continuously monitor environmental acoustic parameters in many locations. This data can be analyzed and used to update strategic noise maps and action plans.

This thesis focuses on the use of big data and data science technologies to improve the management of acoustic pollution in cities. A methodology for analyzing urban acoustic environments using unsupervised machine learning techniques has been developed to identify and classify different acoustic behavior patterns in the city. In addition, procedures based on federated learning techniques are established that allow knowledge sharing of data without the need to share the data itself, thereby improving the identification of acoustic behavior patterns. The suitability of predicting the long-term environmental acoustic pattern of a position based on information collected in a short-term interval using artificial neural networks is also evaluated. In summary, the thesis concludes that data science techniques can be applied to identify complex patterns in acoustic pollution and improve its management.

PALABRAS CLAVE

Acústica atmosférica, entornos acústicos urbanos, computación en estadística, análisis de datos, aprendizaje automático, patrones de comportamiento acústico, redes de comunicaciones, redes inalámbricas de sensores acústicos, agrupación, redes neuronales

KEYWORDS

noise pollution, urban soundscapes, statistical computing, data analysis, machine learning, acoustic behavioral patterns, communication networks, wireless acoustic sensor networks, clustering, neural networks

"All Models are wrong, but some are useful".
George P. Box (1919-2013).

ÍNDICE GENERAL

SIGLAS Y ABREVIATURAS

ANN, Redes Neuronales Artificiales (Artificial Neural Networks)

BCN, Ciudad de Barcelona

IoT, Internet de las Cosas (Internet of Things)

SNM, Mapa Estratégico del Ruido (Strategic Noise Map)

UE, Unión Europea

WASN, Redes Inalámbricas de Sensores Acústicos (Wireless Acoustic Sensor Networks)

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I – INTRODUCCIÓN

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1.1. JUSTIFICACIÓN DE LA INVESTIGACIÓN

A medida que el tamaño de las ciudades crece, el bienestar y la calidad de vida de los ciudadanos se han convertido en una prioridad para los gestores de la ciudad [1]. Aunque se sabe bien que el ruido es uno de los contaminantes de mayor preocupación para los ciudadanos [2] y que la Organización Mundial de la Salud ha recomendado recientemente la reducción de la exposición al ruido de las fuentes más comunes de ruido comunitario [3], otros factores del ambiente acústico, además de los niveles excesivos de ruido, deberían ser considerados en su evaluación.

La Directiva Europea 2002/49/CE tiene como objetivo establecer un enfoque común para la evaluación y gestión del ruido ambiental con el fin de estandarizar los procedimientos y métricas. El objetivo es evitar, prevenir y reducir los efectos perjudiciales, incluyendo el malestar, para los ciudadanos como resultado de la exposición a diferentes fuentes de ruido [4].

Para cumplir con este objetivo es necesario identificar, medir y determinar la exposición al ruido ambiental, para ello, los gobernantes de las ciudades están desarrollando estrategias de datos para capturar, transformar y analizar información utilizando tecnologías de Internet de las cosas (IoT, por sus siglas en inglés de "Internet of Things") y big data.

En particular, la directiva europea 2002/49/CE [4] insta a las aglomeraciones de personas, es decir, ciudades o grupos de ciudades cercanas, a crear su mapeo estratégico de ruido (SNM, por sus siglas en inglés "Strategic Noise Map") y compartir los resultados con los ciudadanos. Además, los resultados de estos mapas de ruido deben llevar al establecimiento de planes de acción de reducción de ruido donde se definen zonas de protección de exposición al ruido. Para crear informes de rendimiento con los datos obtenidos en el mapa de ruido estratégico y definir áreas especiales de protección contra el ruido dentro de la ciudad, los datos suelen ser analizados mediante análisis descriptivo, con estadísticas básicas como la media o la mediana del indicador de ruido definido obtenido para todo el período de evaluación. En general, utilizando estas estadísticas, se proponen dos tipos principales de áreas basadas en los lugares donde los valores son más altos que cierto nivel de sonido recomendado, conocidas como áreas de régimen especial, y otros donde su exposición al ruido es más baja que el promedio, conocidas como áreas tranquilas.

Sin embargo, el entorno acústico de un área es un fenómeno complejo que necesita ser caracterizado no solo por los niveles de ruido en el área, sino también por otras propiedades, como su comportamiento en diferentes períodos del día y su variación a largo plazo. Por lo tanto, el uso de técnicas de ciencia de datos podría ayudar a los consistorios a analizar los datos para aumentar el conocimiento sobre los entornos acústicos.

Murphy et al. [5] analizaron los problemas metodológicos relacionados con la implementación de la directiva en diferentes países de la Unión Europea (UE), y trataron específicamente el cálculo y mapeo de ruido, destacando las implicaciones de estos problemas para el intercambio transfronterizo de resultados. Además, una investigación reciente [6] resume los desafíos que enfrentarán los miembros de la UE y concluye que se debe aprovechar la oportunidad de establecer una base de datos común de exposición al ruido basada en métodos comunes, animando a las administraciones locales a establecer marcos comunes.

En los últimos años, las grandes ciudades están desplegando redes inalámbricas de sensores acústicos (WASN, por sus siglas en inglés "Wireless Acoustic Sensors Network), basadas en tecnologías IoT [7], para realizar un monitoreo continuo de los parámetros acústicos ambientales en muchas ubicaciones [8].

Estos datos pueden ser analizados y utilizados para actualizar los SNM y los planes de acción. Estas WASN están compuestas normalmente por dos tipos diferentes de estaciones: sensores de ubicación fija para monitoreo a largo plazo y sensores de ubicación temporal para monitoreo a corto plazo. Estos últimos pueden tomar la forma de sensores desplegados temporalmente, vehículos instrumentados con un sensor acústico junto con un sistema de geoposicionamiento para ubicar la medición, o dispositivos habituales para la medición de sonido conocidos como sonómetros [9].

Mientras que las estaciones fijas permanecen en un lugar durante toda su vida útil, permitiendo el monitoreo continuo de los niveles de ruido para identificar tendencias y estacionalidad, las estaciones temporales se colocan en un sitio particular durante un período de tiempo establecido (minutos, horas o días) para medir el campo acústico al recopilar datos a corto plazo.

Los nodos acústicos que componen estas redes fijas capturan continuamente información sobre el entorno sonoro durante largos períodos de tiempo, generando una gran cantidad de datos. Estos datos acústicos, junto con otros datos ambientales, como la calidad del agua [10] o la contaminación del aire [11], están siendo utilizados por los gestores de la ciudad para tomar decisiones y proponer acciones de mejora. Además, este sistema de ciudad inteligente ha dado lugar a la creación de los llamados mapas de ruido dinámicos, donde los SNM se actualizan con mayor frecuencia, por ejemplo cada día, integrando datos obtenidos de sensores acústicos y la aplicación de modelos predictivos de propagación del sonido en las ciudades [12].

Las ventajas proporcionadas por la tecnología IoT [13], incluyendo el bajo consumo de energía del equipo y la amplia cobertura de área, permiten un fácil despliegue de un gran número de dispositivos en toda la ciudad, así como la transmisión de valores de parámetros acústicos en intervalos cortos de tiempo, por ejemplo cada minuto [14]. El análisis de esta gran cantidad de información generada por el WASN puede considerarse un problema de big data [15].

Un patrón o comportamiento acústico ambiental hace referencia a la distribución y variación de los niveles de sonido en un entorno específico y permiten describir el entorno acústico de una determinada localización. Estos patrones pueden verse afectados por una variedad de factores, como el uso del suelo, las condiciones climáticas y la actividad humana. En entornos urbanos, el patrón acústico ambiental suele estar caracterizado por altos niveles de contaminación acústica de fuentes como el tráfico, la construcción y las actividades industriales. Sin embargo, estas fuentes de ruido crean un entorno acústico complejo y dinámico que depende en gran medida de la hora del día y la ubicación.

Para reconocer patrones o comportamientos acústicos ambientales, se recomienda utilizar el promedio o la mediana de los indicadores de ruido para el período de evaluación general, por lo general, de al menos un año, según la Directiva Europea [4]. Por lo tanto, los datos a corto plazo generalmente no se consideran debido a la falta de capacidad para capturar componentes de estacionalidad, como días festivos o fines de semana. Después del análisis de estadísticas a largo plazo previamente enunciadas, generalmente se reconocen dos tipos principales de patrones acústicos ambientales: áreas de régimen especial y áreas tranquilas. Las áreas de régimen especial incluyen lugares donde el indicador de ruido supera un umbral alto, mientras que las áreas tranquilas incluyen lugares donde el indicador de ruido está por debajo de un umbral bajo. Aunque pueden existir otros patrones con comportamientos complejos, se requieren técnicas estadísticas avanzadas para reconocerlos.

En cuanto a la identificación del patrón acústico ambiental a largo plazo de una ciudad, Torija et al. [16] investigaron el tiempo necesario de estabilización, la variabilidad a corto plazo y la impulsividad del nivel de presión sonora para caracterizar con precisión la composición temporal de los paisajes sonoros urbanos. Los autores utilizaron datos de medidores de nivel de sonido para analizar los niveles de presión sonora en entornos urbanos y encontraron que se requería un tiempo de estabilización de al menos 30 minutos para obtener mediciones confiables del nivel de presión sonora. El mismo estudio sugirió que se deben tomar mediciones durante un período de tiempo más largo para lograr una caracterización más precisa de los paisajes sonoros urbanos, y que también se debe considerar la variabilidad a corto plazo y la impulsividad de los niveles de presión sonora. En un estudio posterior, Gajardo et al. [17] analizaron datos recolectados de medidores de nivel de sonido en varios entornos urbanos y concluyeron que los promedios horarios de los niveles de sonido pueden no ser representativos de los verdaderos niveles de exposición al ruido. Por lo tanto, se recomendó utilizar períodos de medición más largos, como 24 horas, para obtener una representación más precisa de los niveles de ruido en entornos urbanos. Por otro lado, en cuanto a la predicción del nivel de sonido equivalente utilizando mediciones a corto plazo, Brambilla et al. [18] se enfocaron en el tiempo de estabilización para las mediciones de ruido del tráfico vial y concluyeron que se necesita un tiempo de al menos 10 minutos para estimar de manera confiable el nivel de presión sonora equivalente de un período de 1 hora; además, factores como el volumen de tráfico, la composición del tráfico y el tipo de carretera pueden afectar el tiempo de estabilización necesario.

1.2. OBJETIVOS

Esta investigación parte de la necesidad de los consistorios para encontrar soluciones que les permitan identificar los comportamientos acústicos que conforman la ciudad y así mantener actualizado el SNM, informar mejor al ciudadano y adaptar los planes de acción a los cambios observados. Además, los resultados a obtener con esta tesis buscan establecer metodologías de trabajo y análisis compatibles con la directiva europea 2002/49/CE [4] que aseguren que son fácilmente aplicables en todas las ciudades europeas y faciliten el intercambio de información entre las mismas tanto al nivel de dato, como de comportamientos acústicos y por lo tanto planes de acción sobre dichos comportamientos acústicos. Por lo tanto, el objetivo general de esta tesis es explorar, desarrollar y evaluar diferentes técnicas basadas en el aprendizaje automático y en la ciencia de datos para la identificación y predicción de patrones de contaminación sonora en las ciudades inteligentes.

Para ello, se han establecido los siguientes objetivos específicos:

1. Desarrollar y evaluar modelos que permitan identificar patrones de comportamiento acústico de los diferentes nodos que conforman la WASN de la ciudad, más allá de las áreas de régimen especial y áreas tranquilas que permitan una mayor concreción de las circunstancias particulares y mayor personalización de los planes de acción
2. Establecer una metodología que permita normalizar la identificación de patrones y la compartición de información entre ciudades para poder enriquecer tanto los patrones acústicos como los planes de acción con los respectivos de otras ciudades.
3. Aprovechar los datos a corto plazo para estimar el patrón de comportamiento acústico mediante técnicas de ciencia de datos, facilitando y acelerando la identificación del entorno acústico más allá de las localizaciones asociadas de las estaciones de medida fijas.

1.3. ORGANIZACIÓN DEL DOCUMENTO

El documento de tesis se divide en cuatro capítulos principales y tres anexos, los cuales incluyen la siguiente información:

- **Capítulo I:** consiste en la introducción de la tesis e incluye los apartados de justificación de la investigación, objetivos, y organización del documento.
- **Capítulo II:** aglutina los tres artículos científicos desarrollados y seleccionados para la presentación de la tesis por compendio de publicaciones.
- **Capitulo III:** expone las conclusiones globales obtenidas de la investigación y presenta posibles líneas futuras de investigación que podrían seguirse como continuación de la tesis.
- **Capítulo IV:** recoge todas las referencias bibliográficas utilizadas para la escritura del documento de tesis.
- **Anexo 1:** presenta los criterios de calidad de las publicaciones presentadas en el Capítulo II, incluyendo el índice de impacto de la revista, el puesto y el cuartil en el que se posicionaba por área de conocimiento en el Journal Citation Report (JCR) del año de publicación o si no estuviese disponible, el último publicado.
- **Anexo 2:** presenta otras publicaciones y méritos logrados durante el desarrollo de la presente tesis, como comunicaciones en congresos, premios y participaciones en las jornadas de investigación.
- **Anexo 3:** presenta otros méritos logrados previamente al desarrollo de la presente tesis, como formación previa, artículos de investigación publicados, contratos de investigación en competición pública, comunicaciones en congresos de investigación, premios y experiencia docente en universidades.

II – PUBLICACIONES

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De la presente tesis se derivaron tres artículos científicos con el objetivo de realizar un compendio de publicaciones para su presentación. Todos los artículos fueron corregidos por revisores anónimos y aprobados para su publicación en revistas indexadas en JCR. A continuación, se muestra un breve resumen de cada uno de los artículos

- **Publicación 1:** La primera publicación titulada "Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data", se enfoca en el análisis de los entornos acústicos urbanos de la ciudad de Barcelona mediante técnicas de análisis no supervisado de clústeres, a partir de los datos obtenidos por la red de sensores acústicos. Los resultados de este estudio muestran la existencia de diferentes tipos de entornos acústicos urbanos, lo que permite una mejor comprensión y planificación de las políticas y acciones para la reducción de la contaminación acústica, complementando los mapas de riesgo estratégicos que desarrollan siguiendo la normativa comunitaria.
- **Publicación 2:** La segunda publicación titulada "Analysis and Evaluation of Clustering Techniques Applied to Wireless Acoustics Sensor Network Data", aborda la evaluación y comparación de diferentes técnicas de análisis de clústeres aplicadas a los datos de la red de sensores acústicos. Este estudio proporciona información valiosa para la selección y aplicación de técnicas de análisis de clústeres en el procesamiento de los datos de la red de sensores acústicos. En particular. se compararon y evaluaron diferentes métodos de clustering, incluyendo K-Means, DBSCAN, SOM, entre otros, con el objetivo de determinar cuál de ellos proporciona la mejor caracterización de los entornos acústicos urbanos, mostrando la metodología a seguir por los consistorios.
- **Publicación 3:** La tercera publicación "Machine Learning Prediction of the Long-Term Environmental Acoustic Pattern of a City Location Using Short-Term Sound Pressure Level Measurements", se centra en

la aplicación de técnicas de aprendizaje automático supervisado para predecir el patrón acústico a largo plazo de un lugar de la ciudad utilizando mediciones de nivel de presión sonora a corto plazo. Este estudio muestra el potencial de las técnicas de aprendizaje automático para predecir la evolución del entorno acústico urbano y apoyar la planificación y toma de decisiones en la reducción de la contaminación acústica.

2.1. RESEARCH PAPER 1: CLUSTER ANALYSIS OF URBAN ACOUSTIC ENVIRONMENTS ON BARCELONA SENSOR NETWORK DATA

Pita A, Rodriguez FJ, Navarro JM. Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data. International Journal of Environmental Research and Public Health. 2021; 18(16):8271. https://doi.org/10.3390/ijerph18168271 .

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Article

Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data

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Abstract: As cities grow in size and number of inhabitants, continuous monitoring of the environmental impact of sound sources becomes essential for the assessment of the urban acoustic environments. This requires the use of management systems that should be fed with large amounts of data captured by acoustic sensors, mostly remote nodes that belong to a wireless acoustic sensor network. These systems help city managers to conduct data-driven analysis and propose action plans in different areas of the city, for instance, to reduce citizens' exposure to noise. In this paper, unsupervised learning techniques are applied to discover different behavior patterns, both time and space, of sound pressure levels captured by acoustic sensors and to cluster them allowing the identification of various urban acoustic environments. In this approach, the categorization of urban acoustic environments is based on a clustering algorithm using yearly acoustic indexes, such as L_{day}, $L_{evening}$, L_{night} and standard deviation of L_{den}. Data collected over three years by a network of acoustic sensors deployed in the city of Barcelona, Spain, are used to train several clustering methods. Comparison between methods concludes that the k-means algorithm has the best performance for these data. After an analysis of several solutions, an optimal clustering of four groups of nodes is chosen. Geographical analysis of the clusters shows insights about the relation between nodes and areas of the city, detecting clusters that are close to urban roads, residential areas and leisure areas mostly. Moreover, temporal analysis of the clusters gives information about their stability. Using one-year size of the sliding window, changes in the membership of nodes in the clusters regarding tendency of the acoustic environments are discovered. In contrast, using one-month windowing, changes due to seasonality and special events, such as COVID-19 lockdown, are recognized. Finally, the sensor clusters obtained by the algorithm are compared with the areas defined in the strategic noise map, previously created by the Barcelona city council. The developed k-means model identified most of the locations found on the overcoming map and also discovered a new area.

Keywords: environmental noise assessment; clustering; k-means; strategic noise map; urban acoustic environment; wireless sensor network data

Citation: Pita, A.; Rodriguez, F.J.; Navarro, J.M. Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8271. https://doi.org/10.3390/ijerph18168271

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1. Introduction

As the size of cities grows, the well-being and quality of life of citizens have become a priority for city managers [1]. Although it is well known that noise is one of the pollutants of greatest concern to citizens [2] and the World Health Organization has recently recommended the reduction of exposure to noise from the most common sources of community noise [3], other factors of the acoustic environment in addition to excessive noise levels should be taken into account in its assessment.

The European directive 2002/49/EC [4] encouraged agglomerations of people, i.e., cities or groups of cities nearby, to create their strategic noise mapping (SNM) sharing the results with citizens. Moreover, the results of these noise maps led to the establishment of noise-reduction action plans where noise exposure protection zones are defined. To create performance reports with the data obtained in the strategic noise map and to define special noise protection areas within the city, data are usually analyzed by descriptive analysis, with basic statistics such as the average or median of the defined noise indicator obtained for the overall assessment period. In general, using these statistics, two main types of areas are proposed relying on the places where values are higher than a certain recommended sound level, known as special regime areas, and others where their noise exposure is lower than the average, known as quiet areas.

In recent years, large cities are deploying Wireless Acoustic Sensor Networks (WASN), based on Internet of Things (IoT) technologies [5], in order to perform continuous monitoring of environmental acoustic parameters at many locations [6]. The acoustic nodes that compose these networks continuously capture information about the sound environment over long periods of time, generating a large amount of data. These acoustic data, together with further environmental data, such as water quality [7] or air pollution [8], are being used by city managers to make decisions and propose improvement actions. Moreover, this smart city system has given rise to the creation of the so-called dynamic noise maps where SNM are more often updated, each day for instance, by integrating data obtained from acoustic sensors and the application of predictive models of sound propagation in cities [9].

The advantages provided by IoT technology [10], including low power consumption of the equipment and wide area coverage, allow for easy deployment of a large number of devices throughout the city as well as transmitting values of acoustic parameters every short time interval, e.g., every minute [11]. The analysis of this large amount of information generated by the WASN can be considered a big data problem [12].

Therefore, this work is focused on performing a cluster analysis of urban acoustic environments, evaluating the suitability of applying an unsupervised machine learning model to automatically classify several groups of nodes with different behavior patterns, both time and space, of sound pressure levels. For the description of this technique, data captured during three years in a WASN deployed in the city of Barcelona, Spain, are used [13]. In this work, the categorization of urban acoustic environments is based on a clustering algorithm using the following yearly acoustic indexes, L_{day}, L_{evening}, L_{night} and standard deviation of L_{den}. A detailed analysis of the obtained clusters is conducted, showing both geographical and temporal additional information to that provided by the city's SNM [14].

This paper is organised into the following sections. After this introduction, a review of the state of the art of machine learning in environmental acoustics is presented in Section 2. Section 3 presents the data-set and the proposed methodology for unsupervised identification. In next Section 4, results obtained from the analysis are shown and discussed. Finally, Section 5 provides the main conclusions of this research.

2. Machine Learning for Analysis of Environmental Acoustics

Machine learning (ML) is a type of artificial intelligence whereby an algorithm or method will extract patterns out of data [15]. ML methods are often divided into three major categories: supervised, unsupervised and reinforced learning [15]. The second is being used in this work, in which, in contrast to supervised and reinforced learning, no labeled input and output data are needed to train the model. The goal of these unsupervised techniques is to find out interesting or useful structures within the data.

As in other research fields, ML is being applied in the area of acoustics and audio signal processing [16]. The application of ML in acoustics is a field of research that has recently attracted great interest in the scientific community. Application examples can be found in a wide range of acoustics fields, such as speech signal processing [17], underwater acoustics [18], medical diagnosis [19], design of acoustic materials [20], bioacoustics [21], room acoustics [22] and environmental acoustics [23].

Signals generated by sound sources, e.g., human speech and musical instruments, contain useful insights that can be used by ML techniques to detect and model complex patterns. Regarding ML approaches, sound captured by acoustic transducers can be classified into two groups depending on the nature of the data created: (i) audio signal, from which it is possible to apply techniques such as event detection [24], classification of sound sources [25], and source location [26], and (ii) acoustic parameters calculated from the audio signal, that have been used to predict sound pressure level values [27] or estimate loudness level values [28] for instance.

As enunciated above, ML techniques are data-driven and they are typically fed with a large amount of data to obtain optimal results. The acquisition and processing of these data require advanced monitoring and management systems. Technological advances have developed new ways of obtaining massive data on environmental quality parameters in cities, the most commonly used being the crowd-sourced data using smartphone applications [29] and the deployment of wireless acoustic sensor networks [30]. WASN consists of a set of nodes with acoustic transducers that are deployed at locations in the area of interest. These acoustic nodes continuously capture sound with high quality, allow long-term monitoring of urban acoustic environments [31], and also can contribute to create dynamic noise maps [32].

During the last few years, WASNs have been deployed in cities around the world and several studies have been published regarding machine learning techniques for environmental acoustics. Most of the works found in the literature apply supervised machine learning methods to the audio signal, the first group that was defined above. In this approach, the method is firstly trained with labeled data-set, i.e., annotated sound recordings. After the resulting model is evaluated and optimized, the algorithm is then implemented and run in the acoustic nodes.

In the city of New York, a large data-set [33] of labeled audio recording was created by taking advantage of a WASN [34] for the development and evaluation of machine learning techniques, also known as deep-learning techniques because of the high amount of data used to train the model, for real-world urban noise monitoring. Using this data-set, methods for both detection [35] and classification [36] of acoustic scenes and events have been carried out. Recently, a deep learning structure has been developed with this data-set for sound event retrieval [37] of urban sound events, such as car horns and human speech, on multi-label audio recordings.

In an European project, DYNAMAP [38], several machine learning techniques were evaluated for anomalous noise source detection [39], such as birds, people talking, sirens, etc., in order to remove unrelated to road traffic noise events, and then, generate a noise map.

Other supervised ML techniques were applied for sound source classification. A pattern classification algorithm, using Mel-frequency cepstral coefficients as features, was presented in Reference [40] to identify the main noise source of the acoustic environment. Two types of supervised classifiers, Gaussian mixture model and artificial neural networks, were compared in this latter work. An aggregation scheme that combine local features, short-term sound recording features, with long-term descriptive statistics was presented by Ye et al. [41] using a convolutional neural network for the classification of urban sound events.

On the other hand, the application of machine learning to acoustic parameters calculated from the audio signal is a promising topic wherein there are still a few publications that use their advantages to create analytical models in the environmental acoustics field. Segura-Garcia et al. [42] explored the application of the ordinary Kriging technique to perform spatial interpolation of sound pressure level values obtained by a WASN in a small town and automatically generate a noise map. In Reference [43], predicted road-traffic noise level produced with a noise mapping software together with urban form indicators were considered to develop a neural network model. With this machine learning model, statistical noise maps for other cities can be estimated. Recently, a Long Short-Term Memory deep neural network technique was presented to model temporal dependency of sound levels and therefore to predict near-time future values at a certain location [27].

Other studies in the literature implement machine learning algorithms to create models for predicting sound pressure levels at a location. To do this, instead of using acoustic data as input, they use features of location of the sound source, for instance traffic flow and street width to predict road traffic noise [44,45]. In Reference [46], geospatial features are used as input of a random forest algorithm obtaining a model to predict seasonal sound pressure level at different locations. Neural networks can also be used to estimate the sound pressure level that will be produced by an aerofoil in its design phase [47].

Within the previously cited DYNAMAP project [38], which aim is to develop a dynamic noise mapping system of road traffic noise, unsupervised machine learning techniques including clustering and dimensionality reduction have been used to optimize the choice and the number of monitoring sites [48]. Using hourly averaged L_{Aeq1h} acoustic data of a 24 h measurement campaign in the city of Milan, Italy, a methodology for a more efficient way to estimate the mean L_d and L_n levels in urban roads compared with the legislative road classification [9] was presented. Moreover, in order to associate each of the streets of the pilot zone with one of the two noise profiles detected in the clustering and then calculate the dynamic map, different non-acoustic parameters were evaluated [9]. Recently, the intermittency ratio indicator was combined with the L_{Aeq1h} data to improve the classification of different types of road in two identified clusters [49].

In this current research, an analysis of urban acoustic environments of the city of Barcelona is made applying clustering techniques for the identification and classification of different urban acoustic profiles, rather than only urban roads. To achieve this goal, data collected in a long-term period of three years by a WASN are used to train different clustering techniques. In our approach, the categorization is based on a clustering algorithm using yearly acoustic indexes, instead of daily based, allowing to perform comparison with the special acoustic zones defined in the city's SNM.

3. Materials and Methods

In this section, the acoustic data-set and the statistics calculated are introduced first. Then, a classical descriptive analysis is briefly presented. Finally, the performed unsupervised learning method is described.

3.1. Data-Set Definition

The network of acoustic nodes deployed in Barcelona by the city council during last years consists of 86 sound sensors [13,50]. The data-set used in this research was collected by 70 of the 86 sound sensors which provide long-term analysis, from January 2018 until December 2020. As it is shown in Figure 1, the acoustic nodes are evenly distributed throughout the city, but the city center concentrates the largest number of nodes.

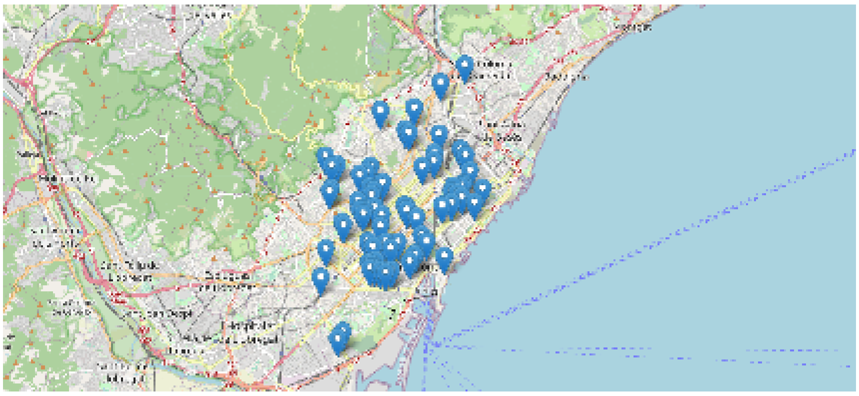

Figure 1. Map showing the location of the 70 acoustic nodes deployed in the city of Barcelona, Spain.

Each node captures sound pressure of its location in a continuous mode, 24 h/7 days a week, using a Cesva TA120 [51] remote sonometer. The accuracy of this type of sensors is defined as class 1 precision sensor according to the International Standard IEC 61672-1 [52]. Most of the sensors are attached to post lamps or similar urban structures at about 4 m above the floor level as is required in ISO1996-2 [53]. Then, the node transmits the dataframe to the central database that stores and processes all the data [13] to be shown in the *Plataforma de Sensors i Actuadors de Barcelona* [54], also known as smart city platform.

The sound pressure $p(t)$ is usually measured continuously over a given time period $T = [t_1, t_2]$ for all $t \in T$, to quantify the sound level on a single value using the equivalent sound pressure level in dB, denoted as $L_{\mathrm{eq}T}$ [53],

$$L_{\mathrm{eq}T} = 10 \cdot \log\left[\frac{1}{T}\int_{t_1}^{t_2} \frac{p^2(t)}{p_0^2}\mathrm{d}t\right] \text{ where } T = t_2 - t_1, \tag{1}$$

where p_0 is the sound pressure reference value equal to 20 µPa. In particular, deployed nodes compute the A frequency-weighting equivalent sound pressure level of one minute period, denoted as $L_{\mathrm{Aeq1}m}$ in dBA unit, applying Equation (1).

In this work, sound pressure level results are presented applying a long-term average of $L_{\mathrm{Aeq1}m}$. Different time periods T can be defined, for instance, it is denoted as $L_{\mathrm{Aeq1}d}$ for a 24 h day period and L_{Aeq1y} for a generic year period. Moreover, the equivalent sound pressure level in a specific year Y is denoted as $L_{\mathrm{Aeq}Y}$, for instance L_{Aeq2020} represents the equivalent sound pressure level for 2020. These values are calculated using an energetic average with the following Equation [53],

$$L_{\mathrm{Aeq}T} = 10 \cdot \log\left[\frac{1}{n}\sum_{i=1}^{n} 10^{\frac{L_{\mathrm{Aeq}_i}}{10}}\right], \tag{2}$$

where n is the total number of 1-unit time intervals in period T and L_{Aeq_i} is the equivalent sound pressure level in the interval i obtained by the sensor applying Equation (1). For instance, to calculate $L_{\mathrm{Aeq1}h}$, 60 values of $L_{\mathrm{Aeq1}m}$ are averaged.

The data provided by the Barcelona city council contains acquired data from January 2018 until December 2020, exported from the smart city platform in several Excel™ files in a semicolon tabulated format with a total storage size of 488 MBytes. After the data is prepared, see Section 3.2 for details, several acoustics indicators are calculated regarding Directive 2002/49/EC [4] in order to perform a descriptive statistical analysis, also discussed in Section 3.2, and to calculate the clustering model, presented in Section 3.3. This Directive [4] establishes that member states must calculate the acoustic parameters L_{den} and L_{night} for the preparation and revision of the SNM. L_{den}, defined in Equation (3), refers to the day–evening–night noise indicator obtained for an overall assessment period, which is usually a one-year period.

$$L_{\mathrm{den}} = 10 \cdot \log\left[\frac{1}{24}\left(12 \cdot 10^{\frac{L_{\mathrm{day}}}{10}} + 4 \cdot 10^{\frac{L_{\mathrm{evening}}+5}{10}} + 8 \cdot 10^{\frac{L_{\mathrm{night}}+10}{10}}\right)\right], \tag{3}$$

where L_{day}, L_{evening} and L_{night}, also denoted as L_{d}, L_{e} and L_{n}, respectively, are the A-weighted long-term average sound level. In this paper, L_{d}, L_{e} and L_{n} are calculated using Equation (2), determined over all the day periods (07:00–19:00), evening periods (19:00–23:00) and night periods (23:00–07:00), respectively, over the assessment period.

3.2. *Data Preparation and Exploratory Data Analysis*

Previous to the application of the machine learning technique, the raw data in Excel™ files has to be prepared in a format that enables analysis and model design. This preparation phase includes data cleaning and feature selection.

Firstly, a data quality analysis was conducted, identifying nulls and the completeness of the data. Due to some technical mistakes, such as connections errors, maintenance and breaks, all the information is not usually available. Therefore, an analysis of the completeness of the data must be carried out to identify the amount of available and missing data. This analysis resulted in a total data-set with 97,181,718 records, i.e., 97,181,718 min, equivalent to 1,619,695 h, 67,487 days or 184 years. A total of 1,735,999 of the records were nulls (1.76%). Some values of this completeness analysis for several nodes are shown in Table 1 as an example. This table includes information regarding the first day with available data, the amount of days with records and the amount of minutes with valid or null records.

Table 1. Example of data completeness analysis for several acoustic nodes.

Node ID	First Day	Days with Records	Total Records	Valid	Null	% Null
BCN_1	9 July 2018	853	1,228,320	1,208,463	19,857	1.62%
BCN_2	1 January 2018	1031	1,484,640	1,449,202	35,438	2.39%
BCN_3	1 January 2018	1037	1,493,280	1,468,077	25,203	1.69%
BCN_4	1 January 2018	1047	1,507,680	1,485,358	22,322	1.48%
BCN_5	10 October 2018	762	1,097,280	1,074,836	22,444	2.05%
BCN_6	1 January 2018	1043	1,501,920	1,477,480	24,440	1.63%
BCN_7	1 January 2018	1044	1,503,360	1,477,990	25,370	1.69%
BCN_8	1 January 2018	980	1,411,200	1,384,799	26,401	1.87%
BCN_9	1 January 2018	1042	1,500,480	1,476,821	23,659	1.58%
BCN_{10}	3 September 2018	813	1,170,720	1,162,474	8246	0.70%

As Table 1 shows, different amount of records are available for each node. The main reason is that the nodes were deployed on different dates. In fact, there are nodes that were deployed in early 2019.

Secondly, using this prepared data some statistics were calculated to perform the analysis. These statistics are usually called Key Performance Indicators (KPIs) when they are applied in data-driven decision making. The statistics obtained in this research were processed in a daily and yearly assessment period. To calculate the daily statistics, only the non-null values were considered. Regarding the yearly statistics, the days without data were removed.

Together with L_d, L_e, L_n and L_{den}, percentile values were also estimated. P_N denotes percentile values below which N% of the observations may be found. The reader should note that in acoustics, the literature defines L_N as the level exceeded for N% of the time [53], thus for instance P_{90} corresponds with L_{10}. In Table 2, calculated daily statistics for node BCN_1 in a 15 days period are shown as an example.

Once the KPIs are obtained, some basic exploratory analysis can be performed to look for some important features of the data. Although this is not the main objective of this paper, some results are shown to illustrate the experiment. For instance, the sound pressure level time series can be analyzed for each node independently. Figure 2 shows the L_{den1d} statistics along the available dates. The red vertical lines delimit the period of national state of alarm decreed by the country, with a lockdown from 15 March 2020 to 21 June 2020. Through these graphs, a discussion could arise regarding the effects of the COVID-19 disease in noise pollution. Although this analysis is out of the scope of the current work, readers should note that the impact of the COVID-19 lockdown period in noise levels and soundscapes has been analyzed in different cities, such as Barcelona [55] and Milan [56].

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Table 2. Example of summary statistics for node BCN_1.

Node ID	Date	L_{d1d}	L_{e1d}	L_{n1d}	L_{den1d}	$L_{01\,1d}$	$L_{10\,1d}$	$L_{50\,1d}$	$L_{90\,1d}$	$L_{99\,1d}$
BCN_1	1 August 2018	64.48	64.64	59.09	67.51	69.36	66.10	62.60	52.49	41.44
BCN_1	2 August 2018	64.74	64.89	59.10	67.65	70.20	66.30	62.70	53.79	40.94
BCN_1	3 August 2018	64.66	64.72	59.35	67.70	70.06	66.10	62.70	54.09	44.56
BCN_1	4 August 2018	62.09	62.95	58.15	66.05	67.20	63.70	60.20	53.08	42.34
BCN_1	5 August 2018	61.56	62.09	58.21	65.77	66.36	62.90	59.10	51.90	41.30
BCN_1	6 August 2018	63.60	64.28	59.22	67.28	68.56	65.40	62.10	52.00	42.94
BCN_1	7 August 2018	63.84	63.72	59.18	67.17	69.62	65.40	62.10	51.80	41.24
BCN_1	8 August 2018	64.91	64.00	59.26	67.55	69.70	65.91	62.30	52.19	43.38
BCN_1	9 August 2018	65.21	63.82	59.50	67.71	70.30	66.90	62.70	53.70	42.20
BCN_1	10 August 2018	64.05	65.19	60.21	68.14	69.68	66.00	62.50	53.90	41.56
BCN_1	11 August 2018	63.17	63.42	58.97	66.84	70.56	64.60	60.70	52.80	43.54
BCN_1	12 August 2018	60.48	62.86	57.70	65.49	68.00	62.80	58.80	50.79	39.64
BCN_1	13August 2018	64.72	64.19	59.32	67.57	71.94	65.90	61.90	51.70	41.16
BCN_1	14 August 2018	64.28	64.38	58.92	67.31	70.46	65.90	62.20	52.09	41.34
BCN_1	15 August 2018	60.83	62.34	59.40	66.45	67.10	63.50	59.70	52.29	41.34

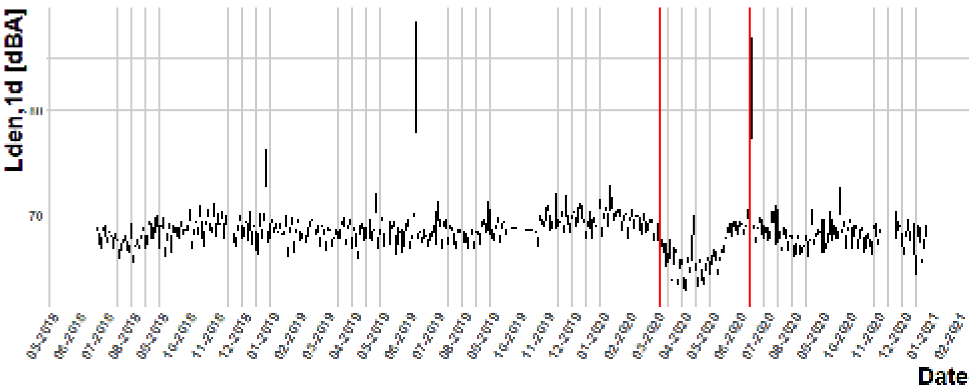
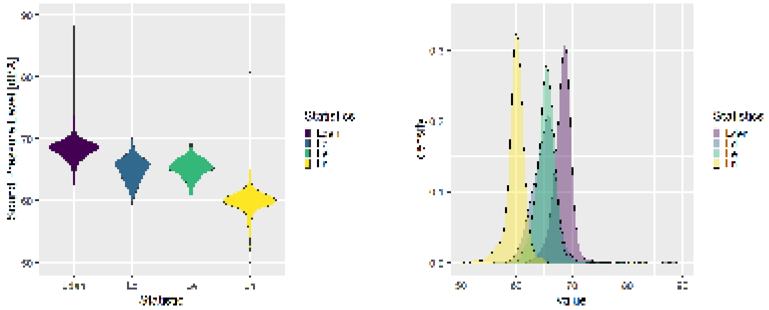


Figure 2. L_{den1d} time series for node BCN_1. Note that Spanish lockdown corresponds with the period between red lines.

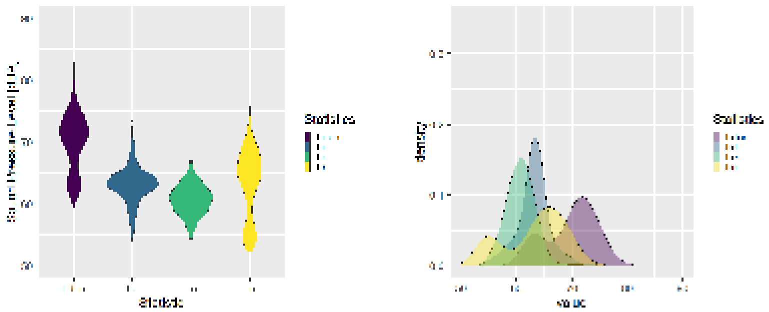
Moreover, a graphical analysis about the probability distribution of the statistics can be derived from these data. In the following Figures 3 and 4, examples of distribution plots for BCN_1 and BCN_{27}, respectively, are shown finding different behaviors. Node BCN_1 has a mean sound pressure level during the night period lower than daily and evening, see Figure 3, but BCN_{27} has a probability function for the night period with two modes with one peak with higher sound pressure level than the peak of the daily function, see Figure 4.

Additionally, the variability of the BCN_{27} node's statistics is higher than BCN_1 node's ones. These statistics and the variability are going to be used in this work to model the node's behavior.



(a) Violin plot **(b)** Histogram plot

Figure 3. Statistics probability distribution analysis for Node BCN_1.



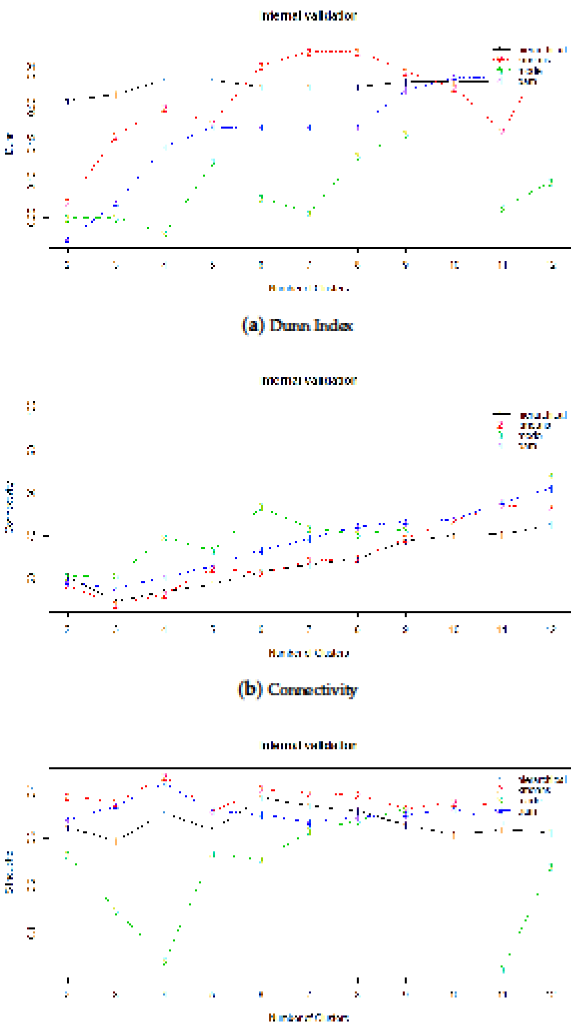
(a) Violin plot **(b)** Histogram plot

Figure 4. Statistics probability distribution analysis for Node BCN_{27}.

3.3. *Unsupervised Learning Modeling: K-Means*

The goal of the modelling stage is to identify different behaviors in the acoustic nodes that can be correlated with the environmental impact and public health. As it was introduced in Section 2, clustering techniques learn patterns from data and group the elements in some clusters with the same behavior.

In this research, several clustering algorithms were trained, including k-means clustering [57], hierarchical agglomeration [58], partitioning around medoids [59] and expectation maximization algorithm [60] using the following yearly acoustic indexes, L_{day}, L_{evening}, L_{night} and standard deviation of L_{den}. A comparison of the results using Dunn Index [61], Connectivity [62] and Silhouette Width [63] concludes that k-means has the best performance for these data. Figure 5 shows that k-means maximizes Dunn Index and Silhouette Width and minimizes Connectivity.



(a) Dunn Index

(b) Connectivity

(c) Silhouette Width

Figure 5. Validation measures for a given set of clustering algorithms and number of clusters.

The method considered in the following, called k-means clustering [57], is an unsupervised learning algorithm which groups the unlabeled data-set into different clusters, where k defines the number of predefined clusters that need to be created in the process.

This algorithm is iterative with two steps in each iteration $t = 1, 2, \ldots$. In the first step, called the assignment step, each node is assigned to the nearest centroid using a distance. Thus, each node N_i is assigned to the cluster centroid $C_j^{(t-1)}$ if $j = \arg\min_{l=1}^{k}(d(N_i, C_l^{(t-1)}))$ where $d(N_i, C_l^{(t-1)})$ represents the distance between node N_i and cluster centroid $C_l^{(t-1)}$. In the second step, called the update step, the new centroids are calculated as the element-wise mean of the nodes assigned to each centroid using the following equation:

$$C_j^{(t)} = \frac{\sum_{i \in A_j^{(t)}} N_i}{|A_j|}, \quad (4)$$

where $A_j^{(t)} = \{i | N_i \text{ is assigned to } C_j^{(t-1)}\}$ is the set that includes the nodes assigned to the cluster centroid $C_j^{(t-1)}$ in the previous step.

The algorithm iterates this two steps until the centroids have stabilized, i.e., there is no change or it is residual in their values because the clustering has been successful or the defined number of iterations has been achieved. To initialise the algorithm, k random centroids $C_j^{(0)}$ are calculated for a chosen integer k. The euclidean distance was considered in this research, so for a node N_i represented by their m components $N_i = (n_{i1}, n_{i2}, \ldots, n_{im})$ and k cluster centroids $C_j^{(t)}$ represented by their m components $C_j^{(t)} = (c_{j1}^{(t)}, c_{j2}^{(t)}, \ldots, c_{jm}^{(t)})$ the distance is defined by the following equation:

$$d(N_i, C_j^{(t)}) = \sqrt{\sum_{k=1}^{m} (n_{ik} - c_{jk}^{(t)})^2}. \quad (5)$$

To avoid any variable to be dominant due to different measurement scales rather than relevance, the variables should be scaled to bring them down to a similar scale. Normalization, dividing the centered variables by their standard deviation ($\frac{X-\bar{X}}{\sigma_X}$ for every variable X), has been applied to data previous to the training of the k-means algorithm.

In this work, L_{d1y}, L_{e1y} and L_{n1y} indicators will be used as inputs to model the behavior of the nodes in different periods of the day, so the temporal variability during a day is taken into account. Moreover, yearly standard deviation of L_{den1d} to identify the variability of the nodes during a year, denoted as $sd_{1y}(L_{den1d})$. As a comparison will be performed with the SNM of the city, the selection of these variables as inputs is also based on Directive 2002/49/EC [4]. In particular, this Directive recommends as noise indicators L_{den1y} and L_{n1y} for the preparation and revision of SNM, and where appropriate, L_{d1y}, and L_{e1y}, for road-traffic noise, rail-traffic noise, aircraft noise around airports and noise on industrial activity sites. Directive 2002/49/EC [4] also proposes that every five years, SNM showing the situation in the preceding calendar year should be carried out. However, this year should be a relevant year, as regards the emission of sound, and an average year, as regards the meteorological circumstances. In these terms, 2020 can not be considered as a relevant year due to COVID-19 pandemic lockdown. Therefore, 2019 is the most recent year with stable data.

In order to show the relevance and the relation between these indicators, L_{d2019}, L_{e2019}, L_{n2019} and $sd_{2019}(L_{den1d})$, a smoothed color density scatterplot representing all the nodes can be seen in Figure 6. The smoothed color density helps to identify dense zones that groups nodes with similar behavior. The first row of plots compares the sound pressure level statistics pairwise. The black line is the so-called identity line meaning that both statistics are equal. The nodes in the upper right part of each plot show high sound pressure level values that affects citizen well being. Moreover, it can be observed that there are nodes that L_{n2019} is higher than L_{d2019} or L_{e2019}, causing noise annoyance in the citizens. The second row of plots compares each sound pressure level statistic with the standard deviation of L_{den1d}. In these plots, it can be identified different types of nodes: nodes with low sound pressure level and low standard deviation related with quite zones, nodes with high sound pressure level and low standard deviation related with a constant high noise pollution and nodes with high standard deviation that have some days with low sound pressure level and other days with high sound pressure level. A dense zone around the point L_{d2019} = 70 dBA, L_{e2019} = 70 dBA, L_{n2019} = 65 dBA and $sd_{2019}(L_{den1d})$ = 1.2 dBA groups nodes with a constant noise pollution along both the day and the year.

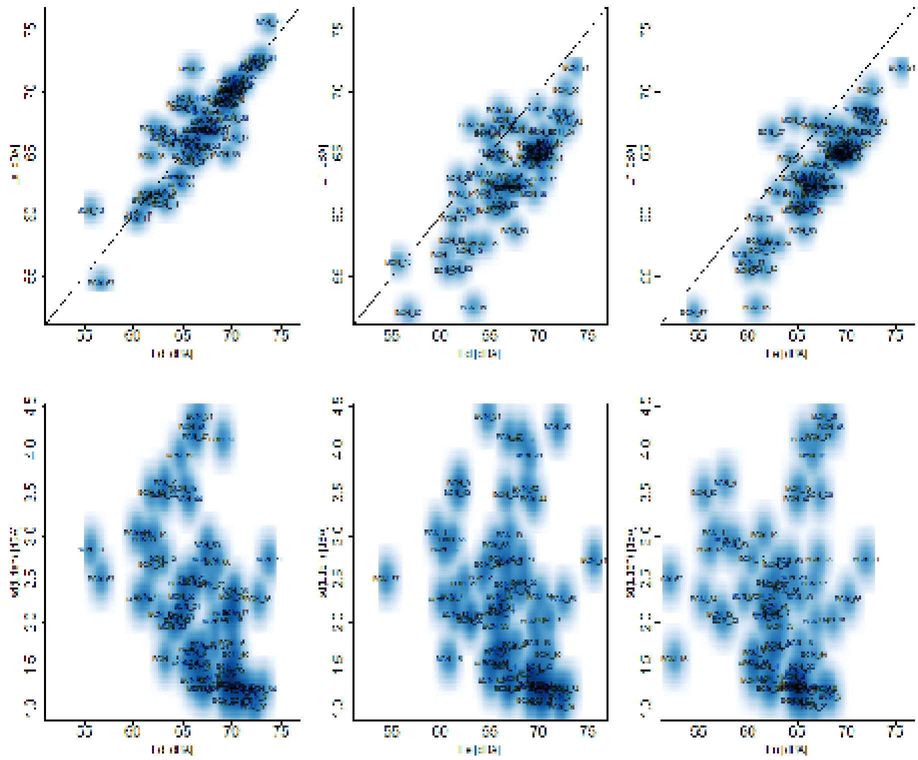
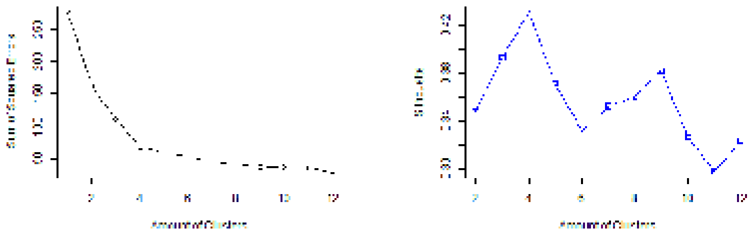


Figure 6. Scatter plot of the L_{d2019} , L_{e2019}, L_{n2019}, and $sd_{2019}(L_{den1d})$ metrics representing all the nodes. Black line represents identity line, i.e., equal value for both KPIs.

An important fact of k-means algorithm is that the amount of clusters has to be fixed before the model is trained. To determinate the appropriate amount of clusters, k-means algorithm has been trained for $k = 1, \ldots, 12$ and two amount of cluster selection techniques called *Elbow Method* [64] and *Silhouette* [63] have been considered. The selection of these techniques is based on the objective of the research, to find groups of nodes with the same behavior, so the focus is to evaluate the similarity of the nodes within the same cluster, independently of the rest of the clusters. Elbow and Silhouette are calculated on the relationship within the clusters. Figure 7a shows the within cluster sum of squares error for k clusters, with k from 1 to 12. The optimal k is the one related with the knee of the curve, i.e., the one that the increase in the number of clusters is not related with a high relative reduction in sum of squares error. In this case according to the Elbow Method, it is $k = 4$ where the slope changes from -0.39 to -0.12. Figure 7b shows the average Silhouette width for k clusters, with k from 1 to 12 and the optimal k is the first maximum. In this case is $k = 4$, matching with the Elbow method estimation too.



(a) Within cluster sum of squares errors using Elbow method

(b) Silhouette width index average per k

Figure 7. Amount of Cluster Selection Techniques.

As the k-means algorithm is randomly initialized, 100 experiments with random seeds were run to verify if a local or optimal solution is reached. In 96 of them, the solution presented in Table 3 in Section 4 was reached, obtaining the lowest sum of squares error for the same amount of clusters.

Table 3. Size and centroids of clusters for k=3, 4 and 9 using data collected during 2019.

Cluster	L_{d2019}	L_{e2019}	L_{n2019}	$sd_{2019}(L_{den1d})$	Size
k-means with 3 clusters					
1	69.85	69.50	65.12	1.64	35
2	63.36	63.27	59.54	2.36	26
3	66.05	68.25	66.71	3.78	9
k-means with 4 clusters					
1	70.74	70.79	66.39	1.50	23
2	66.40	66.04	62.28	2.06	27
3	66.05	68.25	66.71	3.78	9
4	61.11	60.57	56.24	2.61	11
k-means with 9 clusters					
1	68.92	69.72	67.00	2.27	4
2	68.69	66.75	62.37	2.44	7
3	65.89	68.25	66.65	3.92	8
4	60.78	60.33	56.09	2.67	10
5	73.30	74.11	71.11	2.50	2
6	70.16	70.00	65.23	1.32	14
7	64.19	64.89	62.33	2.40	10
8	66.78	66.37	61.76	1.50	11
9	72.46	72.34	67.69	1.16	4

3.4. *Software and Technology*

The preparation, transformation, analysis and modelling of the data have been performed using the Statistical Programming Language R [65], combining a local environment using R version 3.5.1 with a cloud environment provided by RStudio Cloud using R version 4.0.3. The cloud environment has been used to parallelize some tasks. The following libraries have been involved in the tasks: stringr (Version 1.4.0), dplyr (Version 1.0.5), tidyr (Version 1.1.3), cluster (Version 2.1.1), ggplot2 (Version 3.3.3), hrbrthemes (Version 0.8.0), imputeTS (Version 3.2) and zoo (Version 1.8-9).

To ensure the reproducibility of the research, in every task that includes a random step, the seed using the R function set.seed() has been fixed. Due to changes in random numbers generation in R version 4.0.0, the way to generate them to be sure that the analysis will be reproducible in every R version has also been defined.

4. Results and Discussion

In this section, results obtained from applying the clustering technique, see Section 3.3 for details, to the collected data, see Section 3.2 for details, are analyzed and discussed. Firstly, the selection of the optimum amount of cluster k is reviewed, and a description of the selected clusters is detailed. Secondly, a spatial and a temporal analysis of the results are presented. Finally, a discussion about the results regarding the report from the SNM of Barcelona is presented.

4.1. Clustering Analysis

Although both selection methods agreed with k = 4 clusters, considering Silhouette metric k = 3, k = 4 and k = 9 clustering results have been analysed to compare the knowledge that can be extracted from them. For a given value of k, k-means algorithm groups the nodes in k-clusters. Then, the centroid is calculated for each cluster following Equation (4). These centroids help to identify the different behavioral patterns from an acoustic perspective. Centroids and features calculated for k = 3, 4 and 9 are shown in Table 3.

If k = 4 is chosen, the algorithm divides the nodes in four clusters related with high (cluster 1 or black), medium (cluster 2 or magenta) and low (cluster 4 or brown) ranges of sound pressure level values and another particular group (cluster 3 or cyan) with a singular behavior. On one hand, clusters 1, 2 and 4 have similar behavior, i.e., a comparable daily and evening sound pressure level values and a significantly lower night sound pressure level values. Moreover, the higher values, the lower variability that are shown in these three clusters. On the other hand, cluster 3 has almost the same daily and nightly sound pressure level values but higher evening sound pressure level values. Moreover, the nodes included in this cluster 3 show the highest variability during the year 2019. Regarding k = 3 case, the algorithm divide the nodes in three clusters, two of them related with high (cluster 1) and low (cluster 2) ranges of sound pressure level values and another particular group (cluster 3) with a similar behavior to the third one in k = 4 clustering. Finally, for a k = 9 value, the algorithm divides the nodes in nine clusters related with very high (cluster 5 and 9 with medium and low variance, respectively), high (cluster 1 and 2 with medium variance and cluster 6 with low variance), medium (cluster 7 and 8 with medium and low variance, respectively) and low (cluster 4) ranges of sound pressure level values. Although clustering with k = 9 identifies more behaviors than the others, some of the clusters have a small number of nodes ceasing to be statistically significant, for instance, cluster 5 has only two nodes. Moreover, proposing action plans for such a large number of clusters can be a complex and inefficient task from a practical point of view.

In conclusion, the three models identify the same particular group with different behavior (cluster 3 in all options) from the rest of nodes that are classify depending on their ranges of sound pressure level values. These results reinforce the selection of the optimal k = 4 value.

4.2. Description of k = 4 Clustering

Once the quantity of clusters is fixed to k = 4, every node is assigned to a cluster depending on its distance to the centroids, as it is graphed in Figure 8.

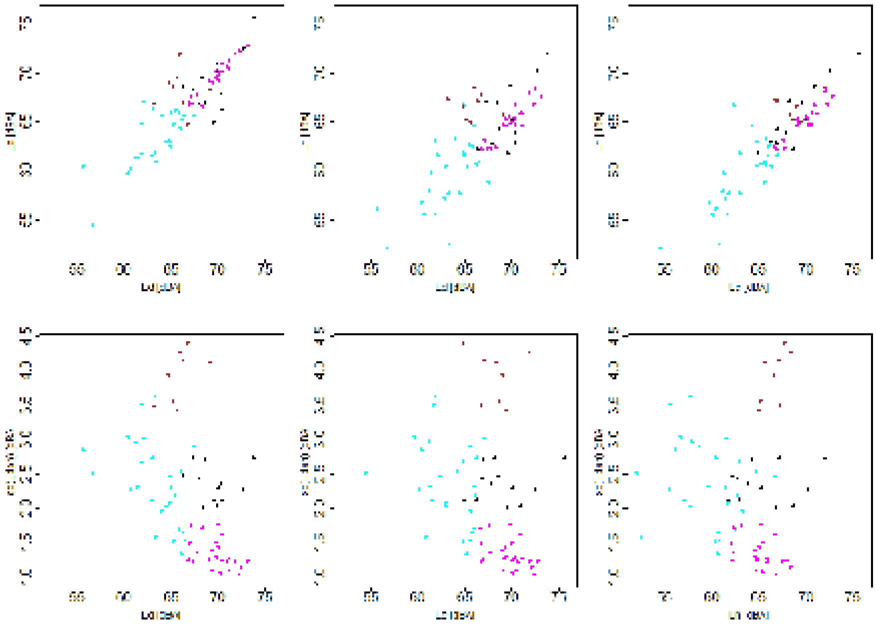


Figure 8. Nodes assignment to each cluster based on centroids for $k = 4$. Color legend: cluster 1 (black), cluster 2 (magenta), cluster 3 (cyan) and cluster 4 (brown).

Regarding the different range of values, cluster 4 belongs to the range with the lowest sound pressure level values and cluster 2 is in the intermediate values range, as can be seen in the top row graphs of Figure 8. Furthermore, clusters 1 and 3 contain the nodes with the highest sound pressure level values. Bottom row graphs of Figure 8 show the relation of the clusters with the variability. In one hand, cluster 3 presents high variability in the three periods of the day that can represents an acoustic environment with discontinuous and impulsive sound sources. In the other hand, cluster 1 presents low variability so the citizen are exposed to an acoustic environment where constant and stationary sound sources are predominant.

4.3. Geographical Analysis of the Clusters

A SNM is a set of maps that serve to globally assess the population's exposure to noise produced by different noise sources in a given area, and to serve as the basis for the development of action plans in a city. Moreover, they have to be updated periodically, at least every 5 years. Therefore, it can be helpful to figure out the geographic relationship between the acoustics nodes, to identify areas of the city that are related with the clusters. Taking advantage of the performed $k = 4$ clustering, it is possible to combine the results with the spatial information to perform a geographical analysis of the city's sound environments. Figure 9 shows three maps where the location icons represents the node's location. If the location icon is colored, the color represents the assigned cluster. Inside the icon, there is a plot symbol that shows, if colored, the equivalent sound pressure level $L_{den2019}$ according to ISO 1999 [53].

(**a**) Nodes' location and cluster membership information (**b**) Nodes' location, $L_{den2019}$ range and cluster membership information (**c**) Nodes' location and $L_{den2019}$ range information

Figure 9. Maps developed for the geographical analysis with combined spatial, sound level and cluster information.

Looking at the maps, geographic patterns appear with concentrations of nodes of the same cluster in areas of the city. Nodes of the cluster 1, those with the highest sound pressure level values, are located in the southwestern section of the city, while the northeastern section is related with lower sound pressure level values. More details can be obtained if the location of nodes belonging to cluster 1 is consulted. These nodes are related with locations near wide streets with high volume of vehicular traffic in south and west of the city such as *Avinguda Paralell* (nodes BCN_2, BCN_3, BCN_4 and BCN_{32}), *Avinguda Diagonal* (nodes BCN_8, BCN_{14}, BCN_{16} and BCN_{39}) *Travessera de Dalt* (nodes BCN_{20}, BCN_{21}, BCN_{64}, BCN_{65} and BCN_{66}) which are the natural entrances to Barcelona city. Regarding cluster 3, it has been found that the location of its nodes is related with evening and nightly leisure, zones with some pubs such as *La Ribera* (node BCN_{26}), *Carrers del Escudellers* (node BCN_{23}), entertainment zones such as *Gracia District* (nodes BCN_{43}, BCN_{44}, BCN_{45} and BCN_{47}) or shopping streets such as *Passeig de Gracia* (node BCN_{37}).

The maps included in Figures 1 and 9 are available in an interactive discovery version, developed in python [66], accessible by this github repository link [67] clicking on *Open in Colab* button (accessed on 16 May 2021).

4.4. Temporal Analysis of the Clusters

In a big city like Barcelona, acoustic environments may change over time due to sound sources mobility in space and variability in time and amplitude. There may be several reasons for these changes, among them the following are worth mentioning: modifications in the mobility of the citizens, effects derived by the SNM's action plans to improve the acoustic quality of the city, tourism and leisure places reallocation or special situations such as a lockdown derived by a pandemic situation. So, it is important to monitor the evolution of the statistics and the implications in the clusters composition.

As presented in Section 3.3, the k-means method was trained with a one year data, also called window, in particular 2019, allowing to identify the node's statistics and the cluster to which belongs. Once the clusters have been identified, it is possible to investigate behavioral changes of nodes over time using a sliding window. This monitoring technique can be related with a long-term noise pollution strategy, if a one-year sliding window is considered to have enough previous information. The data-set includes data from January 2018 until December 2020, thus the node's cluster to which it belongs is calculated from 31 December 2018 until 31 December 2020.

Firstly, a study of the monthly evolution with a yearly sliding window of the amount of nodes per cluster is represented in Figure 10. Sound sources may have seasonality due to external effects, such as tourism or work-periods, that change during seasons of the year. Therefore, a one-year window is appropriate to identify trend, cycle patterns or special events because it is not affected by seasonality.

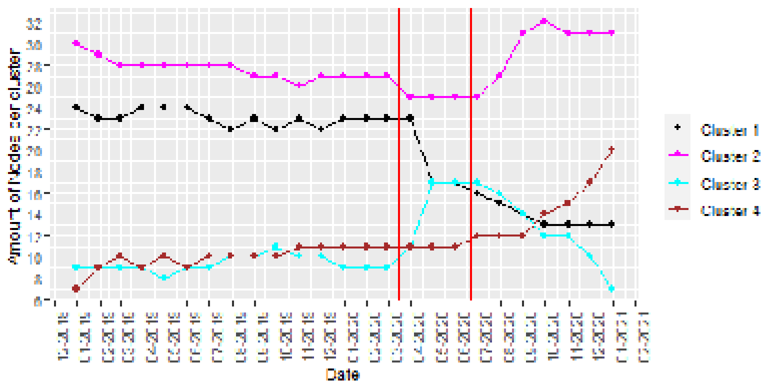


Figure 10. $k = 4$ clusters assignment (yearly sliding window).Note that Spanish lockdown corresponds with the period between red lines.

The graphs in Figure 10 show that, before lockdown was established in March 2020, the cluster distribution is stable. Note a small reduction in clusters 1 and 2, those in the ranges with higher sound pressure level values, indicating that noise pollution was decreasing in Barcelona. During the lockdown period, a noticeable increase in the amount of nodes belonging to the cluster 3 appears as expected, as this cluster is linked with higher variability. As the size of the sliding window is one year, this monitoring analysis helps smart cities to identify the tendency of the acoustic environments and the long-term effects of action plans.

Reducing the size of the sliding window to one month previous to the date, short-term changes and seasonality can be observed. Then, a study of the monthly evolution with a monthly sliding window of the amount of nodes per cluster is represented in Figure 11.

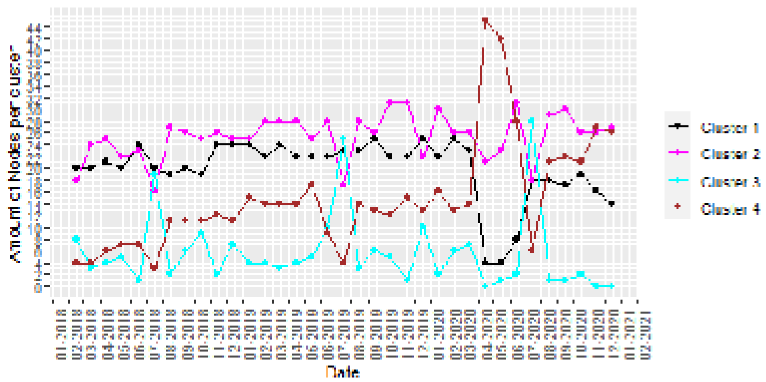


Figure 11. $k = 4$ clusters assignment (monthly sliding window). Note that Spanish lockdown corresponds with the period between red lines.

It can be observed in Figure 11 that there was a seasonal variation in July of every year, causing an increase in the amount of nodes belonging to cluster 3. When lockdown was established in March 2020, there was a significant change in the noise pollution, increasing the nodes belonging to cluster 4 that is related with quiet areas. After the state of alarm was over by the end of June, the clusters' distribution became similar to the previous pandemic situation except for a small reduction in clusters 1 and 3, which is related with a lower noise pollution.

As a conclusion, once the unsupervised algorithm is trained, this temporal analysis with different sliding window sizes can help city managers to properly monitor acoustic areas and their noise pollution according to their objectives. Moreover, new nodes could be included in this monitoring model allowing to estimate the area to which they would be assigned and also to compare with nodes in other zones or cities.

4.5. Discussion Regarding the Machine Learning Model Results and the City SNM Report

The SNM of Barcelona city [14,68], which last release is from 2017, is divided into three different maps and related reports that graphically describe the exposure of the citizens to the sound sources in different areas following the recommendations of the Directive 2002/49/EC [4]. The noise map, *Mapa de Soroll* in Catalan, shows the sound pressure levels using isophonic curves coming from different sources and in different time periods. The capacity map, *Mapa de Capacitat* in Catalan, classifies the city in zones of different acoustic sensitivity, determining the maximum limits of noise permitted by regulations. Finally, the sites that exceed the permitted levels are included in the overcoming map, *Mapa de Superació* in Catalan.

Examining the places that were identified in the overcoming map, a comparison has been performed with the results obtained with the proposed machine learning method. Table 4 contains an overview of this comparison. In the first two columns, a list of the zones that are highlighted in SNM report for the overcoming map and their classification in different periods of the day are shown. In the rest of the columns, a count of the nodes per cluster corresponding to each zone has been performed including the total amount of nodes per zone in the last column. In general, Table 4 shows that cluster 1 is mainly related with day and evening periods in the overcoming map, while cluster 3 is mainly related with night period.

The first four rows of Table 4 present information regarding places where day and evening periods have a high level of noise exposure. The following are included in the overcoming map: *Sarrià - Sant Gervasi*, corresponding with node BCN_{18} from cluster 2 and nodes BCN_{22}, BCN_{50} from cluster 1, *Avinguda Diagonal* corresponding with nodes BCN_{14}, BCN_{16} and BCN_{39} from cluster 1 and BCN_{17} and BCN_{36} from cluster 2, *Ronda General Mitre* corresponding with nodes BCN_{20}, BCN_{21}, BCN_{64}, BCN_{65} and BCN_{66} from cluster 1 and *Carrer Balmes* corresponding with nodes BCN_6, BCN_7 and BCN_8 from cluster 1. In summary, cluster 1 has 13 of its 23 nodes located in zones that are included in the overcoming map. The other five nodes, except node BCN_{51} that is far from these zones, are near to the previous places. It is important to mention that the remaining four nodes of cluster 1 are related with *Avinguda Parallel* which was not included in the SNM report, but the machine learning method has identified them. Therefore, it is recommended to include them in the next release of this overcoming map.

Table 4. Overcoming map zones and clusters summary. Note that percentage (X%) is calculate over each zone. Note that d, e and n in brackets correspond to day, evening and night period, respectively.

Zone	SNM Class	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total Zone
Sarrià-Sant Gervasi	Overcoming Map (d, e and n)	2 (67%)	1 (33%)	0 (0%)	0 (0%)	3
Avinguda Diagonal	Overcoming Map (d and e)	3 (60%)	2 (40%)	0 (0%)	0 (0%)	5
Ronda General Mitre	Overcoming Map (d and e)	5 (100%)	0 (0%)	0 (0%)	0 (0%)	5
Carrer Balmes	Overcoming Map (d and e)	3 (100%)	0 (0%)	0 (0%)	0 (0%)	3
Avinguda Parallel	No included in SNM	4 (80%)	1 (20%)	0 (0%)	0 (0%)	5
Gràcia	Overcoming Map (n)	0 (0%)	0 (0%)	4 (100%)	0 (0%)	4
Ciutat Vella	Overcoming Map (n)	0 (0%)	4 (67%)	2 (33%)	0 (0%)	6
Others	—	6 (15%)	19 (49%)	3 (8%)	11 (28%)	39
Total	—	23	27	9	11	N = 70

The last two rows of Table 4 present information regarding places where the night period has a high level of noise exposure, and the following are included in the overcoming map: *Sarrià-Sant Gervasi*, corresponding with node BCN_{18} from cluster 2 and nodes BCN_{22} and BCN_{50} from cluster 1, *Gràcia*, corresponding with nodes BCN_{43}, BCN_{44}, BCN_{45} and BCN_{47} from cluster 3 and *Ciutat Vella*, corresponding with nodes BCN_{10}, BCN_{24}, BCN_{27} and BCN_{53} from cluster 2 and nodes BCN_{23} and BCN_{26} from cluster 3.

Barcelona city council has also defined in the SNM report two Special Regimen Acoustic Zones (SRAZ), which are subzones of the previously commented, related with nightly entertainment activities. These two zones are *Vila de Gràcia*, corresponding with nodes BCN_{43}, BCN_{44}, BCN_{46} and BCN_{47} from cluster 3 and *Barri Gótic i Rambla del Raval*, corresponding with node BCN_{24} and BCN_{27} from cluster 2 and nodes BCN_{23} from cluster 3. In summary, cluster 3 has 9 elements, 5 of them are included in the SRAZ and can be observed in Figure 9. Other nodes from cluster 3 but not included in the SRAZ are near them, except node BCN_{42} which is isolated from the rest. As a result, the proposed unsupervised learning technique can help to identify new locations with certain acoustic conditions.

5. Conclusions

Urban acoustic environments should be continuously monitored in large cities, because of the fact that sound sources affect the well-being and quality of life of citizens. In recent years, wireless acoustic sensor networks have been deployed in cities to capture information about the sound environment over long periods of time and at many locations. This network of sensors generates huge amount of data that can not be simply processed but a machine learning algorithm can be applied in order to obtain data insights, predictions and relevant information from the data.

This paper has presented the analysis of urban acoustic environments applying unsupervised machine learning techniques, specifically k-means method, to identify and classify different acoustic profiles of the city using yearly averaged sound pressure level indicators as input of the clustering approach. It has been shown that the k-means method can find out relationships between input variables and group the node locations according to their similarity. This technique does not need labeled input and output data to train the model and automatically create clusters of nodes that share an acoustic behavior. To explore the suitability of this technique, sound pressure level values acquired by 70 acoustic nodes during a three year campaign in the city of Barcelona have been used. After the data-set was prepared, different acoustic indicators, L_{den}, L_{day}, $L_{evening}$, L_{night} and some statistics have been calculated to train several algorithms with clean and adequate feature inputs.

The modelling phase has been carried out using yearly average indicators from data of 2019, because it has shown to be a reference year regarding Directive 2002/49/EC. The optimum amount of clusters has been chosen using Elbow and Silhouette methods, resulting in $k = 4$. However, clustering with $k = 3$ and $k = 9$ have been also analyzed to compare the knowledge that can be extracted from them. In general, two different behaviors have been detected. One type where clusters have higher sound pressure level values during day and evening periods than during night period, and other type where sound pressure level values are higher during evening period than during day and night periods. Moreover, as the average sound pressure level of the cluster increases the variability of the values decreases.

After the model is developed, acoustic nodes have been assigned to created clusters to perform both spatial and temporal analysis of the results. The geographical analysis allows to identify areas of the city that are related with the different clusters and detect relationship between the acoustics nodes. Applying different sliding window sizes, behavioral changes over time have been investigated. With a size of one year, the tendency of the acoustic environments and the long-term effects of action plans have been analyzed. Reducing the size of the sliding window to one month, short-term changes and seasonality effects have been studied. Finally, a comparison between the results obtained by the machine learning model and the last strategy noise mapping report from the city has been performed. Most of the locations appearing on the overcoming map have been found with the developed k-means model. In addition, an area has been discovered that should be considered within the overcoming map in the next revision of the map. Moreover, the developed model can be applied regularly to detect nodes with similar behavior to previously identified clusters and to follow the temporal evolution of the clusters.

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2.2. RESEARCH PAPER 2: ANALYSIS AND EVALUATION OF CLUSTERING TECHNIQUES APPLIED TO WIRELESS ACOUSTICS SENSOR NETWORK DATA

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Analysis and Evaluation of Clustering Techniques Applied to Wireless Acoustics Sensor Network Data

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Abstract: Exposure to environmental noise is related to negative health effects. To prevent it, the city councils develop noise maps and action plans to identify, quantify, and decrease noise pollution. Smart cities are deploying wireless acoustic sensor networks that continuously gather the sound pressure level from many locations using acoustics nodes. These nodes provide very relevant updated information, both temporally and spatially, over the acoustic zones of the city. In this paper, the performance of several data clustering techniques is evaluated for discovering and analyzing different behavior patterns of the sound pressure level. A comparison of clustering techniques is carried out using noise data from two large cities, considering isolated and federated data. Experiments support that Hierarchical Agglomeration Clustering and K-means are the algorithms more appropriate to fit acoustics sound pressure level data.

Keywords: unsupervised learning; environmental noise assessment; urban acoustic environment; wireless sensor network data; knowledge discovery; clustering algorithms; data clustering

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1. Introduction

The European directive 2002/49/EC [1] encouraged agglomerations of people, namely, cities or groups of cities nearby, to create their strategic noise mapping (SNM) sharing the results with citizens. Moreover, the results of these noise maps led to the establishment of noise-reduction action plans where noise exposure protection zones are defined. To create performance reports with the data obtained in the strategic noise map and to define special noise protection areas within the city, data are usually analyzed by descriptive analysis, with basic statistics, such as the average or median of the defined noise indicator obtained for the overall assessment period. In general, using these statistics, two main types of areas are proposed relying on the places where values are higher than a certain recommended sound level, known as special regime areas, and others where their noise exposure is lower than the average, known as quiet areas. However, the acoustic environment of an area is a complex phenomenon that needs to be characterised not only by the noise levels in the area, but also by other properties such as its behavior in different time periods of the day and its long-term variation. Therefore, it would be interesting to explore the application of clustering techniques for the identification of areas with different behavior in relation to the noise environment.

Murphy et al. [2] analyzed the methodological issues concerning the implementation of the directive across different countries of the European Union (EU), and dealing specifically with noise calculation and noise mapping, highlighting the implications of these issues for cross-country sharing of results. Moreover, a recent research [3] also summarizes the challenges to be faced by the EU Members and concludes that the opportunity to set up a common database of noise exposure based on common methods should be seized on time, encouraging local administrations to establish common frameworks. In the period 2021–2027, the European Commission will invest in a High Impact Project on European data spaces and federated cloud infrastructures to encourage the establishment of EU-wide common, inter-operable data spaces in strategic sectors, such as mobility and health, and public administrations with data spaces initiatives, such as Gaia-X [4] and Federated European Infrastructure for Genomics data and Cancer Images data [5]. In the future, these data spaces can be used to join noise pollution data owned by public administrations to improve the health of citizens by the creation of more accurate predictive models, or obtaining better insights due to the more available data. In line with this trend, the application of unsupervised learning algorithms using federated data are proposed in this work to identify different acoustic environments that can help city managers to define personalized action plans for each behavior and share data in a common framework.

In recent years, large cities are deploying Wireless Acoustic Sensor Networks (WASN), based on Internet of Things (IoT) technologies [6], to perform continuous monitoring of environmental acoustic parameters at many locations [7]. The acoustic nodes that compose these networks continuously capture information regarding the sound environment over long periods, generating a large amount of data. These acoustic data, together with further environmental data, such as water quality [8] or air pollution [9], are being used by city managers to make decisions and propose improvement actions. Moreover, this smart city system has given rise to the creation of the so-called dynamic noise maps where SNM is more often updated, each day for instance, by integrating data obtained from acoustic sensors and the application of predictive models of sound propagation in cities [10]. The improvement of SNM has been the goal of researchers, such as Puyana-Romero et al. [11] who concludes that colors add supplementary and more intuitive information on soundscape to those provided by the acoustic parameters. In this work, acoustic datasets from WASN deployed in Barcelona and Madrid cities, Spain, are used for comparison of several machine learning clustering techniques.

Machine Learning has been used with acoustic data, both audio signal and sound level indexes, to help cities to manage noise in recent literature. On one hand, supervised learning techniques were applied to identify the main noise source of the acoustic environment using Mel-frequency cepstral coefficients as features with Gaussian Mixture Model and Artificial Neural Networks as algorithms [12]. In Reference [13], Convolutional Neural Networks (CNN) were evaluated to classify urban sound events using local features of short-term sound recording features and with long-term descriptive statistics. Additionally, CNN was implemented to detect anomalous noise source detection to remove unrelated road traffic noise events and then generate a noise map [14]. Another study using CNN over acoustic signal recordings developed a system to detect the presence of an unmanned aerial vehicle in a complex urban acoustic scenario focusing on cities security [15]. On the other hand, the unsupervised learning technique Hierarchical Agglomeration was trained to optimize the choice and the number of monitoring sites [16] for defining a methodology to estimate the mean L_d and L_n levels in urban roads with the noise profiles detected in the clustering [10]. Additionally, the K-means method was trained in Reference [17] to identify sound pressure level patterns.

In this paper, the performance of several data clustering techniques is evaluated for discovering and analyzing different behavior patterns of the sound pressure level. A comparison of clustering techniques is carried out using noise data from two large cities, considering isolated and federated data. After this introduction, datasets, applied techniques, and evaluation metrics are described in the next Section 2. Then, the results of the comparison together with a discussion and an analysis of these results are presented in Section 3. Finally, the main conclusions of this work are summarized in Section 4.

2. Materials and Methods

This section presents materials and methods applied during this research. Two datasets, described in Section 2.1, containing sound pressure level indicators for fixed locations during a long period were used. Additionally, a third federated dataset has been created, joining the previous one involving the nodes of both cities together. The list and references for the clustering techniques used in this work can be found in Section 2.2. Once the models are trained, an evaluation of their performance allows for comparing the different algorithms using three different metrics that analyze the internal structure of the clusters. The definition of the metrics is presented in Section 2.3. Last, the software and hardware used to perform all the processing and analysis can be found in Section 2.4.

2.1. Data Sources

This research has considered datasets from two different WASNs deployed in big cities, Barcelona and Madrid, Spain, and collected sound pressure level values.

On one hand, the network of acoustics nodes deployed in Barcelona, denoted in this work by BCN_X, by the city council during the last years consists of 86 sound sensors [18,19]. The dataset used in this research was collected from 70 of the 86 sound sensors that were chosen for reasons of stability of the data over time and homogeneity in the spatial distribution of the nodes. The data were provided by the Barcelona City Council after a request from the authors. In the Acknowledgments section, the names of the data managers are indicated. As a summary, the data captured using Cesva TA120 [20] remote sonometers, considering international standards [21,22], is aggregated and sent to a data platform called *Plataforma de Sensors i Actuadors de Barcelona* [23]. A detailed explanation about the technological structure of the WASN and the data pipeline process involved can be found in Camps et al. [18]. A description of the data source, the transformations carried out, the variables created, along with the distribution of the nodes is provided in a previous article of the authors [17].

On the other hand, the acoustic pollution monitoring network of the city of Madrid has 31 permanent stations, denoted in this work by MAD_X, in charge of the control and continuous monitoring of the existing noise levels. Garrido et al. [24] described Madrid's WASN in detail showing how sound pressure level measurement dataset of these stations was retrieved from the acoustic pollution sensors and stored in a database management system platform that allows data analysts to work with the data in a structured way. The data are available on the Madrid council's open data portal [25]. In particular, data from recent years can be downloaded in the acoustic pollution data repository [26]. In the current research, only data from 2019 from both cities have been selected to explore a regular year period and avoid the pandemic period. More details regarding descriptive analysis and data processing can be found in previous authors' studies [17,27] for both cities. Figure 1 shows the location of the chosen nodes in both cities.

(a)

(b)

Figure 1. (**a**) Location of the of the 70 acoustic nodes in the city of Barcelona, Spain and (**b**) Location of the 31 acoustic nodes in the city of Madrid, Spain.

These datasets are transformed into a normalized common structure that allows the comparison. The common structure is an structure table where rows represent each node with the following features: L_{d2019}, L_{e2019}, L_{n2019} and $sd_{2019}(L_{den1d})$. Three first sound pressure level features have been selected considering the recommendations established in Directive 2002/49/EC [1] and to take into account levels during different time periods of the day. The last feature has been chosen to take into account long-term variation of the main parameter L_{den} in Directive 2002/49/EC [1]. These acoustic parameters are defined below.

ISO 1996-2: 2017 [22] developed by the technical committee ISO/TC 43/SC 1 Noise describes how sound pressure levels intended as a basis for assessing environmental noise limits or comparison of scenarios in spatial studies can be determined. Determination can be performed by direct measurement and by extrapolation of measurement results through calculation. In this research, the definition, notations, and calculations performed over acoustic data follow the referred ISO [22]. As the sound pressure $p(t)$ is measured continuously over a given time period $T = [t_1, t_2]$ for all $t \in T$, to quantify the sound level on a single value using the equivalent sound pressure level in dB, denoted as L_{eqT}, Equation (1) is used.

$$L_{eqT} = 10 \cdot \log\left[\frac{1}{T}\int_{t_1}^{t_2} \frac{p^2(t)}{p_0^2}\mathrm{d}t\right] \text{ where } T = t_2 - t_1, \tag{1}$$

where p_0 is the sound pressure reference value equal to 20 µPa. In particular, deployed nodes compute the A frequency-weighting equivalent sound pressure level of one minute period, denoted as $L_{\mathrm{Aeq}1m}$ in dBA unit, applying Equation (1).

From these one minute period data, L_d, L_e and L_n, defined as the A-weighted long-term average sound pressure level for day, evening and night periods respectively, are calculated using Equation (2). These features are determined over all the day periods (07:00–19:00 h), evening periods (19:00–23:00 h), and night periods (23:00–07:00 h), respectively, across all the assessment periods.

$$L_{\mathrm{Aeq}T} = 10 \cdot \log\left[\frac{1}{n}\sum_{i=1}^{n} 10^{\frac{L_{\mathrm{Aeq}_i}}{10}}\right], \tag{2}$$

where n is the total number of 1-unit time intervals in period T and L_{Aeq_i} is the equivalent sound pressure level in the interval i obtained by the sensor applying Equation (1). For instance, to calculate $L_{\mathrm{Aeq}1h}$, 60 values of $L_{\mathrm{Aeq}1m}$ are averaged.

Finally, the daily standard deviation $sd_{2019}(L_{den1d})$ is computed. L_{den}, defined in Equation (3), refers to the day–evening–night noise indicator obtained for an overall annoyance in the assessment period [1] for one year.

$$L_{den} = 10 \cdot \log\left[\frac{1}{24}\left(12 \cdot 10^{\frac{L_{day}}{10}} + 4 \cdot 10^{\frac{L_{evening}+5}{10}} + 8 \cdot 10^{\frac{L_{night}+10}{10}}\right)\right] \tag{3}$$

2.2. Unsupervised Learning Algorithms

There are a large number of algorithms in the literature dedicated to data clustering. In this research, several representative algorithms from three unsupervised learning approaches, in particular, hierarchical, partitional, and model-based techniques have been considered to evaluate which one performs better over acoustic data. As it is mentioned in Section 1, Hierarchical Agglomeration and K-means have been previously applied to acoustic data. In this paper, other clustering algorithms, together with the mentioned above, were trained to fit the data:

1. HC: Hierarchical Agglomeration [28];
2. DIANA: a divisive hierarchical algorithm [29];
3. KM: K-means [30];
4. PAM: Partitioning Around Medoids [31];
5. CLARA: the sampling-based algorithm [29];

6. SOM: Kohonen Self-Organizing Maps [32];
7. SOTA: the Self-Organizing Tree Algorithm [33];
8. GAUSS: Expectation Maximization (EM) algorithm over a finite mixture of Gaussian distributions [34].

Hierarchical Agglomeration [28] and DIANA [29] methods, belonging to hierarchical clustering methods, create the clusters grouping the elements in hierarchical steps. K-means [30], PAM [31] and CLARA [29] methods, belonging to partitional clustering methods, are based on centroids and they iterative the algorithm until convergence. Moreover, SOM [32] technique applies an unsupervised neural network, and SOTA [33] is an evolution of the SOM algorithm which included a binary tree topology, both belonging to model-based methods, in this case in machine learning algorithms. Finally, GAUSS [34] technique is based on the maximization of the likelihood for a statistical distribution, belonging to model-based methods, in this case in statistical normal distributions.

In Reference [35], a revision of different approaches for grouping similar objects into different groups is presented with an analysis of the advantages and disadvantages of every algorithm family. The features for the clustering algorithms chosen for this work are summarized in Table 1.

Table 1. Advantages and disadvantages of clustering algorithms used in this work.

Family	Algorithms	Advantages	Disadvantages
Hierarchical	HC, DIANA	suitable for the data set with arbitrary shape and attribute of arbitrary type, the hierarchical relationship among clusters easily detected, and relatively high scalability in general	relatively high in time complexity in general.
Partitional	KM, AM, CLARA	relatively low time complexity and high computing efficiency in general	not suitable for non-convex data, relatively sensitive to the outliers, easily drawn into local optimal, the number of clusters needed to be preset, and the clustering result sensitive to the number of clusters.
Model-Based	SOM, SOTA, GAUSS	diverse and well developed models providing means to describe data adequately and each model having its own special characters that may bring about some significant advantages in some specific areas	relatively high time complexity in general, the premise not completely correct, and the clustering result sensitive to the parameters of selected models.

2.3. *Evaluation Metrics*

For the evaluation and comparison of the clustering algorithms, Berry et al. [36] proposed two criteria for clustering evaluation and selection of an optimal clustering scheme: compactness and separation. Later, Hand et al. [37] introduce a new criteria: connectedness. In this article, these three internal characteristics are chosen to be calculated and analyzed.

Connectedness is related to what extent observations are placed in the same cluster as their nearest neighbors in the data space. To measure that connectivity [38], Equation (4) is applied. For each element i, the n_{ij} represents the j-th nearest neighbor of i using a distance (often euclidean distance) and $I_{i,n_{ij}}$ is a boolean function that takes value $\frac{1}{j}$ when i and n_{ij} are not in the same cluster and zero otherwise. This metric is called the Connectivity metric.

$$Connectivity = \sum_{i=1}^{N}\sum_{j=1}^{M} I_{i,n_{ij}} \tag{4}$$

where N is the number of elements to group into K clusters and M is a parameter that determines the number of neighbors that contribute to the Connectivity measure, fixed to ten in this research as established in [39]. The Connectivity metric is equal to or higher than zero and the lower the value the better the clustering trained so must be minimized.

Compactness is related to cluster cohesion or homogeneity, measuring how close are the objects within the same cluster, usually by looking at the intra-cluster or within-cluster variance. A lower within-cluster variation is an indicator of good compactness, and, hence, a good clustering. So compactness must be minimized. The different indices for evaluating the compactness of clusters are based on distance measures, such as the cluster-wise within average/median distances between observations.

Separation measures how well-separated a cluster is from other clusters quantifying the degree of separation between clusters, usually by measuring the minimum distance between cluster centroids or the pairwise minimum distances between objects in different clusters. Therefore, separation must be maximized.

When the number of clusters increases, by definition compactness and separation used decrease. To manage this trade-off, some methods combine the two measures into a single score. The Dunn index [40] and Silhouette width [41] are both examples of non-linear combinations of compactness and separation.

The Dunn index aims to identify dense and well-separated clusters. It is defined as the ratio between the minimal inter-cluster distance to maximal intra-cluster distance. Equation (5) shows how to calculate the Dunn index for clustering with K partitions.

$$Dunn = \frac{\min_{1 \le i \le j \le K} d(i,j)}{\max_{1 \le k \le K} \hat{d}(k)} \tag{5}$$

where $d(i,j)$ is the distance between cluster i and j (measuring separation) and $\hat{d}(k)$ is the intra-cluster distance of cluster k (measuring compactness). As separation should be maximized and compactness minimized, it results in that Dunn index must be maximized.

Silhouette width estimates the average distance between clusters considering how well an observation is clustered, in particular, how close each element in one cluster is to elements in the neighboring clusters. To calculate Silhouette width, it is necessary to first calculate the average dissimilarity a_i between the element i and all other elements of the cluster k to which i belongs (C_k) using Equation (6).

$$a_i = \frac{1}{|C_k| - 1} \sum_{j \in C_k, i \neq j} d(i,j), \tag{6}$$

representing the compactness of an element to the cluster to which belongs.

Secondly, for each element i, the average dissimilarity $d(i,C)$ of i to all elements of C are calculated and the minimum is computed, as enunciated in the following Equation (7).

$$b_i = min_{1 \le l \le K, i \notin C_l} \frac{1}{|C_l|} \sum_{j \in C_l} d(i,j) \tag{7}$$

where K in the number of clusters. This metric represents the separation of an element from the rest of the clusters.

Lastly, using results from Equations (6) and (7), the Silhouette width for an element i is calculated applying Equation (8).

$$S_i = \begin{cases} \frac{b_i - a_i}{\max(a_i, b_i)} & if \quad |C_k| > 1 \\ 0 & if \quad |C_k| = 1 \end{cases} \quad (8)$$

It is important to note that, the Silhouette coefficient of clustering is the mean of the Silhouette width of all the elements. Therefore, the objective is to maximize this index.

There are other internal validation metrics available to be used in the validation of an unsupervised learning algorithm [42–47] that could be alternatives to the selected ones. However, the chosen measures cover the three clustering criteria in order to evaluate and compare the trained clustering models [37].

2.4. *Software and Hardware*

The preparation, transformation, analysis, and modeling of the data have been performed using the Statistical Programming Language R [48] with the configuration presented in Table 2 for two environments, on-premise and cloud. The latter one has been used to parallelize some tasks.

Table 2. Libraries and Software Versions

Software Environment	Version
On-Premise	R version 4.1.0 called "Camp Pontanezen" AMD Ryzen 7 3700X 8-Core Processor 3.60 GHz with 16 GB RAM and a GTX 1660 Super GDDR5 GPU.
Cloud	R version 4.2.0 called "Vigorous Calisthenics" RStudio Cloud Server
Library	**Version**
stringr	1.4.0
dplyr	1.0.5
tidyr	1.1.3
cluster	2.1.1
ggplot2	3.3.3
clValid	0.7
mclust	5.4.8
kohonen	3.0.10

To ensure the reproducibility of the research, in every task that includes a random step, the seed using the R function set.seed() has been fixed. Due to changes in random numbers generation in R version 4.0.0, the way to generate them to be sure that the analysis will be reproducible in every R version has also been defined.

3. Results and Discussions

In this section, the results of the performance of the different unsupervised learning algorithms are shown to evaluate and compare them with the three metrics explained in Section 2.3. Moreover, a selection of the best clustering algorithm to work with acoustic data to identify behavior patterns is completed. Additionally, a more detailed discussion of the resulting clustering is presented. This discussion is carried out by comparing cluster outputs from both federated data, that is, dataset containing data from both cities, and non-federated data, that is, dataset containing data from only one city.

For each normalized dataset, clustering algorithms listed in Section 2.2 are trained several times, increasing the number of clusters from 3 to 12, to fit the three different datasets presented in Section 2. For the interest of the research, the case $k = 2$ is avoided because it uses to separate the nodes in one group of high sound pressure level values and another of low sound pressure level values, not adding value since that is what city managers usually do. This particular case has been enunciated in previous literature [16,27] that would not help to discover new knowledge.

Firstly, Table 3 shows the results for the Connectivity metric of the different techniques.

Table 3. Evaluation and comparison of clustering techniques over WASN data based on the Connectivity metric.

	Number of Clusters									
Algor. [1]	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
					BCN [1]'s WASN data					
HC [1]	9.10	13.89	17.09	23.23	26.30	29.52	37.63	40.19	41.00	45.05
KM [1]	7.78	12.56	24.89	22.37	28.27	29.44	38.80	47.25	54.12	53.34
DIANA	26.85	28.33	37.19	40.71	45.27	48.09	51.31	53.45	55.73	58.23
PAM	15.20	20.51	25.78	33.39	38.66	44.63	46.66	47.84	55.92	62.45
CLARA	15.20	19.74	22.84	33.39	36.49	42.51	46.01	50.15	58.31	58.44
SOM	7.78	12.56	24.89	32.98	40.81	53.87	56.66	54.86	70.92	83.47
GAUSS	21.38	39.29	33.10	53.58	43.54	40.99	42.92	NA [2]	98.71	68.33
SOTA	29.91	34.73	36.59	44.04	47.04	48.21	62.99	72.67	74.18	82.76
					MAD [1]'s WASN data					
HC [1]	11.98	19.48	23.13	25.89	32.93	35.93	39.33	41.66	44.27	46.08
KM [1]	10.08	21.10	25.50	28.10	33.08	38.07	39.48	41.81	44.43	50.40
DIANA	10.95	18.51	25.50	28.10	31.70	36.11	42.94	44.26	46.88	50.81
PAM	21.05	21.87	23.96	31.10	35.63	38.23	43.82	46.57	49.19	50.42
CLARA	21.05	21.87	23.96	31.10	36.15	38.74	44.25	47.00	49.62	50.85
SOM	15.31	21.10	28.35	36.85	40.19	43.76	49.56	49.87	52.88	56.58
GAUSS	23.95	47.00	41.32	41.72	58.44	43.63	45.97	60.70	54.00	55.86
SOTA	18.36	21.97	28.15	29.24	36.80	38.53	40.64	46.66	48.98	NA [2]
					Federated MAD [1] and BCN [1] joined WASN data					
HC [1]	12.26	16.52	20.38	22.53	27.76	33.53	40.42	48.79	52.38	54.84
KM [1]	30.02	35.89	31.19	33.40	43.14	45.00	50.82	52.97	57.73	64.06
DIANA	18.08	28.51	34.08	41.73	49.59	52.55	56.41	62.90	64.32	66.23
PAM	23.01	28.18	28.79	34.66	49.68	58.94	62.72	64.30	66.58	67.86
CLARA	24.92	28.18	32.40	38.59	44.21	50.22	52.50	61.45	68.14	67.11
SOM	23.03	29.11	31.19	37.76	48.08	57.93	61.27	66.99	77.79	75.84
GAUSS	69.57	63.19	93.73	79.91	81.40	83.81	87.62	89.39	97.70	97.46
SOTA	30.55	41.53	44.74	53.57	60.29	62.13	68.76	75.11	78.06	83.70

[1] Abbreviations: Algor.: Algorithm, HC: Hierarchical Agglomeration and KM: K-means, MAD: Madrid, BCN: Barcelona. [2] No convergence.

A first comparison of the resulting values offers that the best algorithm for the Connectivity metric, the optimum algorithms are Hierarchical Agglomeration and K-means. Note that values are highlighted in Table 3. From these results an important insight could be extrapolated, that the number of optimal clusters for the Connectivity metric holds in three.

Now, in Table 4 the Dunn index obtained for all the algorithms and 3 to 12 clusters are shown.

Table 4. Evaluation and comparison of clustering techniques over WASN data based on the Dunn index.

Algor. [1]	3	4	5	6	7	8	9	10	11	12
					Number of Clusters					
BCN [1]'s WASN data										
HC [1]	0.218	0.236	0.236	0.227	0.227	0.227	0.234	0.234	0.234	0.245
KM [1]	0.161	0.199	0.178	0.255	0.275	0.275	0.248	0.226	0.166	**0.282**
DIANA	0.073	0.074	0.098	0.102	0.102	0.125	0.146	0.157	0.165	0.171
PAM	0.069	0.146	0.172	0.173	0.173	0.173	0.222	0.240	0.240	0.240
CLARA	0.069	0.075	0.163	0.173	0.210	0.210	0.210	0.240	0.210	0.246
SOM	0.161	0.199	0.178	0.179	0.163	0.145	0.131	0.154	0.094	0.100
GAUSS	0.050	0.028	0.125	0.076	0.056	0.133	0.164	NA [2]	0.063	0.099
SOTA	0.091	0.101	0.101	0.101	0.101	0.101	0.059	0.059	0.059	0.059
MAD [1]'s WASN data										
HC [1]	0.144	0.166	0.212	0.212	0.347	0.347	0.347	0.347	0.364	**0.388**
KM [1]	0.191	0.165	0.220	0.253	0.347	0.347	0.347	0.347	0.364	0.358
DIANA	0.158	0.141	0.220	0.253	0.282	0.290	0.295	0.295	0.336	0.352
PAM	0.088	0.145	0.183	0.074	0.220	0.290	0.290	0.290	0.290	0.290
CLARA	0.088	0.145	0.183	0.074	0.220	0.295	0.295	0.295	0.309	0.309
SOM	0.193	0.165	0.165	0.084	0.165	0.129	0.061	0.129	0.181	0.244
GAUSS	0.086	0.032	0.116	0.147	0.075	0.171	0.070	0.066	0.105	0.258
SOTA	0.125	0.193	0.193	0.193	0.255	0.255	0.282	0.290	0.290	NA [2]
Federated MAD [1] and BCN [1] joined WASN data										
HC [1]	0.120	0.131	0.163	0.163	0.163	0.153	0.160	0.193	0.225	0.225
KM [1]	0.071	0.031	0.143	0.169	0.170	0.172	0.167	0.170	0.236	**0.251**
DIANA	0.075	0.082	0.089	0.103	0.110	0.122	0.145	0.146	0.157	0.158
PAM	0.061	0.101	0.100	0.167	0.110	0.083	0.071	0.071	0.093	0.095
CLARA	0.103	0.101	0.123	0.137	0.103	0.143	0.159	0.096	0.092	0.103
SOM	0.027	0.101	0.143	0.126	0.109	0.071	0.110	0.084	0.071	0.078
GAUSS	0.033	0.031	0.019	0.045	0.041	0.040	0.053	0.058	0.072	0.072
SOTA	0.044	0.044	0.044	0.051	0.059	0.059	0.059	0.059	0.079	0.079

[1] Abbreviations: Algor.: Algorithm, HC: Hierarchical Agglomeration and KM: K-means, MAD Madrid, BCN Barcelona. [2] No convergence.

It is observed that this metric aims to create a higher amount of clusters, prioritizing separation from compactness. Again, note that the highest values are highlighted. For the Dunn index, Hierarchical Agglomeration and K-means algorithms are also the top performers.

Finally, Table 5 shows the Silhouette Width for all the clustering techniques and for the same number of clusters and the datasets previous indicated.

Hierarchical Agglomeration and K-means algorithms also maximize the Silhouette Width.

For this metric, it is shown in Table 5 that the Barcelona dataset and the federated dataset are recommended to be split into 4 clusters, but for the Madrid dataset, the recommendation is 3 clusters. However, a hypothesis could be that Madrid only has three of the four behaviors identified in the full dataset.

As a summary, regarding the federated dataset, see Table 3 for details, the Connectivity metric is minimized with the Hierarchical Agglomeration algorithm for $k = 3$ clusters. It is important to note that, when the amount of elements to group is small, an increase in the number of clusters will increase Connectivity, thus this metric tends to select low values for the number of clusters. Then, the Dunn index selects K-means and Hierarchical Agglomeration clustering with $k = 12$ clusters as can be seen in Table 4. Finally, the Hierarchical Agglomeration algorithm for $k = 4$ has been selected by the Silhouette Width metric, see Table 5, showing that the Hierarchical Agglomeration method has a good equilibrium between the three clustering characteristics presented in Section 2.3.

Table 5. Evaluation and comparison of clustering techniques over WASN data based on the Silhouette Width.

Algor. [1]	Number of Clusters 3	4	5	6	7	8	9	10	11	12
BCN [1]'s WASN data										
HC [1]	0.294	0.353	0.317	0.386	0.368	0.358	0.327	0.308	0.318	0.312
KM [1]	0.376	**0.431**	0.356	0.404	0.395	0.392	0.362	0.376	0.369	0.377
DIANA	0.138	0.308	0.299	0.310	0.324	0.319	0.318	0.321	0.338	0.318
PAM	0.368	0.415	0.358	0.350	0.334	0.344	0.350	0.362	0.335	0.345
CLARA	0.368	0.418	0.361	0.350	0.339	0.343	0.346	0.353	0.338	0.338
SOM	0.376	0.431	0.356	0.348	0.323	0.297	0.293	0.342	0.257	0.197
GAUSS	0.147	0.041	0.268	0.255	0.315	0.338	0.361	NA [2]	0.022	0.240
SOTA	0.336	0.245	0.284	0.264	0.280	0.277	0.243	0.238	0.257	0.226
MAD [1]'s WASN data										
HC [1]	0.376	0.301	0.307	0.287	0.317	0.291	0.294	0.291	0.272	0.230
KM [1]	**0.396**	0.382	0.341	0.320	0.319	0.290	0.292	0.294	0.275	0.261
DIANA	0.395	0.320	0.341	0.320	0.270	0.252	0.258	0.251	0.245	0.261
PAM	0.306	0.375	0.365	0.329	0.307	0.290	0.243	0.228	0.223	0.211
CLARA	0.306	0.375	0.365	0.329	0.303	0.287	0.250	0.235	0.231	0.218
SOM	0.354	0.382	0.287	0.192	0.246	0.222	0.187	0.162	0.182	0.156
GAUSS	0.239	0.023	0.167	0.171	0.072	0.195	0.174	0.112	0.144	0.127
SOTA	0.361	0.294	0.259	0.282	0.263	0.250	0.261	0.246	0.275	NA [2]
Federated MAD [1] and BCN [1] joined WASN data										
HC [1]	0.399	**0.415**	0.359	0.309	0.297	0.347	0.355	0.388	0.396	0.385
KM [1]	0.303	0.371	0.380	0.389	0.371	0.378	0.394	0.391	0.406	0.385
DIANA	0.382	0.395	0.335	0.326	0.349	0.335	0.345	0.341	0.341	0.331
PAM	0.411	0.379	0.379	0.383	0.366	0.339	0.315	0.330	0.337	0.341
CLARA	0.310	0.379	0.366	0.374	0.356	0.379	0.382	0.346	0.280	0.359
SOM	0.411	0.380	0.380	0.383	0.366	0.330	0.341	0.317	0.305	0.293
GAUSS	0.192	0.187	0.086	0.028	0.077	0.099	0.205	0.209	0.232	0.213
SOTA	0.230	0.298	0.279	0.282	0.251	0.249	0.241	0.239	0.286	0.280

[1] Abbreviations: Algor.: Algorithm, HC: Hierarchical Agglomeration and KM: K-means, MAD Madrid, BCN Barcelona. [2] No convergence.

After this first discussion, more details for $k = 3$ and $k = 4$ clusters cases are explained below. Applying the Hierarchical Agglomeration algorithm using $k = 3$, the data are divided into different groups, as it is graphed in a Dendogram in Figure 2. This Figure 2 shows the three main patterns that the algorithm has identified. To study the behavior of these three clusters, four box-plots graphs are shown in Figure 3, corresponding to the parameters used for the training phase, L_{d2019}, L_{e2019}, L_{n2019} and $sd_{2019}(L_{den1d})$. It can be observed in Figure 3 that, the first cluster is related to the nodes with high sound pressure levels during the day and evening period, medium sound pressure levels during the night, and the lowest standard deviation of the three clusters, to sum up, there are 42 nodes with a stable and high noise level. The second cluster includes 29 nodes, and presents high sound pressure levels during the three periods reaching maximum noise level values, in addition to the highest standard deviation, in other words, the variation over the mean is high. Finally, the third cluster includes 30 nodes with the lowest sound pressure level during all periods. Moreover, its standard deviation is at an intermediate value between the two other clusters.

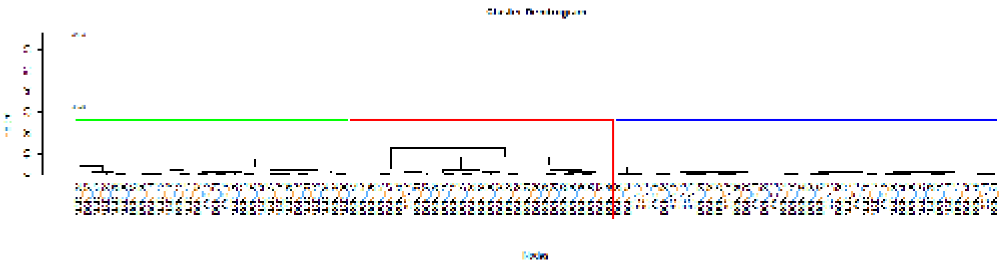
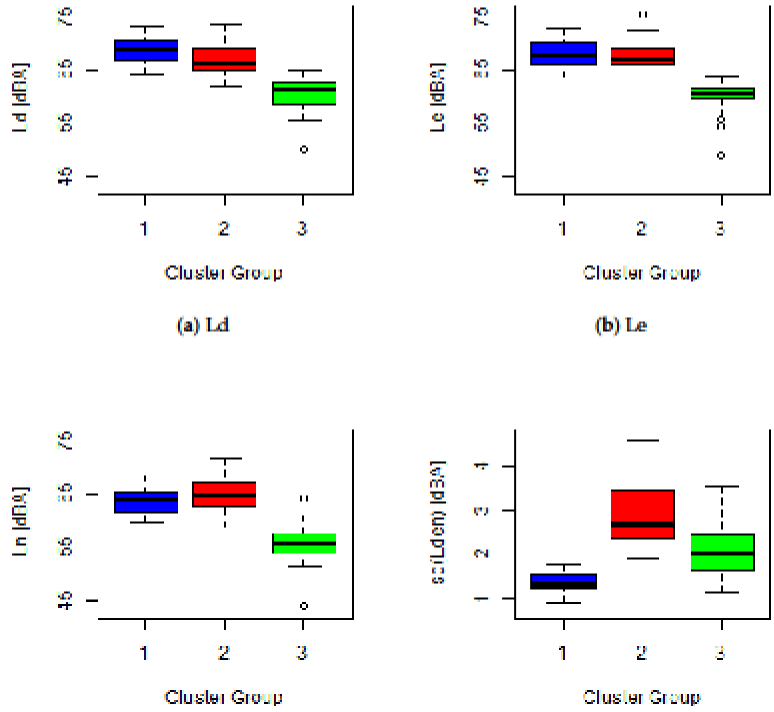


Figure 2. Nodes distribution within clusters by distance for $k = 3$ Hierarchical Agglomeration clustering. abbreviations: MAD_X Madrid Stations, BCN_X Barcelona Stations. Clusters groups are colored as presented in Table 6.



(a) Ld **(b)** Le

(c) Ln **(d)** sd(Lden)

Figure 3. Boxplot representation of the statistical distributions of the variables L_{d2019} (**a**), L_{e2019} (**b**), L_{n2019} (**c**) and $sd_{2019}(L_{den1d})$ (**d**) by cluster for $k = 3$. Hierarchical Agglomeration clustering model. Clusters groups are colored as presented in Table 6.

A summary of the three discovered clusters obtained with federated data is presented in Table 6 in which the number of nodes per city is broken down together with the centroid of each acoustics parameter.

Table 6. Size and centroid of clusters using data collected during 2019 for $k = 3$ Hierarchical Agglomeration clustering.

Cluster	L_{d2019}	L_{e2019}	L_{n2019}	$sd_{2019}(L_{den1d})$	Size	#MAD [1]	#BCN [1]	Color
1	68.7	68.2	63.6	1.36	42	12	30	blue
2	67.0	67.7	65.1	2.93	29	0	29	red
3	60.5	60.0	55.7	2.08	30	19	11	green

[1] Abbreviations: MAD Madrid Stations, BCN Barcelona Stations.

It is remarkable that, as can be seen in Table 6, cluster number 2 only contains nodes belonging to Barcelona city, suggesting that this type of behavior is specific to this city. Moreover, the relative proportion of Madrid's nodes in cluster number 1 is lower than in cluster number 3, showing that Madrid has nodes with lower sound pressure levels on average than Barcelona.

Now, Hierarchical Agglomeration is applied for $k = 4$ clusters. Figure 4 shows that previous cluster 1 (blue) with 42 nodes, obtained with $k = 3$, is split into two groups with 21 nodes each (blue and magenta).

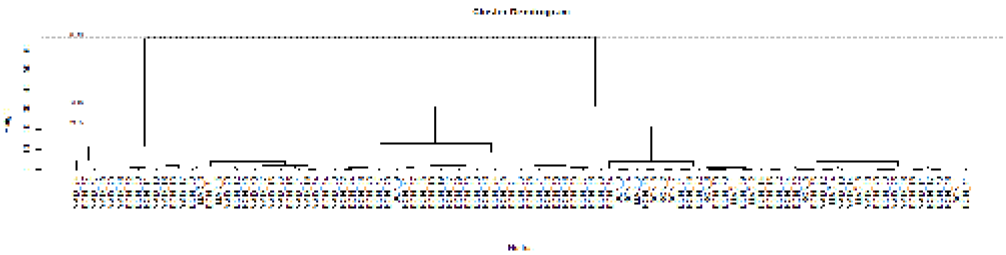


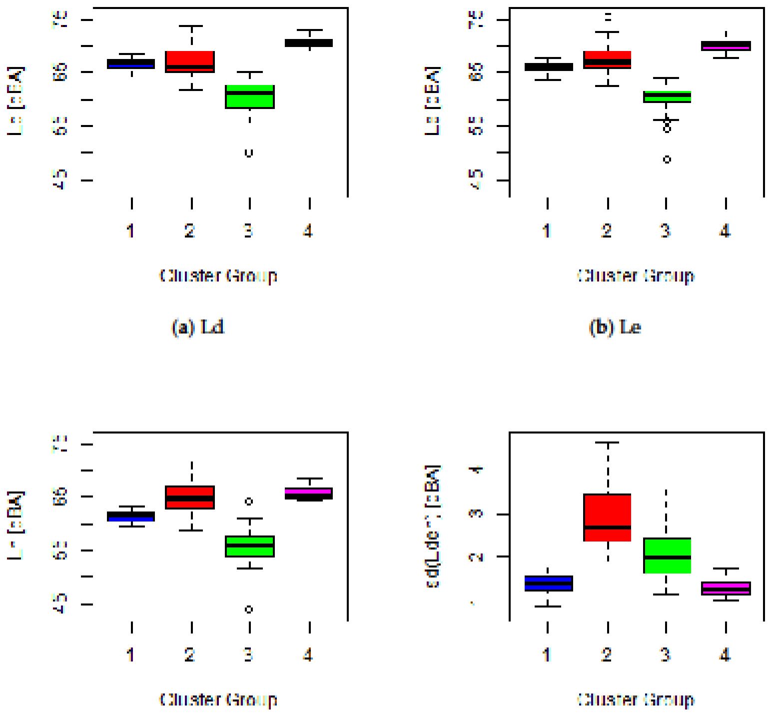
Figure 4. Nodes distribution within clusters by distance for $k = 4$ Hierarchical Agglomeration clustering. abbreviations: MAD_X Madrid Stations, BCN_X Barcelona Stations. Clusters groups are colored as presented in Table 7.

Table 7. Size and centroid of clusters using data collected during 2019 for $k = 4$ Hierarchical Agglomeration clustering.

Cluster	L_{d2019}	L_{e2019}	L_{n2019}	$sd_{2019}(L_{den1d})$	Size	#MAD [1]	#BCN [1]	Color
1	66.7	66.0	61.5	1.41	21	9	12	blue
2	67.0	67.7	65.1	2.93	29	0	29	red
3	60.5	60.0	55.7	2.08	30	19	11	green
4	70.7	70.4	65.8	1.31	21	3	18	magenta

[1] Abbreviations: MAD Madrid Stations, BCN Barcelona Stations.

As it can be observed in the boxplots in Figure 5, the new blue cluster presents a lower sound pressure level than magenta and red, with a significant reduction in level during the night period. However, the new magenta cluster is the one with the highest sound pressure level and the lowest variance of the 4 clusters. In this case, the red cluster has the highest standard deviation.



(a) Ld (b) Le

(c) Ln (d) sd(Lden)

Figure 5. Boxplot representation of the statistical distributions of the variables L_{d2019} (a), L_{e2019} (b), L_{n2019} (c) and $sd_{2019}(L_{den1d})$ (d) by cluster for $k = 4$. Hierarchical Agglomeration clustering model. Clusters groups are colored as presented in Table 7.

Table 7 summarizes the clusters showing distribution and centroids. As in the previous case, Madrid only presents three of four behaviors, explaining the outputs of the Silhouette Width metric of $k = 3$ for Madrid data, and $k = 4$ for both Barcelona and federated data, see details in Section 3.

Regarding the selection based on the Dunn index, from a noise pollution management perspective, it is neither useful nor easy to handle 12 clusters with only 2.6 nodes on average in Madrid and 5.8 nodes on average in Barcelona. This requires establishing 12 strategies with their associated action plans, therefore K-means for $k = 12$ is discarded from this analysis.

Another way to compare the results is using an external clustering validity index. If federated data clusters are considered the ground truth partition of the nodes, external evaluation metrics can select the more appropriate clustering completed in isolation. The Chi index is an external clustering validity index based on the chi-squared statistical test, very competitive that, on average, beats other external evaluation metrics [49]. The Chi index takes a value in [0, 2], where 0 is given by the worst clustering solution, and 2 is the best value that the Chi index can achieve. Chi index results are clear to read, require no further interpretation, and help to select the optimal number of clusters based on the ground truth class.

Table 8 shows results in cross tables a comparison between the k = 3 Hierarchical Agglomeration clustering considering the federated dataset, in rows, and the optimal cluster models trained considering isolated datasets, which are k = 3 and k = 4 K-means for Barcelona dataset, upper-left and lower-left, respectively, and k = 3 K-means and k = 2 Hierarchical for Madrid dataset, upper-right and lower-right, respectively. For instance, the upper-left cross table shows the distribution of the Barcelona nodes considering k = 3 K-means using federated data in rows and k = 3 K-means Barcelona data in columns, so the number 9 in the second row and third columns represents the number of Barcelona nodes belonging to cluster number 2 in k = 3 K-means model using federated data and belonging to cluster number 3 in k = 3 K-means model using Barcelona data.

For Barcelona city, the federated dataset improves the result of the clustering compared with the Barcelona isolation data (1.104 maximum Chi index). So k = 4 K-means clustering is the best algorithm for Barcelona city based on the federated dataset clusters (chi index 1.104 versus Chi index 0.759 for k = 3 K-means algorithm). For Madrid city, the k = 3 K-means clustering is the best algorithm with a Chi index of 1.777 (compare to k = 2 Hierarchical Agglomeration with 0.714 Chi index). In this case, a smaller improvement has been made with the federated dataset ($0.223 = 2 - 1.777$), concluding that the clustering created with Madrid data in isolation gives almost the same information that the one created with the federated dataset.

Table 8. Comparison Federated Data k = 3 Hierarchical Agglomeration (in rows) with isolation BCN [1] or MAD [1] data clustering optimal models.

	(a) BCN [1] Data k = 3 K-Means			(b) MAD [1] Data k = 3 K-Means		
Cluster	**1**	**2**	**3**	**1**	**2**	**3**
1	25	5	0	0	0	12
2	10	10	9	0	0	0
3	0	11	0	5	13	1
		Chi index: 0.759			Chi index: 1.777	

	(c) BCN [1] Data k = 4 K-means				(d) MAD [1] Data k = 2 Hierarchical	
Cluster	**1**	**2**	**3**	**4**	**1**	**2**
1	18	12	0	0	12	0
2	5	14	9	1	0	0
3	0	1	0	10	9	10
		Chi index: 1.104			Chi index: 0.714	

[1] Abbreviations: MAD Madrid, BCN Barcelona.

4. Conclusions

Noise pollution is a major concern in cities around the world and wireless acoustic sensor networks are being deployed to acquire information about sound pressure level in many locations and during long-term. Sharing data between administrations in a big data infrastructure, as the EU commission is promoting, can help to obtain better insights and create a common framework. Machine Learning techniques are being applied to learn and analyze these datasets.

In this work, several machine learning clustering techniques have been applied to identify different acoustic environment patterns from sound pressure level datasets. A comparison of clustering techniques for modeling acoustic data from wireless acoustic sensor networks of the cities of Barcelona and Madrid (Spain) has been made. This evaluation has been performed using isolated data and federated data and three parameters as metrics: Connectivity, Dunn index, and Silhouette Width.

From the results, it is observed that both Hierarchical Agglomeration clustering and K-means have the best performance, in both federated and non-federated data. Therefore, they are the more suitable algorithms to fit environmental acoustics parameters, such as sound pressure levels during different periods of the day.

In general, the Connectivity and Silhouette indexes tend to select a low amount of clusters, whereas the Dunn index suggests a large number of groups. Regarding the use case of noise monitoring and management of the noise plans, a small amount of clusters is recommended, therefore the Connectivity or Silhouette index has been used to select the optimal clustering algorithm.

An external clustering validity index, the Chi index, has been also calculated, obtaining insight into the relevance of using federated data to do the clustering. More datasets will be incorporated in future works to further analyze the benefits of using federated datasets instead of isolated datasets.

It has been shown that these techniques can help the local administrations to dynamically detect different patterns of sound pressure level behavior and update the definition of acoustic zones. Moreover, this information can be publicly shared with citizens to know about the acoustic typology of the area in which they live or are planning to buy a house, allowing them better decisions.

Possible future work can continue this research along the following lines:

1. Design a methodology for monitoring the evolution of the acoustic zones to be able to measure the effect of the actions carried out by the consistories included in their action plans.
2. Create an acoustic open data spaces for federated data to identify common clusters.
3. Develop an algorithm to identify the cluster in which belongs to a city spot considering only a small sample of data.

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2.3. RESEARCH PAPER 3: MACHINE LEARNING PREDICTION OF THE LONG-TERM ENVIRONMENTAL ACOUSTIC PATTERN OF A CITY LOCATION USING SHORT-TERM SOUND PRESSURE LEVEL MEASUREMENTS

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Machine Learning Prediction of the Long-Term Environmental Acoustic Pattern of a City Location Using Short-Term Sound Pressure Level Measurements

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Abstract: To manage noise pollution, cities use monitoring systems over wireless acoustic sensor networks. These networks are mainly composed of fixed-location sound pressure level sensors deployed in outdoor sites of the city for long-term monitoring. However, due to high economic and human resource costs, it is not feasible to deploy fixed metering stations on every street in a city. Therefore, these continuous measurements are usually complemented with short-term measurements at different selected locations, which are carried out by acoustic sensors mounted on vehicles or at street level. In this research, the application of artificial neural networks is proposed for estimation of the long-term environmental acoustic pattern of a location based on the information collected during a short time period. An evaluation has been carried out through a comparison of eight artificial neural network architectures using real data from the acoustic sensor network of Barcelona, Spain, showing higher accuracy in prediction when the complexity of the model increases. Moreover, time slots with better performance can be detected, helping city managers to deploy temporal stations optimally.

Keywords: supervised learning; artificial neural networks; big data; wireless sensor network data; knowledge discovery; urban acoustic environment; environmental noise assessment

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1. Introduction

Sound waves, or noise emissions, are one of the pollutants that urban citizens are most concerned about [1]. To identify, measure, and determine exposure to environmental noise, city rulers are developing data strategies to capture, transform, and analyze information using Internet of Things (IoT) and big data technologies.

European Directive 2002/49/EC aims to establish a common approach for the assessment and management of environmental noise in order to standardize procedures and metrics. The goal is to avoid, prevent, and reduce harmful effects, including annoyance, for citizens as a result of exposure to different noise sources [2]. The directive specifically promotes agglomerations of people such as cities or clusters of cities to create strategic noise mapping (SNM) and then share the findings with the public. Additionally, the outcome of these noise maps has led to the formation of action plans for noise reduction in areas identified as having high noise exposure (noise exposure protection zones).

More recently, numerous large cities have begun to deploy Wireless Acoustic Sensor Networks (WASN), which are based on IoT technologies [3], in order to gather noise data that can be analyzed and utilized to update SNM and action plans. These WASNs are usually made up of two different types of stations: fixed-location sensors for long-term monitoring, and temporal location sensors for short-term monitoring. The latter can take the form of temporarily deployed sensors, instrumented vehicles with an acoustic sensor together with a geopositioning system to locate the measurement, or regular sound measure devices known as sonometers [4].

While fixed stations remain at one place all their lifetime, allowing the continuous monitoring of noise levels to identify trends and seasonality, temporal stations are placed in a particular site during an established period of time (minutes, hours, or days) to measure the acoustic soundfield by gathering short-term data.

To recognize environmental acoustic patterns or behaviors, using the average or median of noise indicators for the overall assessment period, generally at least one year, is recommended by the Directive [2]. Therefore, short-term data are not usually considered due to the lack of capability to capture seasonality components such as holidays or weekends. After the analysis of previously enunciated long-term statistics, two principal types of environmental acoustic patterns are usually recognized: special regime areas and quiet areas. Special regime areas include locations where the noise indicator exceeds a high threshold, while quiet areas include locations where the noise indicator is below a low threshold. Although other patterns with complex behavior can exist, advanced statistical techniques are required to recognize them.

In a number of out prior works [5,6], we applied unsupervised learning techniques to group the nodes of a WASN in clusters with the same behavior and recognize complex patterns on this basis. These complex patterns can provide insights to city managers for establishing personalized strategies and defining new acoustic areas. In the current research, the application of a supervised machine learning technique, Artificial Neural Network (ANN), is proposed to predict the long-term acoustic behavior group to which a location belongs by means of short-term measurements. In this way, temporal stations can be used by city managers to identify the environmental acoustic pattern of a site, enhancing the value of the WASN and improving the SNM.

During last few years, machine learning algorithms have been considered in a number of studies involving environmental acoustic data captured by WASNs.

Many of the studies found in the literature use supervised machine learning approaches to analyze audio signals. In New York City, a comprehensive dataset [7] of labeled audio recordings was generated utilizing a WASN [8] for the design and assessment of machine learning techniques. This dataset was used to perform methods for both identification [9] and categorization [10] of acoustic scenes and events. Recently, a deep learning structure was created using this dataset [11] to retrieve urban sound events such as car horns and human speech from multi-label audio recordings. In a European project called DYNAMAP [12], multiple machine learning techniques were evaluated for detecting [13–16] abnormal noise sources such as birds, bikes, vehicles with heavy loads passing over rough surfaces, horn vehicle noise, music in a car or in the street, ambulance sirens, airplanes, thunder storms, etc., in order to eliminate events unrelated to road traffic noise and create a noise map. In addition to the previously mentioned methods, other techniques utilizing supervised machine learning have been utilized for classifying sound sources. Maijala et al. [17] introduced a pattern classification algorithm that used Mel-frequency cepstral coefficients as features to determine the primary noise source in the acoustic environment. In this research, two types of supervised classifiers, namely, artificial neural networks with two hidden layers of 10, 30, 50, or 100 neurons and a Gaussian mixture model, were compared. Ye et al. [18] introduced an aggregation scheme combining local features and short-term sound recording features with long-term descriptive statistics to create a deep convolutional neural network for classifying urban sound events.

Regarding machine learning techniques for sound pressure level and acoustic pattern prediction, a number of studies have been published within the last few years. Das et al. [19,20] proposed an ANN architecture with only one hidden layer to predict annoyance levels of traffic noise. The architecture complexity of the trained ANNs (see Section 2.4 for details about this definition) were Net_3_1, with six variables in the input layer for the first study and Net_1_1, Net_2_1, Net_3_1, Net_4_1, Net_5_1 with five variables in the input layer for the second study. By utilizing short-term data and concentrating on traffic noise, unsupervised machine learning techniques such as dimensionality reduction and clustering were employed to optimize the location and quantity of monitoring sites [21].

A separate publication [22] presented a methodology for more efficiently estimating day-period and night-period sound pressure levels on urban roads in Milan, Italy in comparison to the legislative road classification by using equivalent sound pressure levels of a 1-h period from a 24 hours measurement campaign. Subsequently, in order to link each street in the area of examination to one of the two noise profiles found through clustering, several non-acoustic parameters were examined [22]. In another recent study, the intermittency ratio indicator was paired with the equivalent sound pressure level of a 1-h time frame in order to improve the categorization of different types of streets within the two identified clusters [23].

Regarding the identification of the long-term environmental acoustic pattern of a city, Torija et al. [24] investigated the necessary stabilization time, short-term variability, and impulsiveness of the sound pressure level to accurately characterize the temporal composition of urban soundscapes. The authors used data from sound level meters to analyze sound pressure levels in urban environments, and found that a stabilization time of at least 30 minutes was required to obtain reliable measurements of sound pressure level. The same study suggested that measurements should be taken over a longer period of time to achieve a more accurate characterization of urban soundscapes, and that the short-term variability and impulsiveness of sound pressure levels should be considered as well. In a later study, Gajardo et al. [25] analyzed data collected from sound level meters in various urban environments and concluded that hourly averages of sound levels may not be representative of the true levels of noise exposure. Therefore, using longer measurement periods such as 24 hours, to obtain more accurate representation of noise levels in urban environments was recommended. On the other hand, regarding the prediction of the equivalent sound level using short-term measurements, Brambilla et al. [26] focused on the stabilization time for road traffic noise measurements and concluded that a time of at least 10 minutes is necessary for reliable estimation of the equivalent sound pressure level of 1-h period; in addition, factors such as traffic volume, traffic composition, and road type can affect the required stabilization time.

An environmental acoustic pattern refers to the distribution and variation of sound levels in a specific environment. These patterns can be affected by a variety of factors, such as land use, weather conditions, and human activity. In urban environments, the environmental acoustic pattern is typically characterized by high levels of noise pollution from sources such as traffic, construction, and industrial activities. However, these noise sources create a complex and dynamic acoustic environment which is highly dependent on the time of day and location. In this research, the environmental acoustic pattern of a location refers to the classification of a location using the equivalent sound pressure level during the day, evening, and night periods over a year, as recommended by the Directive [2] and defined in Section 2.2.

The contribution of the current research is to use an unsupervised learning algorithm to estimate the corresponding environmental acoustic pattern of a location among the recognized long-term behaviors based on one-year acoustic data. This is carried out by using one-hour equivalent acoustic data to design and test algorithms based on ANNs, which are trained using shorter periods of time with a large amount of available data and require parallel processing to optimize the data pipelines.

This rest of this paper is structured as follows. The datasets, algorithms, and methodology used for training and testing the models are presented in Section 2. Then, in Section 3, the results obtained from the analysis are displayed and discussed. Finally, Section 4 summarizes the main conclusions of this work.

2. Materials and Methods

In this section, the materials and methods applied during this research are presented. The data source containing the sound pressure level values of the sites and the collection methodology are described in Section 2.1. The environmental acoustic patterns recognized in a previous work [5] are summarized in Section 2.2. Next, the curated short-term datasets used in this research and their transformations are detailed in Section 2.3. Section 2.4 presents the machine learning models that have been trained and evaluated in this work. Finally, the metrics used in the evaluation of the models are defined in Section 2.5.

The data preparation, transformation, analysis, modeling, and visualization were executed utilizing the Statistical Programming Language R [27], which involved the integration of a local environment using R version 4.2.1 with a free cloud-based environment provided by Posit Cloud using R version 4.2.2. The scripts applied in this research are available at the Github repository https://github.com/AntonioPL/BCN_Noise (accessed on 6 January 2023). In order to ensure the reproducibility of the research, the seed was fixed using the R function set.seed() in every task that incorporated a random step

2.1. Data Source

The historical data used in this research contain sound pressure level values from 70 fixed acoustic nodes deployed in Barcelona, Spain, to build a WASN, as described in publications by Camps et al. [28] and Farres et al. [29]. The map in Figure 1 shows the widespread distribution of the nodes in the whole city.

These fixed acoustic nodes are equipped with remote Cesva TA120 [30] sonometers, which capture sound pressure levels continuously 24×7 (24 hours and 7 days a week) and every minute send the A-frequency weighting equivalent sound pressure level of a 1-min period, denoted as $L_{\mathrm{Aeq1}m}$, as defined in Equation (1) following ISO1996-2 [31]:

$$L_{eq1m} = 10 \cdot \log\left[\frac{1}{60}\int_{t_0}^{t_0+60}\frac{p^2(t)}{p_0^2}\mathrm{d}t\right]\ \mathrm{dBA}, \tag{1}$$

where $[t_0, t_0 + 60]$ is a 1-min interval beginning at time t_0, $p(t)$ is the sound pressure level at time t in Pascal pressure units (Pa), and $p_0 = 20\ \mu\mathrm{Pa}$ is the sound pressure reference value.

These data are captured every minute and stored in the central data storage [28], where transformation are performed before the data are absorbed into the smart city platform of BCN called Plataforma de Sensors i Actuadors de Barcelona [32].

More than 97 million of $L_{\mathrm{Aeq1}m}$ records captured by BCN city council in the full years from 2018 to 2020 for the 70 nodes were exported from the smart city platform in 73 Excel™ files with wide data format for use in this research. These files contain sound pressure level values of every minute for every node in the described period. It is worth noting that there were a number of null values due to sensor errors and maintenance periods; these were removed during the curation phase. Basic statistics and available records from the nodes can be found in [5].

2.2. Environmental Acoustic Patterns

To evaluate the environmental acoustic behavior of a site, European Directive 2002/49/EC [2] recommends the use of the $L_{\mathrm{Aeq}T}$ indicators corresponding to day, evening, and night periods over 24 hours for a specific station on every day during one year, denoted as L_{d1y}, L_{e1y} and L_{n1y}, respectively, and the overall assessment period noise indicator DEN (day, evening, night), represented by L_{den}. To take into account the temporal variability of the sound pressure level values during the different periods of the day, the yearly standard deviation of $L_{\mathrm{den1}d}$, denoted $sd_{1\mathrm{y}}(L_{\mathrm{den1}d})$, has been proposed to describe the variability or volatility of the sound pressure level of the nodes during a year [5,6]. In these previous works of ours, four environmental acoustic patterns were recognized using these four noise indicators, calculated from the described dataset as inputs of several unsupervised learning techniques. Therefore, the nodes of BCN's WASN were classified into one of these patterns, and are shown in Figure 1 in different colors together with their locations.

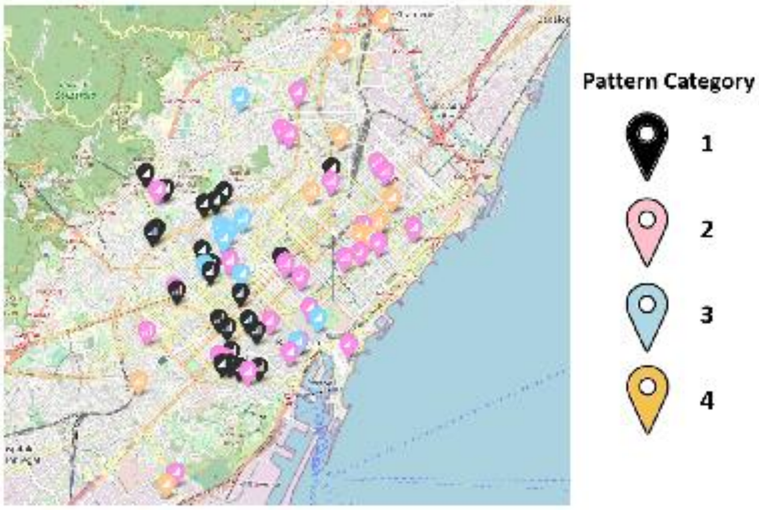


Figure 1. Map showing location and pattern category (indicated by different colors) of the nodes of the WASN of BCN. Category 1 in black, Category 2 in magenta, Category 3 in cyan and Category 4 in brown.

Table 1 shows the average values of the four previously defined noise indicators for the different pattern categories that allow the description of their behaviours. Analytically, there are three pattern categories in which day and evening sound pressure level values are similar and in which both are higher than night sound pressure level values by a statistical significance amount. The first pattern category, shown by the 23 nodes with the black color tag in Figure 1, has higher sound pressure values (L_{d1y}, L_{e1y} and L_{n1y}) than the second pattern category, shown by the 27 nodes with the magenta color tag in Figure 1. Both categories have higher sound pressure values than the fourth category, which includes the 11 nodes shown with the brown color tag in Figure 1. Therefore, these pattern categories represent nodes with high, medium, and low values of sound pressure with the described behavior. Moreover, a negative correlation between sound pressure levels indicators and variability ($sd_{1y}(L_{den1d})$) can be observed, i.e., the fourth category is the one with the highest variability, followed by the second and first categories, in this order. The remaining third category, indicated by the blue color tag, contains nine nodes. This category shows a different behavior than the others, with evening sound pressure level value being higher than the other periods, which all have similar values. Moreover, this third category presents the highest variability of all categories.

Table 1. Environmental acoustic pattern classification of BCN WASN (adapted from Pita, Navarro, and Rodriguez [5]).

Pattern Category	L_{d2019}(dB)	L_{e2019}(dB)	L_{n2019}(dB)	$sd_{2019}(L_{den1d})$	Nodes	Color
1	70.74	70.79	66.39	1.50	23	black
2	66.40	66.04	62.28	2.06	27	magenta
3	66.05	68.25	66.71	3.78	9	cyan
4	61.11	60.57	56.24	2.61	11	brown

These environmental acoustic patterns can be contextualized by features such as the type of roads, use of the area, and noise sources. Interpretation of these characteristics allows for a deeper understanding and appreciation of the behavior patterns of different city areas. This can be valuable for residents, tourists, businesses, and city managers.

Behavior Category 1 groups the locations related to main routes of road traffic, in particular, major thoroughfares and intersections with very high road traffic intensity. Noise levels are relatively consistent during the day, with peak noise levels occurring during rush hour when traffic is heaviest. At night, noise levels decrease somewhat due to reduced traffic volume, though they are still significantly higher than in quiet residential areas. The sound pressure level is high and fluctuation is low, as shown in Table 1.

Behavior Category 2 groups those locations related to the regular areas in a city, which typically include medium-density residential, commercial, and office building areas along with public spaces such as parks, squares, and sidewalks. The noise pollution is moderate to high, with a wide range of noise sources. During the day the noise level is relatively consistent, with peak noise levels occurring during peak hours of activity such as rush hour and lunchtime. At night, noise levels decrease somewhat due to reduced activity, though they remain higher than in quiet residential areas. In this category, the sound pressure level is moderate to high and the fluctuation is moderate, as shown in Table 1.

Behavior Category 3 groups the locations related to shopping, entertainment, and nightlife activity. The noise pollution is high throughout the day, evening, and night due to the high level of human activity and mix of commercial and entertainment venues. During the day, noise levels are high and relatively consistent, with peak noise levels occurring during peak hours of shopping and entertainment activity. In the evening, noise levels continue to be high, and are more fluctuating, with an increase in human activity as people go out for entertainment and nightlife. At night, noise levels are high and fluctuating, with an increase in human activity in nightlife venues such as bars, clubs, and restaurants. In this category, both the sound pressure level and fluctuation are high, as is shown in Table 1.

Finally, Behavior category 4 is related to quiet residential areas in a city, where the noise pollution is low during the day, evening, and night periods. These areas are characterized by lower levels of human activity and fewer noise sources, providing a relatively peaceful and quiet environment for residents. Noise levels are low during the day, with occasional spikes from passing vehicles and aircraft or distant construction and maintenance work. In the evening noise levels decrease even further due to lower traffic and other human activities. Noise levels at night decrease significantly, as expected. However, occasional high noise level events, e.g. from passing vehicles or aircraft, can explain the elevated fluctuation of the sound pressure level shown in Table 1.

In the current research, short-period measurement data are used to estimate the corresponding behavior recognized using long-term data, i.e., the environmental acoustic pattern category is the output variable of the proposed supervised learning algorithm.

2.3. *Curated Modelling Datasets*

To train and evaluate the machine learning models, 24 short-term period curated datasets were prepared and denoted using numbers from 0 to 23, sequentially corresponding with every one-hour time slot of the day. Each instance contains 60 sound pressure level values for a particular node on a specific date at the fixed hour, i.e., dataset number X contains all the sound pressure level values captured from X:00 until X:59 in hh:mm format for every node at any date from January 2018 until December 2020. Table 2 shows the distribution of these 24 datasets, detailing the amount of available, valid, and null instances and the average instances per node for every dataset. As a summary, there are 1,621,145 valid instances, which is 93.66% of the total available instances, with an average of 23,159 instances per node.

The following tasks were applied to these curated datasets to train and test the models implemented with the machine learning technique described in Section 2.4. First, instances with null values were removed. Then, every dataset was randomly split into two subsets, called the training and and test sets. The training subset contained 80% of the curated dataset instances, and was the input for model training, while the test subset contained 20% of the curated dataset instances, and was used to evaluate the models.

Table 2. Hourly sound pressure level datasets.

Dataset (Hourly Time Slot)	Instances	Valid Instances	Instances with Nulls	% Rows with Nulls	Average Instances per Node
0	72,213	68,208	4005	5.55%	974.40
1	72,213	68,107	4106	5.69%	972.96
2	72,213	67,741	4472	6.19%	967.73
3	72,213	67,892	4321	5.98%	969.89
4	72,213	67,870	4343	6.01%	969.57
5	72,213	68,024	4189	5.80%	971.77
6	72,213	68,032	4181	5.79%	971.89
7	72,089	67,885	4204	5.83%	969.79
8	71,967	67,652	4315	6.00%	966.46
9	71,998	67,362	4636	6.44%	962.31
10	71,998	67,257	4741	6.58%	960.81
11	72,029	67,033	4996	6.94%	957.61
12	72,059	66,967	5092	7.07%	956.67
13	72,060	66,931	5129	7.12%	956.16
14	71,998	67,047	4951	6.88%	957.81
15	72,029	67,483	4546	6.31%	964.04
16	72,029	67,476	4553	6.32%	963.94
17	72,121	67,477	4644	6.44%	963.96
18	72,121	67,533	4588	6.36%	964.76
19	72,120	67,526	4594	6.37%	964.66
20	72,151	67,218	4933	6.84%	960.26
21	72,213	67,112	5101	7.06%	958.74
22	72,213	67,206	5007	6.93%	960.09
23	72,213	68,106	4107	5.69%	972.94

2.4. *Artificial Neural Networks*

To estimate the target variable or pattern category described in Section 2.2 using the curated datasets described in Section 2.3, supervised learning algorithms were considered. In particular, several feed-forward multilayer Artificial Neural Networks were built.

A feed-forward multilayer ANN is a mathematical model composed of elements called neurons [33] grouped by layers and relationships between the elements of a layer with the elements of the previous layer by activation functions, as displayed in Figure 2.

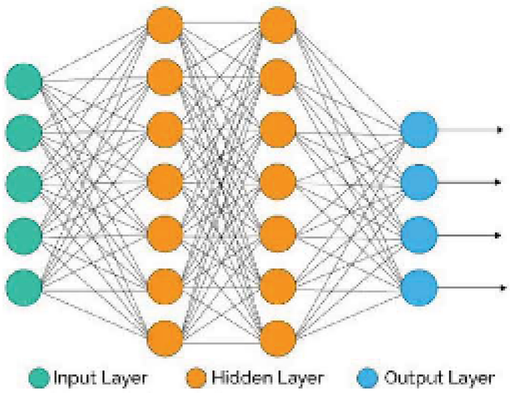


Figure 2. Artificial neural network architecture (adapted from Dastres and Soori [34]).

There are three different types of layers, as can be seen in Figure 2. The input layer, represented by the green circles, is fed the input dataset, meaning that the size of this layer must be equal to the size of every instance in the dataset (60 in this work). The output layer, represented by the blue circles, is populated by the output variable to be estimated, meaning that the size must match the number of categories described in Section 2.2 (four in this work). Moreover, there are one or more intermediate layers, usually known as hidden layers, which are represented by the orange circles in Figure 2. The hidden layers can have different sizes. To fit the parameters of these layers to the data, a backpropagation algorithm [35] was used, with normalized exponential (softmax) as the activation function of the output layer and rectified linear unit (ReLU) as the activation function of the hidden layers.

In this article, the notation $Net\_X_1\_\ldots\_X_n\_Y$ represents a feed-forward ANN architecture with n hidden layers with size X_i for hidden layer i and size Y for the output layer. In particular, eight architectures with a different number of hidden layers and different amounts of neurons in the layers were trained on the 24 datasets described in Section 2.1, resulting in 192 models used in the comparison. The eight detailed architectures are the following: Net_16_4, Net_32_4, Net_64_4, $Net\_16\_16\_4$, $Net\_32\_32\_4$, $Net\_64\_32\_4$, $Net\_16\_16\_16\_4$, and $Net\_64\_32\_16\_4$. Note that all the models have four neurons in the output layer.

2.5. *Performance Metrics*

In this study, the classification performance of the trained models was measured globally and for each category using three different metrics: Accuracy, F1-Score, and Balanced Accuracy.

Accuracy, the percentage of elements correctly labeled by the model, was calculated using Equation (2) to evaluate the global performance of the models:

$$Accuracy = \frac{\sum_{i=1}^{C} TP_i}{N}, \tag{2}$$

where N is the quantity of elements, C is the number of categories, and TP_i is the quantity of elements belonging to real category i correctly labeled by the model as category i for every category i. By definition, the Accuracy is a real number between 0 and 1. A high Accuracy indicates good global performance of the model, with the best result reaching 1 when all the elements are correctly labeled by the model.

On the other hand, F1-Score and Balanced Accuracy were calculated for every category i to evaluate the performance of the model over every category. Thr F1-Score is the harmonic mean of the trade-off metrics, precision and recall, as defined in Equation (3), for every category i:

$$F1 - Score_i = 2 * \frac{Precision_i * Recall_i}{Precision_i + Recall_i}, \tag{3}$$

where

$$Precision_i = \frac{TP_i}{TP_i + FP_i}, and \tag{4}$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i}. \tag{5}$$

FN_i is the quantity of elements belonging to real category i incorrectly labeled by the model as a category different from i, while FP_i is the quantity of elements not belonging to real category i incorrectly labeled by the model as category i. The maximum possible F1-score value is 1, which indicates perfect precision and recall, while the minimum possible value is 0, which is the case if either precision or recall is zero.

Second, Balanced Accuracy is the arithmetical mean of the trade-off metrics, sensitivity and specificity, as shown in Equation (6):

$$Balanced\ Accuracy_i = \frac{Sensitivity_i + Specificity_i}{2}, \tag{6}$$

where

$$Sensitivity_i = \frac{TP_i}{TP_i + FN_i}, \tag{7}$$

$$Specificity_i = \frac{TN_i}{TN_i + FP_i}, \tag{8}$$

and FN_i is the quantity of elements belonging to real category i incorrectly labeled by the model as belonging to a category other than i. The highest possible Balanced Accuracy value is 1, indicating perfect Sensitivity and Specificity, and the lowest possible value is 0, which is the case if both Sensitivity and Specificity are zero.

In summary, when evaluating a particular category, the closer the Balanced Accuracy and F1-Score are to 1, the better the model can correctly classify observations.

3. Results and Discussion

This section presents and discusses the results obtained in the comparison between trained models for the different ANN architectures. This evaluation was carried out in three approaches: global performance, time slot, and environmental acoustic pattern.

First, the performance of the different models on the test datasets was calculated using Accuracy as a global metric. Table 3 shows the Accuracy of the 192 trained models for the eight ANNs defined in Section 2.4 on the test subsets of the 24 datasets representing each hourly time slot, where time slot X corresponds to the interval from X:00 hour to X:59 hour, as defined in Section 2.3.

Table 3. Accuracy of the trained models over the 24-hour time slot datasets. Different colors represent an accuracy heat-map to visually identify patterns.

Model	**Hourly Time Slot** 0	1	2	3	4	5	6	7	8	9	10	11
Net_16_4	0.543	0.574	0.538	0.447	0.609	0.546	0.544	0.552	0.494	0.566	0.538	0.564
Net_32_4	0.597	0.549	0.533	0.546	0.521	0.393	0.454	0.476	0.392	0.459	0.515	0.508
Net_64_4	0.392	0.525	0.472	0.393	0.564	0.556	0.544	0.390	0.460	0.393	0.532	0.516
Net_16_16_4	0.604	0.557	0.475	0.492	0.584	0.538	0.562	0.502	0.517	0.571	0.361	0.259
Net_32_32_4	0.551	0.538	0.531	0.556	0.519	0.543	0.442	0.514	0.504	0.492	0.435	0.535
Net_64_32_4	0.602	0.532	0.565	0.530	0.576	0.550	0.523	0.553	0.549	0.583	0.480	0.390
Net_16_16_16_4	0.515	0.522	0.568	0.559	0.515	0.598	0.527	0.396	0.394	0.524	0.584	0.571
Net_64_32_16_4	0.560	0.561	0.555	0.498	0.528	0.480	0.449	0.488	0.441	0.515	0.396	0.355
Average	**0.545**	**0.545**	**0.530**	**0.503**	**0.552**	**0.525**	**0.506**	**0.484**	**0.469**	**0.513**	**0.480**	**0.462**

Model	**Hourly Time Slot** 12	13	14	15	16	17	18	19	20	21	22	23
Net_16_4	0.615	0.635	0.664	0.544	0.557	0.641	0.622	0.529	0.639	0.683	0.485	0.568
Net_32_4	0.531	0.517	0.490	0.578	0.599	0.571	0.634	0.392	0.423	0.389	0.666	0.386
Net_64_4	0.436	0.551	0.530	0.579	0.485	0.540	0.468	0.588	0.585	0.584	0.150	0.611
Net_16_16_4	0.454	0.537	0.626	0.635	0.610	0.630	0.634	0.657	0.490	0.615	0.548	0.605
Net_32_32_4	0.384	0.339	0.517	0.389	0.385	0.452	0.561	0.504	0.595	0.497	0.494	0.427
Net_64_32_4	0.616	0.385	0.652	0.387	0.631	0.618	0.480	0.612	0.643	0.695	0.557	0.396
Net_16_16_16_4	0.332	0.531	0.575	0.586	0.572	0.614	0.629	0.556	0.665	0.609	0.390	0.396
Net_64_32_16_4	0.380	0.497	0.564	0.382	0.343	0.533	0.370	0.473	0.420	0.334	0.408	0.587
Average	**0.468**	**0.499**	**0.577**	**0.510**	**0.523**	**0.575**	**0.550**	**0.539**	**0.558**	**0.551**	**0.462**	**0.497**

The global performance of the models depends on the time slot and the model, as expected; *Net*_64_32_4, from 21:00 to 21:59, shows the highest Accuracy at 0.6943, resulting in the best combination of architecture and hourly time slot. This is a particular insight, very valuable for city managers; however, this asseveration is difficult to generalize for other cities. Analyzing these results, a discussion is provided in the following paragraphs in order to obtain more general conclusions.

Due to the existence of four categories, adopting a random model supposes an Accuracy of 0.25 in each of them. As shown in Table 3, in general, all models across every hour exceed the random model except one. As the pattern categories are not equally distributed (see Figure 1), a baseline model could be the selection of the most representative category with an Accuracy of 0.39 (=27/70). Even though the Accuracy of the models ranges from 0.150 to 0.694, 160 of the 192 models (83%) have an Accuracy higher than the baseline model. In addition, a one-sided parametric hypotheses testing was carried out with the hypotheses represented in Equation (9):

$$\begin{cases} H_0 : \mu \leq 0.39 \\ H_1 : \mu > 0.39 \end{cases} \tag{9}$$

Considering the central limit theorem, the test statistic follows a Student's t-distribution with 191 degrees of freedom, and the estimator of the test is 18.929, equivalent to a $p - value < 2.2 * 10^{-16}$. Therefore, the null hypothesis is rejected, leading to the conclusion that the improvement when using an ANN to estimate the long-term environmental acoustic pattern of a spot based on short-term data is statistically significant.

Regarding the optimum hourly time slot to capture data that best represent the long-term pattern, Table 3 shows that on average every hourly time slot improves the baseline model; the better hourly time slots to predict environmental acoustic behaviors are 14, 17, 20, 4, and 21, in which the averaged Accuracy is higher than 0.55. Finally, the worst time slots to capture data are 7, 10, 8, 12, 22, and 11, in which the Accuracy is lower than 0.49.

However, outliers decrease the representativeness of the mean value. Therefore, a median Accuracy analysis was performed to minimize the impact of outliers in the above results. The Accuracy distribution for each hourly time slot ordered by the median of the Accuracy is shown in Figure 3. These hourly time slots are colored yellow for daytime periods (from 7:00 a.m. to 7:00 p.m.), orange for evening periods (from 7:00 p.m. to 11:00 p.m.), and gray for night periods (from 11:00 p.m. to 07:00 a.m.), as defined in Directive 2002/49/EC [2].

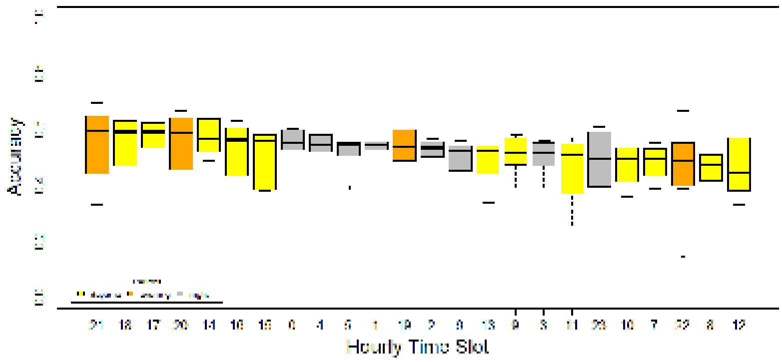


Figure 3. Statistical distributions of the Accuracy variable for each hourly time slot, represented though box and whisker plot and sorted by the median value of the Accuracy in decreasing order.

Figure 3 shows that 21, 18, and 17 are the best hourly time slots, in this order. On the other hand, the worst time slots are 22, 8, and 12. The top seven most accurate hourly time slots are in the interval 14 to 21. From this interval, only 19 is not in the ranking, falling to the twelfth position. Therefore, the period from 14:00 to 22:00 is recommended to capture data and estimate the location acoustic pattern.

Next, the impact of the complexity of the ANN architecture on the performance in the classification was analyzed. Figure 4 shows a comparison of the distribution of the Accuracy performance metric. The fill color represents the number of hidden layers, with light blue, blue, and dark blue standing for 1, 2, and 3, respectively. Although the models with a higher quantity of hidden layers have the highest average Accuracy, the amount of neurons in the layers does not significantly affect Accuracy.

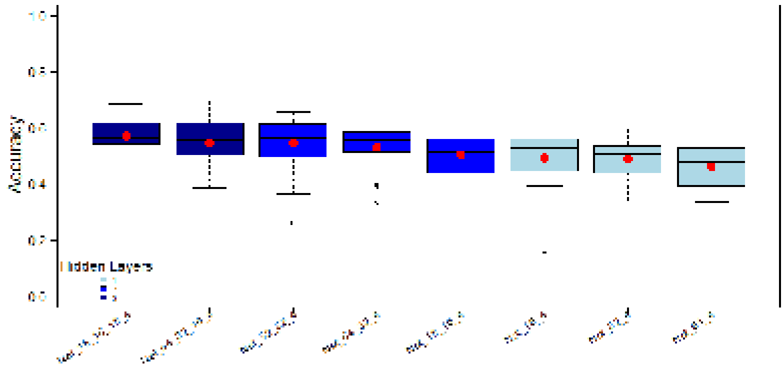
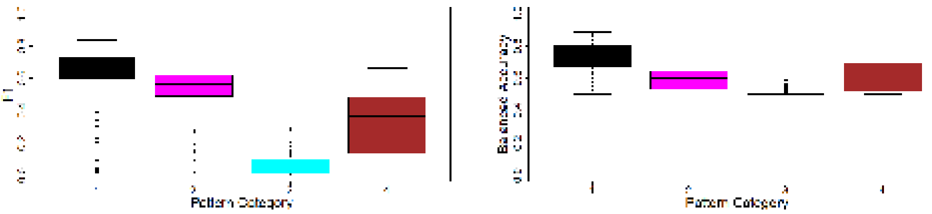


Figure 4. Statistical distributions of the variable Accuracy for every ANN Model ordered by mean value (red circle) represented though box and whisker plots. The colors group the models by their quantity of hidden layers.

Finally, the performance of the models in relation to each pattern category, as described in Section 2.2, was evaluated using Balanced Accuracy and F1-score.

Figure 5 shows that Pattern Category 1 has the best performance on average (0.63 F1-Score and 0.75 Balanced Accuracy), followed by Categories 2 (0.53 F1-Score and 0.59 Balanced Accuracy) and 4 (0.32 F1-Score and 0.60 Balanced Accuracy). Category 3 is the most difficult to predict (0.07 F1-Score and 0.50 Balanced Accuracy). This observation is inverse correlated with the $sd_{2019}(L_{den1d})$ of each pattern category, meaning that its higher the volatility makes this category harder to predict. It is important to note that one-hour time slots are used as a short-term measurement period; thus, improvements in the predictions for Pattern Category 3 can be achieved by combining data from two or more hourly time slots.



(a) (b)

Figure 5. Statistical distributions of F1-Score (a) and Balanced Accuracy (b) performance metrics for every environmental acoustic pattern, represented as box and whisker plots.

To obtain further insights into the prediction ability, an hourly time slot F1-Score performance comparison was carried out for every category.

Figure 6 shows similar trends in Categories 1 and 2 regarding median F1-Score for each hourly time slot. Most of these have low variability, meaning that in general any period could be used to predict these environmental pattern categories. On the contrary, Category 3 has low performance at all time slots, improving in the nightly period, but not enough to be confident in the prediction. Therefore, other strategies, for example, increasing the size of the time period or including several hourly time slots as input data, should be considered in future works. Finally, Category 4 presents a wide range of performance values, highlighting the nightly period 21:00–02:00 as the best period. Moreover, the variability of the F1-Score distribution for Category 4 is the highest of all categories.

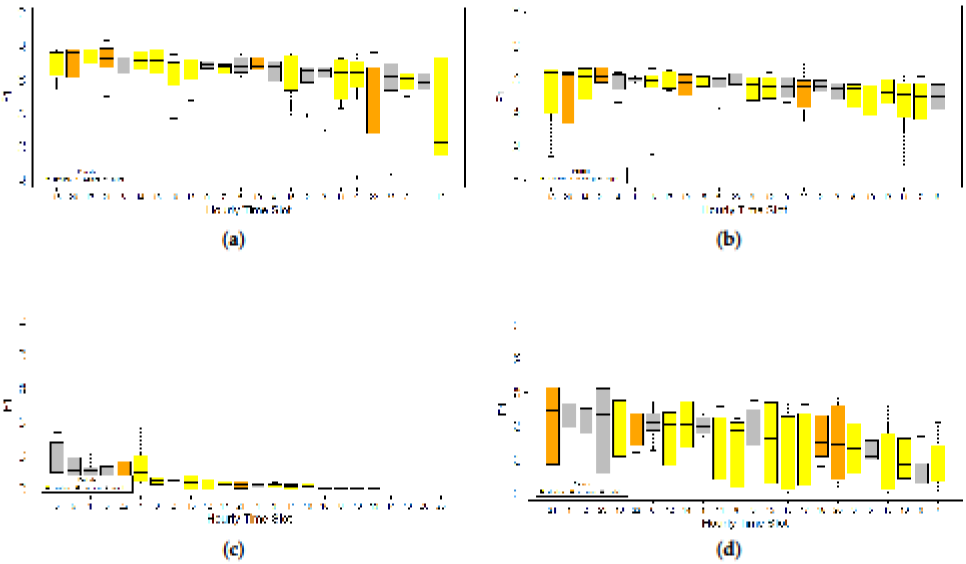


Figure 6. Statistical distributions of the F1-Score variable for every hourly time slot, broken down into the four environmental acoustic behaviors (subfigures **a**, **b**, **c**, and **d** for category patterns 1, 2, 3, and 4, respectively) represented though box and whisker plot.

4. Conclusions

In this paper, we carried out an evaluation of the suitability of predicting the long-term environmental acoustic pattern of a position based on information collected in a short-term interval using artificial neural networks. For this, we used a dataset with sound pressure level values from the city of Barcelona, Spain, captured with a wireless acoustic sensor network. Using several performance metrics, we performed a comparison between 192 models designed with eight different architectures and trained using hourly sound pressure level datasets.

In general, the results show that artificial neural networks can classify short-term acoustic data into one of several recognized long-term environmental acoustic patterns. From a global perspective, models with higher quantity of hidden layers have better performance, even though this performance is not affected by the amount of neurons, and the performance increases if the data are gathered in an hourly time slot included in the interval from 14:00 to 22:00. Regarding particular environmental acoustic patterns, those with lower sound pressure level variability are easier to estimate using hourly sound pressure level measurements.

The provided insights are crucial to define the data collection methodology in order to assure the most accurate pattern category prediction and avoid bias created by stable routines with temporal stations. Moreover, it is recommended to capture data at the same time slot in different locations, as this improves recognition of the specific environmental acoustic behavior of a place.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Networks
BCN	Barcelona City (Spain)
IoT	Internet of Things
GPS	Global Positioning System
ReLU	Rectified Linear Unit
SNN	Strategic Noise Map
WASN	Wireless Acoustic Sensor Network

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III – RESULTADOS OBTENIDOS

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La contaminación acústica es una preocupación importante en las ciudades de todo el mundo y se están desplegando redes de sensores acústicos inalámbricos para adquirir información sobre el nivel de presión sonora en muchas ubicaciones y durante largos períodos de tiempo.

Esta tesis define y desarrolla técnicas y metodologías apoyadas en la ciencia de datos mediante tecnologías big data, con el objetivo de construir soluciones que permitan a los consistorios mejorar la gestión de la contaminación acústica de las ciudades.

En primer lugar, se ha diseñado una metodología de análisis de entornos acústicos urbanos aplicando técnicas de aprendizaje automático no supervisado, para identificar y clasificar diferentes patrones de comportamiento acústicos de la ciudad utilizando indicadores de nivel de presión sonora. Para asegurar que todos los consistorios pueden beneficiarse de estas metodologías, los niveles de presión sonora utilizados son los indicados por la directiva europea 2002/49/CE [4] para la elaboración del SNM, es decir el promedio anual durante el día, la tarde y la noche junto con la variabilidad diaria como entrada para el enfoque de agrupamiento.

Esto permite obtener diferentes patrones de comportamiento acústicos que enriquecen los indicados en la citada directiva. Adicionalmente, se ha realizado un análisis de dicha metodología aplicada a la ciudad de Barcelona en la que las técnicas de optimización utilizadas han mostrado la existencia de 4 patrones de comportamiento diferencias que deben ser gestionados por los gestores de las ciudades. Además, mediante las técnicas descritas en la investigación es posible realizar un seguimiento periódico de la evaluación de los patrones de comportamiento sin necesidad de esperar a la elaboración del siguiente SNM como establece la normativa permitiendo una evaluación continua de las acciones que se establezcan en los planes de acción.

En segundo lugar, compartir datos entre las administraciones en una infraestructura de big data, como promueve la Comisión Europea, puede ayudar a obtener mejores conocimientos y crear un marco común. Para ello, en esta tesis se han establecido procedimientos basados en técnicas de aprendizaje federado que permiten la compartición del conocimiento de los datos sin necesidad de compartir los datos asegurando el control de los mismo por parte de cada consistorio, asegurando además el enriquecimiento de los datos propios con patrones de comportamiento de otras ciudades.

Estos estudios han demostrado que es posible aplicar técnicas de agrupamiento de aprendizaje automático para identificar diferentes patrones de entorno acústico a partir de conjuntos de datos de nivel de presión sonora de varias ciudades En particular, se ha realizado una comparación de técnicas de agrupamiento para modelar datos acústicos de redes de sensores acústicos inalámbricos de las ciudades de Barcelona y Madrid (España). Esta evaluación se ha realizado utilizando datos aislados y datos federados, y tres parámetros como métricas, probando que el uso de datos federados mejora la identificación de patrones de comportamiento acústicos.

Además, se han incluido una serie de recomendaciones a los consistorios sobre el impacto que se obtiene en los patrones acústicos en función de las métricas de evaluación consideradas, facilitando al consistorio la personalización de sus análisis a la situación y necesidades de la ciudad.

En tercer lugar, durante la investigación llevamos a cabo una evaluación de la idoneidad de predecir el patrón acústico ambiental a largo plazo de una posición basada en información recopilada en un intervalo a corto plazo utilizando redes neuronales artificiales. Para ello, utilizamos un conjunto de datos con valores de nivel de presión sonora por hora que sirven de base de entrenamiento de redes neuronales basados en ocho arquitecturas diferentes.

Los resultados muestran que las redes neuronales artificiales pueden clasificar los datos acústicos de corto plazo en uno de varios patrones acústicos ambientales de largo plazo reconocidos.

Además, se identifican las características de las redes neuronales que permiten realizar mejores estimaciones en particular, las arquitecturas con una mayor cantidad de capas ocultas tienen un mejor rendimiento, aunque este rendimiento no se ve afectado por la cantidad de neuronas, y el rendimiento aumenta si los datos se recopilan en un intervalo de tiempo por hora que incluye desde las 14:00 hasta las 22:00. En cuanto a patrones acústicos ambientales particulares, aquellos con una menor variabilidad de niveles de presión sonora son más fáciles de estimar utilizando mediciones de niveles de presión sonora por hora.

En resumen, esta tesis concluye que aplicando técnicas de ciencia de datos como el aprendizaje no supervisado se pueden agrupar los nodos de una WASN en grupos con el mismo comportamiento y reconocer patrones complejos sobre esta base. Estos patrones complejos pueden proporcionar información a los gestores de la ciudad para establecer estrategias personalizadas y definir nuevas áreas acústicas junto con sus planes de acción. Además, para acelerar la identificación de los patrones de comportamiento se propone la aplicación de una técnica de aprendizaje automático supervisado para predecir el grupo de comportamiento acústico a largo plazo al que pertenece una ubicación mediante mediciones a corto plazo. De esta manera, las estaciones temporales pueden ser utilizadas por los gestores de la ciudad para identificar el patrón acústico ambiental de un sitio, mejorando el valor del WASN y fortaleciendo la gestión de la contaminación acústica cumpliendo los objetivos específicos indicados en el Capítulo I de esta memoria.

IV - REFERENCIAS BIBLIOGRÁFICAS

IV - REFERENCIAS BIBLIOGRÁFICAS

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V – ANEXOS

V - ANEXOS

ANEXO 1. Calidad de las Publicaciones

En este anexo se presentan los datos relativos a la calidad de las publicaciones incluidas en la tesis por compendio

1. Pita A, Rodriguez FJ, Navarro JM. Cluster Analysis of Urban Acoustic Environments on Barcelona Sensor Network Data. International Journal of Environmental Research and Public Health. 2021; 18(16):8271. https://doi.org/10.3390/ijerph18168271.

Calidad de la publicación: Año 2021:

- Revista: *1660-4601* International Journal of Environmental Research and Public Health
- Índice de Impacto (2021): 4.614
- Revisión por pares: Sí
- Categoría: Public Environmental & Occupation Health
- Puesto en el JCR: 45/182
- Calidad de la revista: Q1

Figura 1 Citas totales de la revista International Journal of Environmental Research and Public Health a lo largo de los últimos 5 años

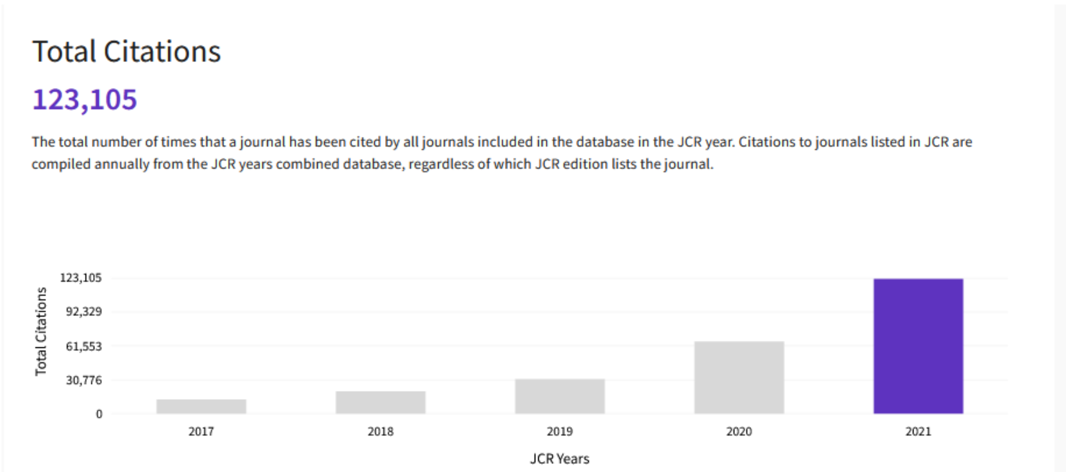


Figura 2 Clasificación JCR histórica de International Journal of Environmental Research and Public Health

EDITION

Social Sciences Citation Index (SSCI)

CATEGORY

PUBLIC, ENVIRONMENTAL & OCCUPATIONAL HEALTH

45/182

JCR YEAR	JIF RANK	JIF QUARTILE	JIF PERCENTILE
2021	45/182	Q1	75.55
2020	42/176	Q1	76.42
2019	32/171	Q1	81.58
2018	38/164	Q1	77.13
2017	43/157	Q2	72.93

2. Pita A, Rodriguez FJ, Navarro JM. Analysis and Evaluation of Clustering Techniques Applied to Wireless Acoustics Sensor Network Data. Applied Sciences. 2022; 12(17):8550. https://doi.org/10.3390/app12178550.

Calidad de la publicación: Año 2021 (último año publicado)

- Revista: 2076-3417 Applied Science
- Índice de Impacto (2021): 2.838
- Revisión por pares: Sí
- Categoría: Physics, Applied
- Puesto en el JCR: 76/161
- Calidad de la revista: Q2

Figura 3 Citas totales de la revista International Applied Sciences a lo largo de los últimos 5 años

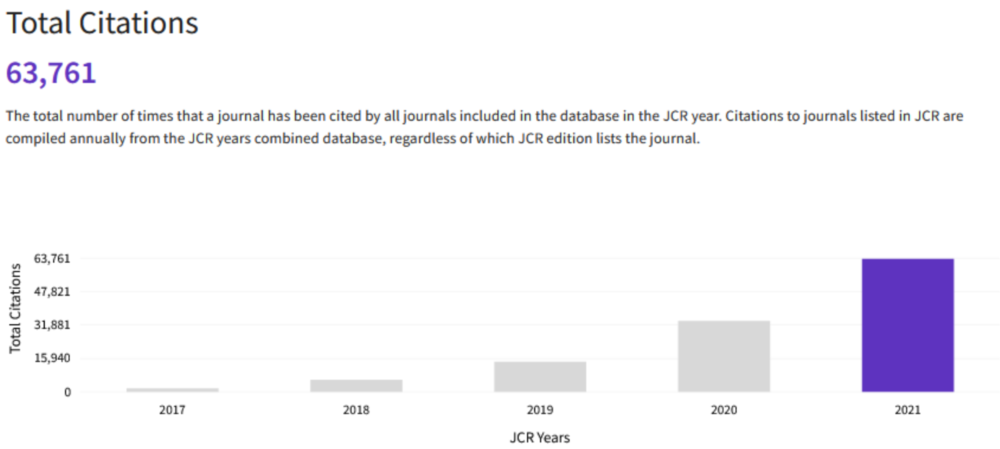


Figura 4 Clasificación JCR histórica de Applied Sciences

EDITION
Science Citation Index Expanded (SCIE)

CATEGORY
PHYSICS, APPLIED
76/161

JCR YEAR	JIF RANK	JIF QUARTILE	JIF PERCENTILE
2021	76/161	Q2	53.11
2020	73/160	Q2	54.69
2019	63/155	Q2	59.68
2018	67/148	Q2	55.07
2017	77/146	Q3	47.60

3. Navarro JM, Pita A. Machine Learning Prediction of the Long-Term Environmental Acoustic Pattern of a City Location Using Short-Term Sound Pressure Level Measurements. Applied Sciences. 2023; 13(3):1613. https://doi.org/10.3390/app13031613.

   Calidad de la publicación: Año 2021 (último año publicado)
   - Revista: 2076-3417 Applied Science
   - Índice de Impacto (2021): 2.838
   - Revisión por pares: Sí
   - Categoría: Physics, Applied
   - Puesto en el JCR: 76/161

- Calidad de la revista: Q2

Figura 5 Citas totales de la revista International Applied Sciences a lo largo de los últimos 5 años

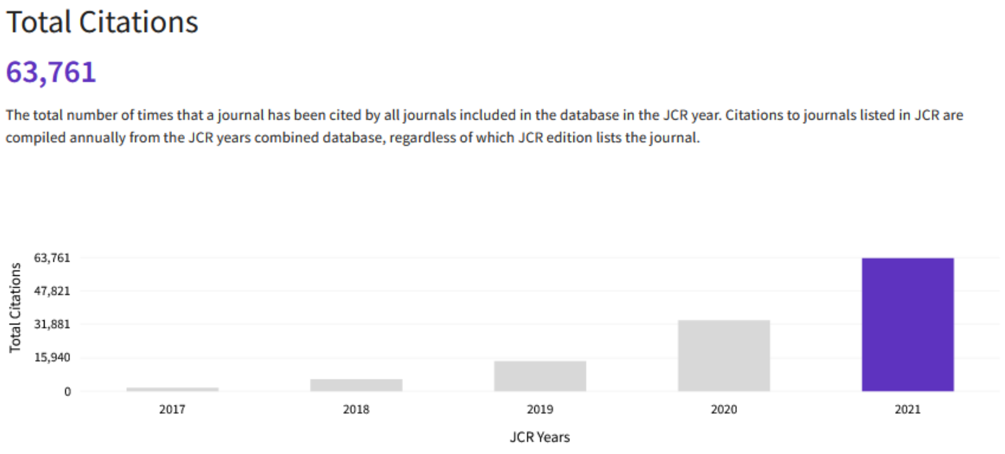
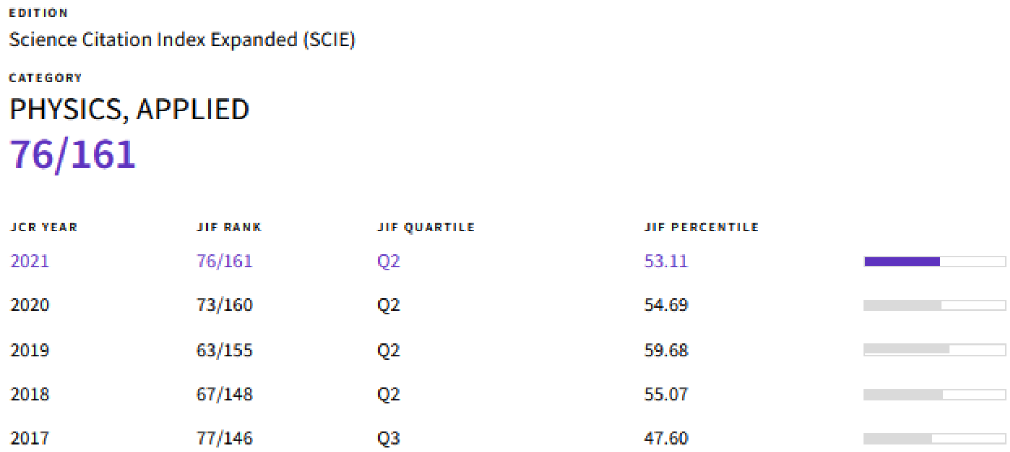


Figura 6 Clasificación JCR histórica de Applied Sciences

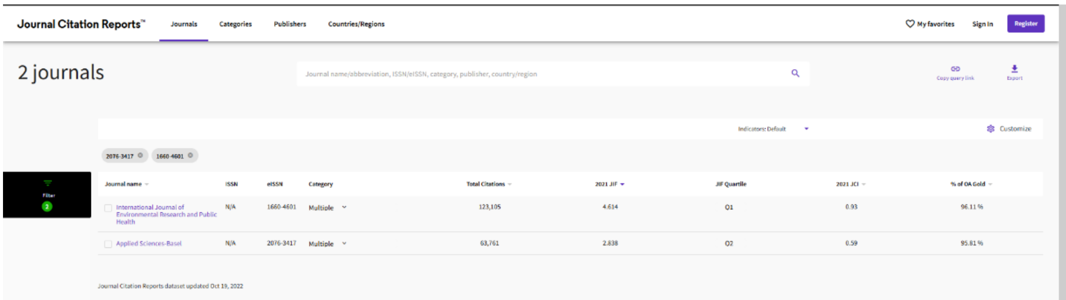

EDITION
Science Citation Index Expanded (SCIE)

CATEGORY
PHYSICS, APPLIED
76/161

JCR YEAR	JIF RANK	JIF QUARTILE	JIF PERCENTILE
2021	76/161	Q2	53.11
2020	73/160	Q2	54.69
2019	63/155	Q2	59.68
2018	67/148	Q2	55.07
2017	77/146	Q3	47.60

Como resumen, la siguiente figura muestra la clasificación de ambas revistas según el Journal Citation Reports. Dicha información está disponible en el siguiente enlace.

Figura 7 Clasificación JCR de las revistas indicadas



Journal name	ISSN	eISSN	Category	Total Citations	2021 JIF	JIF Quartile	2021 JCI	% of OA Gold
International Journal of Environmental Research and Public Health	N/A	1660-4601	Multiple	123,105	4.614	Q1	0.93	96.11 %
Applied Sciences-Basel	N/A	2076-3417	Multiple	63,761	2.838	Q2	0.59	95.81 %

•

ANEXO 2. **Méritos Adicionales durante el Doctorado**

Durante la realización del doctorado de Tecnologías de la Computación e Ingeniería Ambiental se han realizado las siguientes actividades adicionales a los artículos presentados como compendio de publicaciones:

Presentación de Poster en las Jornadas VI Jornadas de Investigación y Doctorado: ODS con Ciencia de la EIDUCAM celebradas el día 26 de junio de 2020 en Murcia.

Figura 8 Poster presentado en las Jornadas VI Jornadas de Investigación y Doctorado

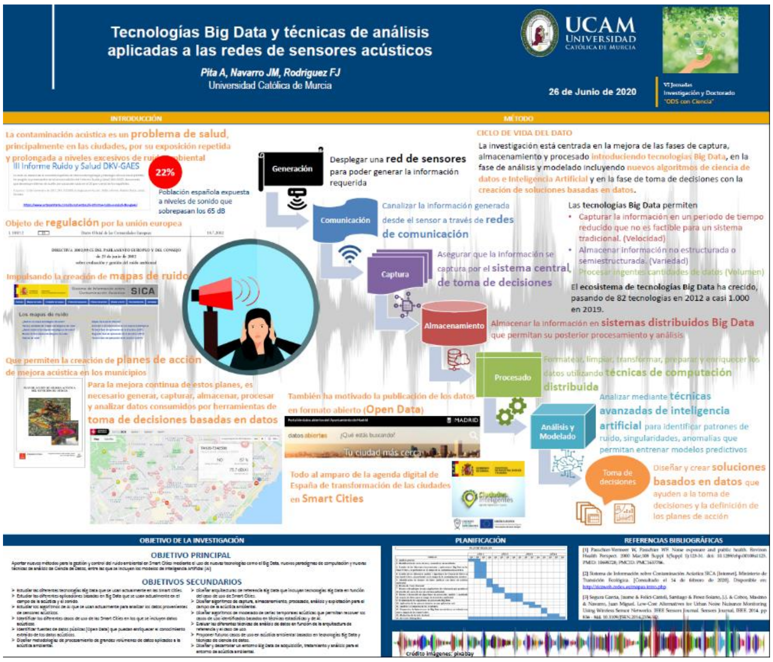
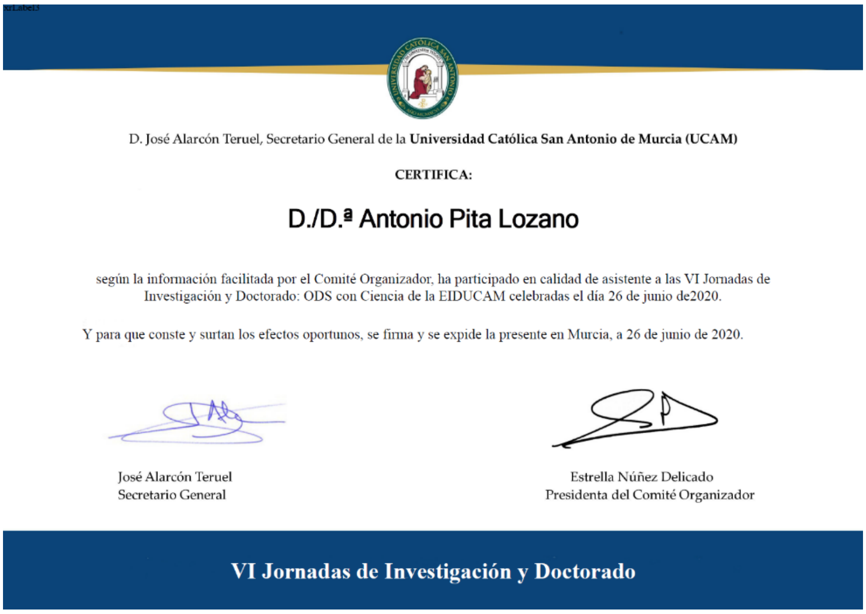


Figura 9 Certificado de participación en las Jornadas VI Jornadas de Investigación y Doctorado



D. José Alarcón Teruel, Secretario General de la **Universidad Católica San Antonio de Murcia (UCAM)**

CERTIFICA:

D./D.ª Antonio Pita Lozano

según la información facilitada por el Comité Organizador, ha participado en calidad de asistente a las VI Jornadas de Investigación y Doctorado: ODS con Ciencia de la EIDUCAM celebradas el día 26 de junio de2020.

Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 26 de junio de 2020.

José Alarcón Teruel
Secretario General

Estrella Núñez Delicado
Presidenta del Comité Organizador

VI Jornadas de Investigación y Doctorado

Presentación de Comunicación Científica Oral en las Jornadas VII Jornadas de Investigación y Doctorado celebradas el día 25 de junio de 2021 en Murcia.

Figura 10 Certificado de Asistencia a las VII Jornadas de Investigación y Doctorado

UCAM
UNIVERSIDAD CATÓLICA DE MURCIA

D. José Alarcón Teruel, Secretario General de la Universidad Católica San Antonio de Murcia (UCAM)

CERTIFICA

Que según la información facilitada por el Comité Organizador de las ***VII Jornadas de Investigación y Doctorado***

Antonio Pita Lozano

ha asistido satisfactoriamente a los actos y actividades desarrolladas durante las VII Jornadas de Investigación y Doctorado "ODS con Ciencia".

Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 25 de junio de 2021.

José Alarcon Teruel
Secretario General UCAM

Estrella Núñez Delicado
Vicerrectora de Investigación
Directora de la Escuela Internacional de Doctorado UCAM

Figura 11 Certificado de Comunicación Oral en las Jornadas VII Jornadas de Investigación y Doctorado

UCAM
UNIVERSIDAD CATÓLICA DE MURCIA

D. José Alarcón Teruel, Secretario General de la Universidad Católica San Antonio de Murcia (UCAM)

CERTIFICA

Que según la información facilitada por el Comité Organizador de las ***VII Jornadas de Investigación y Doctorado***

Antonio Pita Lozano

perteneciente al Programa en Tecnologías de la Computación e Ingeniería Ambiental, ha presentado **Comunicación Científica Oral** titulada:
"Machine Learning Unsupervised Identification of Urban Acoustic Environments Based on Distributed Sensor Network Data"

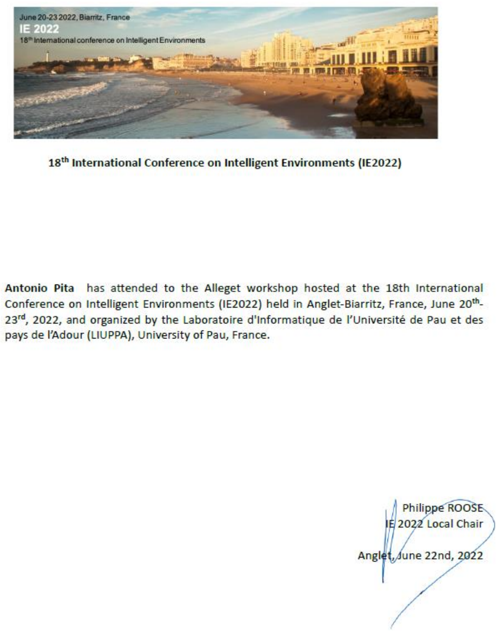
Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 25 de junio de 2021.

José Alarcon Teruel
Secretario General UCAM

Estrella Núñez Delicado
Vicerrectora de Investigación
Directora de la Escuela Internacional de Doctorado UCAM

Presentación de Comunicación Científica Oral en el 19th International Conference on Intelligent Environments (IE 2022) celebrado entre el 20 y el 23 de junio de 2022 en Anglet-Biarriz (Francia).

Figura 12 Certificado de Asistencia a las Jornadas 18th International Conference on Intelligent Environments



June 20-23 2022, Biarritz, France
IE 2022
18th International conference on Intelligent Environments

18th International Conference on Intelligent Environments (IE2022)

Antonio Pita has attended to the Alleget workshop hosted at the 18th International Conference on Intelligent Environments (IE2022) held in Anglet-Biarritz, France, June 20th-23rd, 2022, and organized by the Laboratoire d'Informatique de l'Université de Pau et des pays de l'Adour (LIUPPA), University of Pau, France.

Philippe ROOSE
IE 2022 Local Chair
Anglet, June 22nd, 2022

En la Conferencia se realizó una comunicación titulada "On the Application of Unsupervised Clustering to Sound Pressure Data from an Acoustic Sensors

Network" que posteriormente fue publicada como capítulo del libro Volume 31: Workshops at 18th International Conference on Intelligent Environments (IE2022). El artículo puede consultarse y descargarse en el siguiente link.

Figura 13 Comunicación presentada en las Jornadas 18th International Conference on Intelligent Environments.

170 *Workshops at 18th International Conference on Intelligent Environments (IE2022)*
H.H. Alvarez Valera and M. Luštrek (Eds.)

doi:10.3233/AISE220037

On the Application of Unsupervised Clustering to Sound Pressure Data from an Acoustic Sensors Network

Antonio PITA [a], Francisco J. RODRIGUEZ [a] Juan M. NAVARRO [a]
[a] *Research Group in Advanced Telecommunications (GRITA), Universidad Católica de Murcia (UCAM), 30107 Guadalupe, Spain*

Abstract. Many cities around the world are deploying wireless sensor networks to capture information on different environmental parameters. Noise, as one of the main pollutants with negative effects on health and economy, is monitored through sound pressure level. In this work, the application of unsupervised clustering to sound pressure level data from a wireless acoustic sensors network (WASN) is proposed. Data from a sensor network deployed in the city of Madrid are used to show the usefulness of performing a clustering process with the aim of detecting different patterns of behavior of noise levels. The preliminary results obtained have allowed us to divide the city into several acoustic zones, which help city managers to propose improvement plans.

Keywords. Environmental Noise Assessment; Machine Learning; Urban Acoustic Environment; Artificial Intelligence of Things; Unsupervised Identification; Internet of Things

Introduction

The European Directive 2002/49/EC aims to establish a common approach aimed at avoiding, preventing or reducing, as a priority, the harmful effects, including annoyances, of exposure to environmental noise [1].

To this end, it urges the rulers of cities to determine exposure to environmental noise, make this information available to the population and adopt action plans. The objective of these action plans is to prevent and reduce environmental noise when it has harmful effects on human health and to maintain quality of the acoustic environment when this is satisfactory.

Participación y tercer puesto en la iniciativa “Mi Tesis en 3 minutos celebradas el día 24 de junio de 2022 en Murcia.

Figura 14 Comunicación presentada en las Jornadas 18th International Conference on Intelligent Environments

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D. José Alarcón Teruel, Secretario General de la Universidad Católica San Antonio de Murcia (UCAM)

CERTIFICA

Que según la información facilitada por el Comité Organizador de las ***VIII Jornadas de Investigación y Doctorado "Ética en la Investigación Científica"***

D. Antonio Pita Lozano

perteneciente al Programa de Doctorado en Tecnologías de la Computación e Ingeniería Ambiental, ha obtenido el **3º PREMIO a la Mejor Exposición "Mi Tesis en 3 Minutos"** que lleva por título:

"Tecnologías Big Data y Técnicas de Análisis Aplicadas a las Redes de Sensores Acústicos".

Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 24 de junio de 2022.

José Alarcon Teruel
Secretario General UCAM

Estrella Núñez Delicado
Vicerrectora de Investigación
Directora de la Escuela Internacional de Doctorado UCAM

Presentación de Comunicación Científica Oral en las Jornadas VIII Jornadas de Investigación y Doctorado celebradas el día 24 de junio de 2022 en Murcia.

Figura 15 Certificado de Asistencia a las VIII Jornadas de Investigación y Doctorado

UCAM
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D. José Alarcón Teruel, Secretario General de la Universidad Católica San Antonio de Murcia (UCAM)

CERTIFICA

Que según la información facilitada por el Comité Organizador de las ***VIII Jornadas de Investigación y Doctorado "Ética en la Investigación Científica"***

Antonio Pita Lozano

ha asistido satisfactoriamente a los actos y actividades desarrolladas durante las VIII Jornadas de Investigación y Doctorado "Etica en la Investigación Científica" celebradas en la Universidad Católica de Murcia.

Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 24 de junio de 2022.

José Alarcon Teruel
Secretario General UCAM

Estrella Núñez Delicado
Vicerrectora de Investigación
Directora de la Escuela Internacional de Doctorado UCAM

Figura 16 Certificado de Comunicación Oral en las Jornadas VIII Jornadas de Investigación y Doctorado

UCAM
UNIVERSIDAD CATÓLICA DE MURCIA

D. José Alarcón Teruel, Secretario General de la Universidad Católica San Antonio de Murcia (UCAM)

CERTIFICA

Que según la información facilitada por el Comité Organizador de las ***VIII Jornadas de Investigación y Doctorado "Ética en la Investigación Científica"***

Antonio Pita Lozano

perteneciente al Programa de Doctorado en Tecnologías de la Computación e Ingeniería Ambiental, ha presentado Comunicación Científica Oral titulada:

"Cluster Analysis of Urban Acoustic Environments"

Pita Lozano, Antonio; Rodríguez Martínez, Francisco Javier; Navarro Ruiz, Juan Miguel

Y para que conste y surtan los efectos oportunos, se firma y se expide la presente en Murcia, a 24 de junio de 2022.

José Alarcon Teruel
Secretario General UCAM

Estrella Núñez Delicado
Vicerrectora de Investigación
Directora de la Escuela Internacional de Doctorado UCAM

ANEXO 3. Méritos Adicionales previos al Doctorado

Previo a la realización del doctorado de Tecnologías de la Computación e Ingeniería Ambiental se han realizado las siguientes actividades adicionales a los artículos presentados como compendio de publicaciones:

Formación:

- 1996-2001 Licenciatura en Matemáticas – Universidad de Murcia
- 2001-2003 Diploma de Estudios Avanzados en Algebra – Universidad de Murcia
- 2008-2010 Máster en Dirección de Empresas y Marketing (especialidad en Dirección Financiera) – UNED
- 2010-2011 Máster en Derecho de la Unión Europea – UNED
- 2011-2012 Máster en Asesoramiento Financiero – Instituto Europeo de Posgrado CEU
- 2012-2013 Experto Universitario en Métodos Avanzadoss de Estadística Aplicada - UNED
- 2014-2015 Master en Virtual Analytics y Big Data – UNIR

Research Publications:

- 2004 Journal Article - Pita, Antonio; del Río, Ángel; Ruiz, Manuel. 2004. Groups of units of integral group rings of Kleinian type Transactions of the American Mathematical Society. American Mathematical Society (AMS). 357-8, pp.3215-3237. DOI: 10.1090/s0002-9947-04-03574-3
- 2006 Book Chapter - Pita, Antonio; del Río, Ángel. 2006. Presentation of the group of units of ZD16-. Book: Groups, Rings and Group Rings Chapman and Hall/{CRC}. DOI: 10.1201/9781420010961 Capitulo 30.
- 2007 Journal Article - Jespers, Eric; Pita, Antonio; del Río, Ángel; Ruiz, Manuel; Zalesskii, Pavel. 2007. Groups of units of integral group rings commensurable with direct products of free-by-free groups Advances in Mathematics. Elsevier {BV}. 212-2, pp.692-722. DOI: 10.1016/j.aim.2006.11.005

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- 2018 Journal Article - Gil-Madrona, Pedro; Pita-Lozano, Antonio; Díaz-Suárez, Arturo; López Sánchez, Guillermo Felipe. 2018. Analysis of Perceived Physical and Motor Competence in 10- to 13-year-old Spanish Children Motricidade. Motricidade. pp.Vol 14 No 4 (2018): Motricidade-Vol 14 No 4 (2018): Motricidade. DOI: 10.6063/motricidade.13679

Contratos de Investigación de Competición Pública:

- Ministerio de Educación y Ciencia. Propiedades aritméticas, categóricas y homológicas de anillos y algebras. (Universidad de Murcia). 10/2006-09/2009. 115.434 €. DGES MTM2006-06865
- Fundación Seneca - Aspectos aritméticos, categóricos y homológicos de anillos y algebras. 01/2005-12/2007. 32.776 €. 0482/PI/04
- Ministerio de Ciencia y Tecnología - Propiedades aritméticas, categóricas y homológicas de anillos y algebras. 12/2003-11/2006. 119.380 €. DGES BFM2003-07569-C02-01
- Fundación Seneca - Unidades de anillos de grupo. (Universidad de Murcia). 01/2004-12/2004. 4.110 €. PC-MC/2/00077/FS/02

Comunicaciones en Congresos de Investigación:

- 2013 II Congreso Internacional de Danza, Investigación y Educación a través de la Historia.
- 2019 CTMI 2019: I Conference on Transfer between Mathematics & Industry (Invited Speaker)

Premios:

- 2016 Mejor Científico de Datos de España en la 1 edición de los Data Science Awards

Experiencia Docente en Universidades:

- 2010-2013 Universidad de Murcia - Profesor Asociado
- 2013-2016 Universidad de Almería - Colaborador Docente
- 2014-2018 Universidad de Alcalá – Profesor Colaborador
- 2016-2019 Universidad Internacional de la Rioja - Profesor Colaborador
- 2016- Actual Universidad Oberta de Catalunya – Profesor Colaborador
- 2018- Actual Universidad de Salamanca – Profesor Colaborador