smart cities

MDPI

Article

A Fuzzy Rule-Based System to Infer Subjective Noise Annoyance Using an Experimental Wireless Acoustic Sensor Network

Jose-Angel Fernandez-Prieto [1,*], Joaquin Canada-Bago [1] and Ulrich Birkel [2]

1 Department of Telecommunication Engineering, University of Jaen, 23700 Linares, Spain
2 Department of Electrical Engineering and Information Technology, Technische Hochschule Mittelhessen, 35390 Gießen, Germany
* Correspondence: jan@ujaen.es; Tel.: +34-953648654

Abstract: Over the last few years, several works have been conducted on the design and development of wireless acoustic sensor networks (WASNs) to monitor acoustic noise levels and create noise maps. The information provided by these WASNs is based on the equivalent noise pressure level over time T ($L_{eq,T}$), which is used to assess the objective noise level. According to some authors, noise annoyance is an inherently vague and uncertain concept, and $L_{eq,T}$ does not provide any information about subjective annoyance to humans. Some fuzzy models have been proposed to model subjective annoyance. However, the use of fuzzy rule-based systems (FRBS) that have been adapted to acoustic sensor node resource limitations in real WASN to provide the degree of subjective noise annoyance in real-time remains a largely unexplored region. In this paper, we present the design and implementation of an FRBS that enables the sensor nodes of a real WASN deployed in the city of Linares (Jaen), Spain to infer the degree of subjective noise annoyance in real-time. The hardware used for the sensor nodes is a commercial model, Arduino Due. The results demonstrate that the sensor nodes have sufficient processing capacity and memory to infer the subjective annoyance in real-time, and the system can correctly detect situations that can be considered more annoying by humans.

Keywords: wireless acoustic sensor networks; subjective noise annoyance; fuzzy rule-based system; real deployments

check for updates

Citation: Fernandez-Prieto, J.-A.; Canada-Bago, J.; Birkel, U. A Fuzzy Rule-Based System to Infer Subjective Noise Annoyance Using an Experimental Wireless Acoustic Sensor Network. *Smart Cities* **2022**, *5*, 1574–1589. https://doi.org/10.3390/smartcities5040080

Academic Editors: Véronique Flambard, Sadia Benamrouz-Vanneste and Abir Karami

Received: 10 October 2022
Accepted: 5 November 2022
Published: 9 November 2022

1. Introduction

Noise pollution is one of the main environmental problems in urban areas and affects millions of people worldwide. Different studies [1,2] have demonstrated that long-term exposure to environmental noise affects human social behavior, health (ischemic heart disease, hearing loss, risk of hypertension, etc.), sleep disturbance, and children's cognition. In Europe, more than 100 million people are exposed to damaging levels of environmental noise pollution. Since noise pollution is a serious health issue, the European Commission (EC) adopted an Environmental Noise Directive [3] and the subsequent Common Noise Assessment Methods methodological framework (CNOSSOS-EU) in 2002, requiring member states to obtain real and accurate data on noise sources to provide and publish an accurate mapping of noise levels throughout all urban centers with more than 250,000 citizens and to produce local action plans every five years. Some examples of cities that provide these noise maps are Madrid, Munich, London, Rome, and Helsinki.

The traditional method for obtaining accurate and real data on noise levels is by collecting noise samples by professionals using instruments called sound level meters placed in the area to be mapped. This procedure has some drawbacks, such as the lack of real-time data, the expensive costs of instruments and personnel, the fact that the measurements are carried out only locally and sparsely, and the inability to scale with the demand for higher data granularity in time and space, as recommended by the EC [4]. In this scenario, wireless sensor networks (WSNs) and wireless acoustic sensor networks

(WASNs) [5] play a key role, and currently, they are becoming a reality in smart cities as an alternative that can address these drawbacks and inconveniences. WSNs are the base of the Internet of Things (IoT) that all together give rise to the smart city, which includes the application of "Noise Urban Maps: Sound monitoring in bar areas and centric zones in real time". The range of applications of WSNs is very wide and includes intelligent agriculture, environmental monitoring, public security, public health, transport, etc. [6,7]. WASNs are defined as networks composed of a large number of acoustic sensor nodes. Each node is a resource-constrained device that consists of a processing unit with limited computability and memory, sensing devices (one or more microphones), a communication device, and a limited power source, usually in the form of a battery. Over the last few years, several studies and projects have been proposed to design and develop WASNs for monitoring noise pollution and creating maps of noise levels, as shown in Section 2.

The current noise indicators used to provide information about the objective noise levels are based on the sound pressure level (SPL) and on the equivalent sound pressure level over time T, $L_{eq,T}$ [8]; therefore, noise exposure assessment depends solely on these measurement results (measured in dB). The SPL determines the intensity of the sound that generates a sound pressure (i.e., the sound that reaches a person at a given moment). It is measured in dB, and it ranges from the 0 dB threshold of hearing to the 120 dB threshold of pain. $L_{eq,T}$ is defined as follows:

$$L_{eq,T} = 10\log_{10}\left(\frac{1}{T}\int_0^T \frac{p(t)^2}{p_0^2}dt\right) \tag{1}$$

where p(t) represents the root mean square instantaneous sound pressure level produced by an acoustic wave, $p_o = 2 \times 10^{-5}$ Pa is the reference value corresponding to the minimal audible acoustic signal for a human at 1 kHz, and T is the temporal interval.

$L_{eq,T}$ can be calculated using the sensor nodes of a WASN, and it provides adequate information about the objective noise level. However, it does not provide any information about subjective annoyance [9,10]. There is no direct correlation between the current indicators and the subjective noise annoyance.

Therefore, new indicators, which provide information related to the subjective impact of noise annoyance, are needed. These indicators can express people's feelings through subjective measures [11]. In addition, "annoyance maps could be generated to provide information not only about the objective noise level but also about the subjective impact of the noise pollution" [12].

According to [13,14], noise annoyance is inherently a vague, imprecise, and uncertain concept. These authors argue that noise annoyance models should identify a fuzzy set [15] of possible effects rather than seek a very accurate crisp prediction and that fuzzy rule-based models are considered the most appropriate candidates for this task.

Although some fuzzy models have been proposed to model noise annoyance [13,14,16,17], all of the models need a large number of computer resources to be executed. Therefore, they have not been directly implemented into WASN acoustic sensor nodes due to their resource constraints, and it is necessary to design a fuzzy approach adapted to them, reducing the number of necessary resources. An approach could focus on sending the raw acoustic sensor data to a web server or a cloud platform, executing a fuzzy model and processing with almost unlimited resources. However, the amount of raw measurement data and data rate needed is too large for Low Power Wide Area Networks (LPWANs), such as Sigfox or LoRaWAN, and therefore, data processing must be performed in the acoustic sensor nodes to reduce the data rate.

In this work, we present the design and implementation of an adapted fuzzy ruled-based system (FRBS) [18] that allows the acoustic sensor nodes of a real WASN to infer the degree of subjective noise annoyance in real-time. Each sensor node of the WASN, deployed in the city of Linares (Jaén), Spain, executes an FRBS, which consists of a fuzzification interface, a knowledge base (KB), an inference engine, and a defuzzification interface.

The rest of the paper is structured as follows: Section 2 discusses the related work and motivation and Section 3 describes the FRBS designed and implemented. The experimental results are provided in Section 4, and some conclusions and future works are presented in Section 5.

2. Related Work and Motivation

Over the last few years, several works have devoted their attention to the design and use of WASNs to monitor noise levels and create noise maps [19–24]. In [12], the authors presented a review of the main approaches to date, which focused on the design and development of a WASN for environmental noise monitoring in smart cities. The authors argue that "although WASN are becoming an incipient reality, very few projects have been deployed in some smart cities around the world (most of them as pilots)". Examples of real projects based on WASN have been described by [21,25–28]. In a previous work [29], we presented the design and implementation of a complete low-cost system for a WASN deployed in the city of Linares (Jaén), Spain. The complete system covered the network topology design, hardware, and software of the sensor nodes, protocols, and a cloud server platform.

However, in our previous work [29], and all these previous works and real projects, the measurements and the information provided by the WASN were based on $L_{eq,T}$ [8] or $L_{Aeq,T}$ (applying the A-weighting filter, which is a frequency filter that picks up the frequencies where the human ear is most sensitive). These parameters do not provide any information about subjective annoyance in humans [9,10]. According to [11], "even with similar values of $L_{eq,T}$, people can feel the noise differently according to its frequency characteristics". In this sense, subjective annoyance and road traffic noise have been studied in [30].

Since noise annoyance is inherently a vague, imprecise, and uncertain concept [13,14,31], fuzzy models have been proposed to model noise annoyance. In [16], the authors describe the noise-human response, and a fuzzy logic (FL) model is developed by comprehensive field studies on noise measurements. The model has two subsystems: the first has 549 linguistic rules and the second has 52 linguistic rules. In [13], a framework is proposed to model noise annoyance based on the mathematical theory of fuzzy sets and FRBS, providing the theoretical background for building these models. The resulting model is tested on two large-scale social surveys augmented with exposure simulations. In [17], the authors describe an exposure assessment method of occupational noise based on FL. They conclude that the fuzzy method assists in obtaining a clear approach to the risk assessment of noise exposure, and FL assessment results are more useful for analysis than a conventional assessment. However, in [14,31], the authors proposed an expert system using a fuzzy approach to determine the effects of the noise environment on annoyance. The rules were proposed by a human expert and are based on linguistic variables. Annoyance is considered to be a function of noise levels, exposure duration, noise level in habitat, and age. The model was implemented using Maple 12 software.

One of the main characteristics of these systems is the capacity to incorporate human knowledge in the presence of a lack of accuracy and uncertainty or imprecision. Therefore, these models represent an alternative to express people's feelings by subjective measures instead of objective measures based on $L_{eq,T}$ (measured in dB) or $L_{Aeq,T}$ (measured in dBA). All the previous fuzzy models referenced have been implemented using simulation software, which requires a large number of computer resources, and none of them have been implemented in a real-life scenario.

Although considerable research has been devoted to modeling subjective annoyance using fuzzy models, FRBS adapted to sensor node limitations in a real WASN to provide the degree of subjective noise annoyance in real-time remains a largely unexplored region. In [32], we presented a preliminary approach and basic results about how to integrate an FRBS into a resource-constrained device to calculate a fuzzy noise indicator. The experiments were carried out in a laboratory using a Sun SPOT device, which is obsolete at present.

In this work, we improve the previous approach by (a) optimizing the design of the FRBS to be executed in the current sensor node hardware; (b) introducing new input variables; (c) improving the algorithm to calculate the SPL and $L_{Aeq,T}$; and (d) determining the frequency characteristics of the noise. In addition, the experiments were performed in a real scenario by giving real measurement inputs to the FRBS in a real WASN deployed in the city of Linares (Jaén), Spain, which has been running continuously for three months. In this way, we compare the evolution of the sound pressure level (used as the objective noise level) with the progress of the subjective noise annoyance on different days and in real situations.

3. The Proposed Fuzzy Rule Based-System

A FRBS is a rule-based system in which FL is used as a tool for representing different forms of knowledge about the problem at hand [18]. These systems are an extension to classical rule-based systems because they deal with "IF-THEN" rules whose antecedents and consequents are composed of FL statements (fuzzy rules) instead of the classical logic ones. FRBS incorporates the human knowledge of an expert using FL. Two different kinds of approaches have been proposed within the FRBS: Mamdani FRBS [33,34] and Takagi–Sugeno–Kang FRBS [35]. The main difference between them lies in the consequent knowledge rules. The Mandani approach is composed of a linguistic variable, and in the Takagi–Sugeno–Kang approach, it is expressed as an analytical function of the input variables.

The FRBS proposed in this paper to calculate the degree of subjective noise annoyance is based on the structure of the Mandani FRBS [33,34]. It consists of the following components: a fuzzification authentication interface, a knowledge base (KB), an inference engine, and a defuzzification interface. The fuzzification interface adapts the actual input values to the fuzzy system. The knowledge is stored in a KB that is composed of three elements: membership functions, a set of "IF-THEN" rules, and linguistic variables. These rules are defined through consequences and antecedents. The rules have the following form:

$$\text{IF } X_1 \text{ is } A_1 \text{ and ... and } X_n \text{ is } A_n \text{ THEN } Y \text{ is } B$$

where X_i are the input variables, A_i is a fuzzy set associated with the input variables, Y is the output variable, and B is a fuzzy set related to the output variable.

The inference engine infers the fuzzy output using the input variables and the KB. Finally, the defuzzification interface adapts the value of the fuzzy output to a real output value.

To design the FRBS to be executed in the sensor nodes of the WASN, some simplifications are needed to minimize the computational requirements. We propose the use of the following modifications to the structure of the Mandani FRBS: (a) a reduced number of fuzzy sets is defined in each variable; (b) the input and output interfaces only admit linear conversions; (c) a First Infer Then, Aggregate (FITA) inference engine is needed, and (d) the inference engine works with numerical values of variables, fuzzy sets, and rules instead of linguistic labels.

Figure 1 shows the structure of the FRBS proposed, which is implemented into the acoustic sensor nodes of the real WASN to provide in real-time the degree of subjective noise annoyance in the area where each acoustic sensor node is placed.

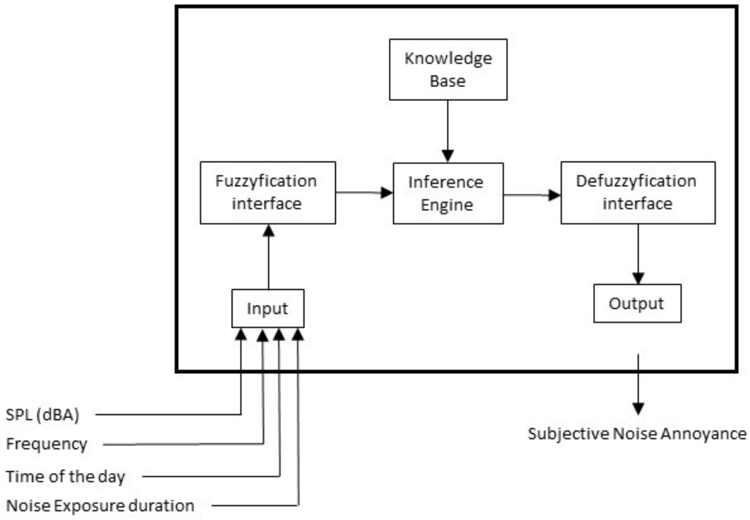


Figure 1. Structure of the FRBS proposed which is executed in the sensor nodes.

The output variable of the system is the subjective annoyance. As input variables, we considered four variables as the most representative ones described in the literature that affect people's perception of subjective noise. There are other variables that have been used in the literature, such as age. This variable can be used for a theoretical model or even if the exact age range is known (in the place where a sensor node is going to be located), for example, a nursery or a home for elderly individuals. However, it is not valid for our real system, where the sensor nodes are placed in different streets of the city, as it is impossible to know the age of the people passing through each location.

The proposed FRBS has the following input variables:

(1) SPL, sound pressure level value. In a previous work [29], we presented the architecture of an algorithm to calculate SPL (dB), $L_{eq,T}$ (dB), and $L_{Aeq,T}$ (dBA) in real-time adapted to the sensor nodes of a WASN. These parameters do not provide any information about subjective annoyance in humans. Implementation details of the algorithm can be found in that reference.

(2) Noise exposure duration, i.e., its persistence over time.

(3) Frequency. According to some studies [36,37], noise frequency components directly impact subjective noise perception in humans. The algorithm we implemented, which is executed in the sensor nodes, determines the critical spectral band, i.e., the frequencies with a higher energy and their degree of importance with respect to background noise or less crucial frequencies.

(4) Time of day when the noise occurs. The END regulation [3] distinguishes three hourly time slots for noise measurements, establishing three indicators: (a) L_{day}, A-weighted average sound level over the daytime period 07:00–19:00; (b) $L_{evening}$, A-weighted average sound level over the evening period 19:00–23:00; and (c) L_{night}, A-weighted average sound level over the night period 23:00–07:00.

Figure 2 shows the fuzzy sets defined for all input variables and the output variable. Table 1 presents the KB set of rules used. This knowledge is based on an expert and peoples' opinions aggregated from different experiments. Different sound pressure levels were generated in the lab (50 dBA, 60 dBA, 70 dBA, 80 dBA, 90 dBA, and 100 dBA), and from these and the other variables, persistence over time (5 s, 10 s, 15 s, 20 s, 25 s, and 30 s), the fundamental frequency of the noise (different tones from 20 Hz to 8 kHz), and the time of day, the subjective noise annoyance level was determined, indicating whether the annoyance was very low, low, medium, high, or very high.

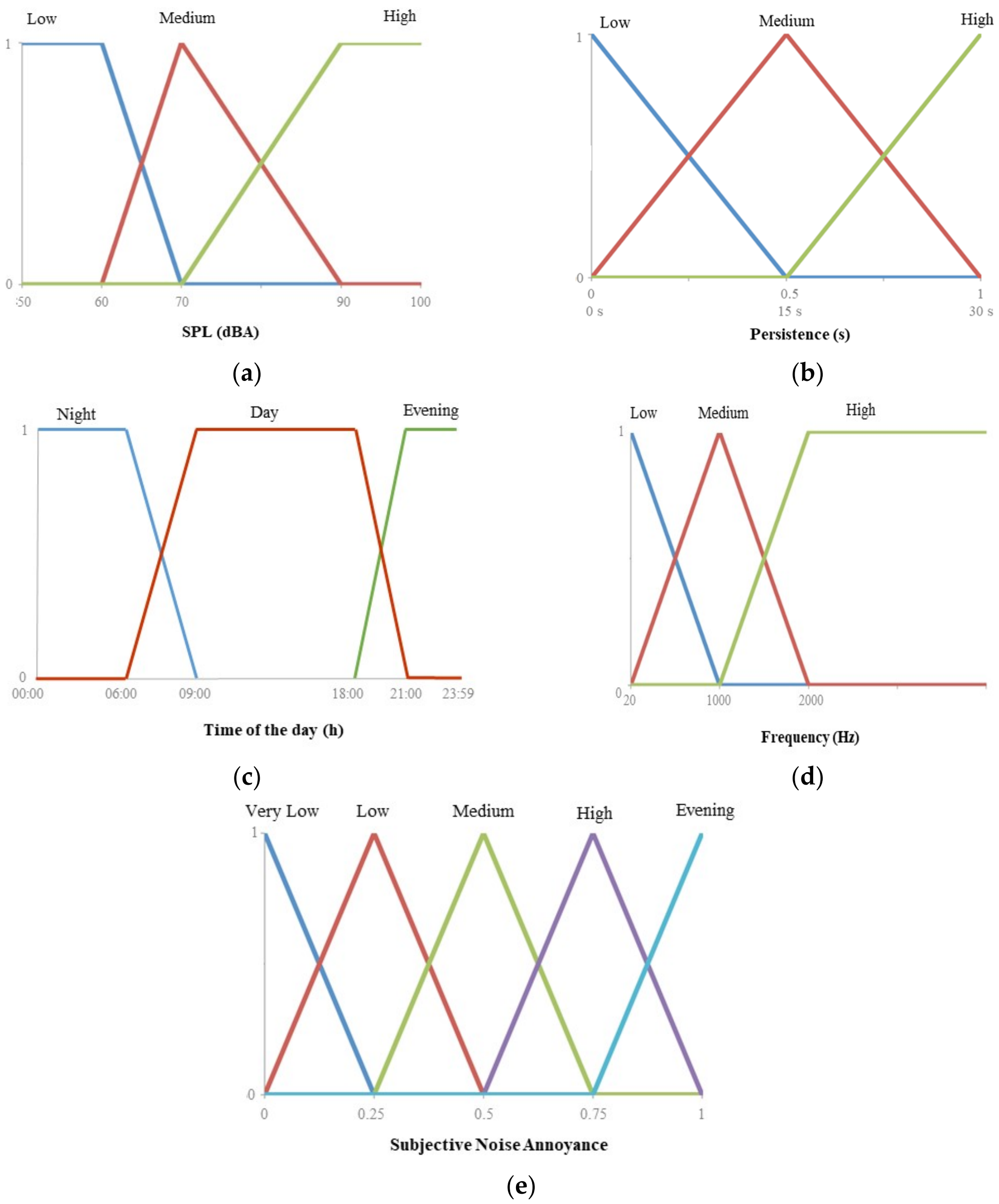


Figure 2. (**a**–**e**) Membership functions defined in inputs and output variables. (**a**) SPL; (**b**) Persistence; (**c**) Time of the day; (**d**) Frequency; and (**e**) Subjective noise annoyance.

Table 1. Set of IF-THEN rules.

SPL	Persistence	Frequency	Time of Day	Subjective Noise Annoyance
L	L	L	D	L
L	L	M	D	VL
L	L		E	L
L	L	H	D	VL
L	L	L	N	H
L	M	L	D	VL
L	M	L	N	H
L	M		E	L
L	M	M	D	L
L	M	H	D	VL
L		L	E	M

Table 1. *Cont.*

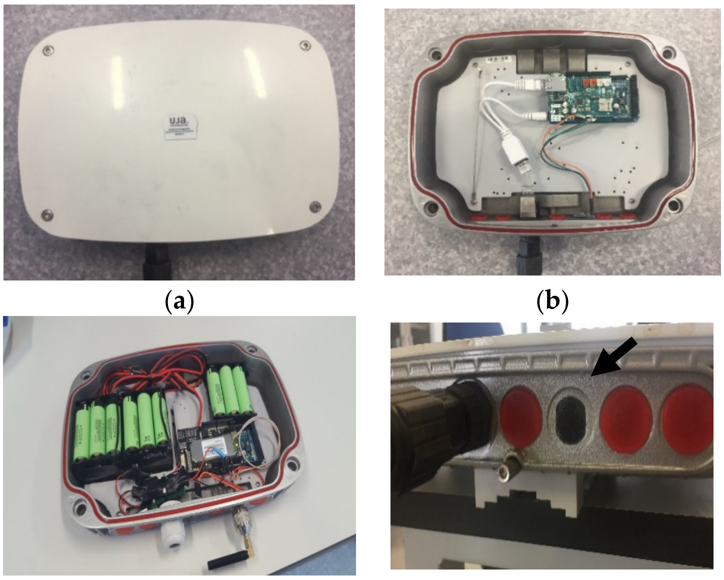
SPL	Persistence	Frequency	Time of Day	Subjective Noise Annoyance
L	H		D	L
L	H	L	N	H
L	H		E	L
M	L		E	M
M	L		D	L
M	L	L	N	VH
M	L	M	N	H
M	L	H	N	H
M	M	L	E	M
M	M		D	M
M	M	L	N	VH
M	M	M	E	M
M	M	M	N	VH
M	M	H	E	M
M	M	H	N	H
M	H	L	E	L
M	H	L	D	M
M	H	L	N	H
M	H	M	E	M
M	H	M	D	H
M	H	M	N	VH
M	H	H	E	H
M	H	H	D	H
M	H	H	N	VH
H	L		D	M
H	L		E	H
H	L		N	VH
H	M		E	H
H	M	M	D	M
H	M	M	N	VH
H	M	H	D	M
H	M	H	N	VH
H	H		E	H
H	H	L	D	H
H	H	M	D	H
H	H		N	VH
H	H	H	D	VH

VL: very low; L: low; M: medium; H: high; VH: very high; D: day; E: evening; and N: night.

4. Results

As the main result, we can say that an FRBS has been designed and implemented in the acoustic sensor nodes of a real WASN deployed in the city of Linares (Jaén), Spain, which has been running continuously for three months, to provide the degree of subjective noise annoyance in real-time.

The FRBS software was developed in the C programming language and implemented in a standard hardware model (i.e., commercial sensor node) of the Arduino platform. In particular, the acoustic sensor node is the Arduino Due device [38], which is based on a 32-bit ARM core microcontroller and is designed to develop solutions related to sensor networks. The microphone used is based on a commercial design [39], and it is integrated with an operational Maxim MAX4466 specifically designed for acoustic solutions. The choice of this device is mainly due to its technical specifications, in terms of the processor and memory, which allow for the execution of the FRBS and the algorithm to calculate SPL, $L_{eq,T}$ (dB), or $L_{Aeq,T}$ (dBA) in real-time. These technical specifications are as follows: Atmel SAM3X8E ARM Cortex-M3 processor 32-bit, clock speed of 82 MHz, 96 Kb of SRAM, and 512 Kb of flash memory. Figure 3 shows the acoustic sensor nodes. For sensor nodes one and three through seven, we used the Arduino Due and the Ethernet shield, and the power consumption was approximately 180 mA. For sensor node two, the Arduino Due and the 3G module, the consumption was approximately 320 mA. Finally, for sensor node nine, using the Arduino Due and the Sigfox module, the consumption was approximately 125 mA. All of the nodes were powered through passive Power over Ethernet (PoE), using 12-V 1-A power adapters and PoE injectors. The electrical plugs were at a maximum distance of 20 m. To prevent problems derived from occasional power outages, the 3G acoustic sensor node was equipped with a battery of 50,250 mAh (3350 mAh × 15 modules), so it has an autonomy of approximately 157 h.



(**a**) (**b**) (**c**) (**d**)

Figure 3. (**a**–**d**) The acoustic sensor nodes. (**a**) Enclosure box; (**b**) Wi-Fi acoustic sensor node; (**c**) 3G acoustic sensor node; and (**d**) Electret microphone.

It is not possible to execute the FRBS and the algorithm to calculate the SPL on other devices of the Arduino platform, i.e., MKR Family or MEGA. However, any other device with similar or better characteristics to Arduino Due can be used.

The computation time to infer the degree of subjective noise annoyance based on the FRBS has been calculated. Using the KB composed of the inputs and output variables and rules defined in Figure 2 and Table 1, the device computes approximately 150 inferences per second, which is equivalent to a reaction time of 6.5 ms. Therefore, the device has enough processing capacity to infer the output value using this KB, and both the number of input variables and the number of rules can be increased for more accuracy.

On the other hand, a WASN was deployed in the city of Linares (Jaén), Spain. This WASN is composed of nine acoustic sensor nodes, each executing the proposed FRBS and obtaining subjective noise annoyance every second. The acoustic sensor nodes were located in those streets of the city that were considered the most critical from the perspective of noise pollution. Figure 4 shows the exact locations of the measurement points in the streets, and Figure 5 shows some locations where the acoustic sensor nodes were installed.

Figure 4. Locations of the measurement points in the streets of the city of Linares (Jaén).

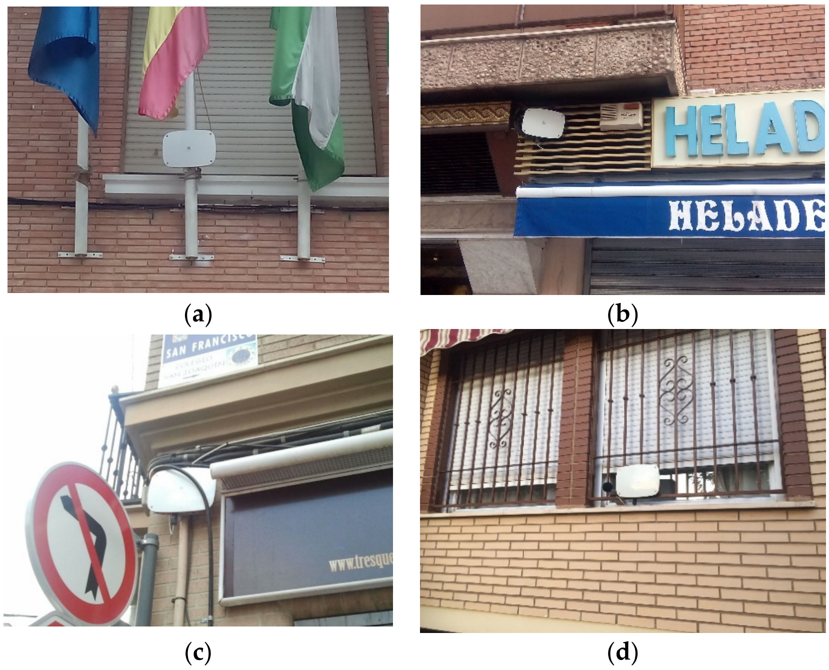


Figure 5. (**a**–**d**) Acoustic sensor nodes deployed in the city.

Figure 6 presents the network topology for the deployed WASN. The City Council of Linares, through the area of urban planning, established those locations of the city that were considered the most critical from the point of view of noise pollution.

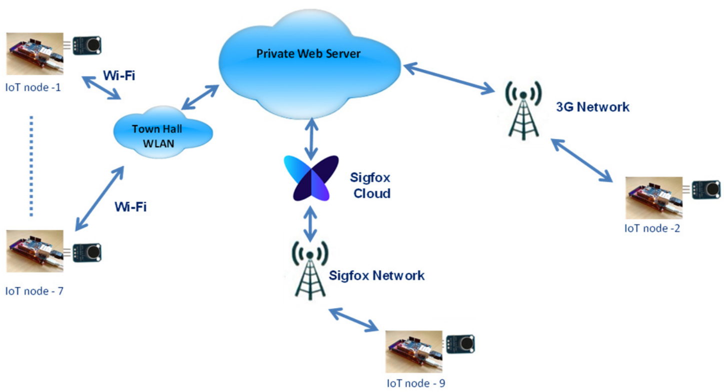


Figure 6. The network topology for the WASN deployed in the city of Linares (Jaén).

Due to the existence of the corporate Wi-Fi network that the City Council of Linares deployed in the city, as well as the absence of power supply restrictions, we proposed using this Wi-Fi network. After analyzing the coverage, it was detected that, in seven of the nine locations, it was possible to use this Wi-Fi network. However, in two locations (nodes two and nine), there was no coverage. For these two locations, we decided to use 3G and Sigfox technologies, respectively.

In addition to the FRBS software and the algorithm to calculate SPL and $L_{Aeq,T}$, all the acoustic sensor nodes include communication software, which is implemented to send data to a Web Server. The sensor nodes with Wi-Fi and 3G connectivity calculate the subjective noise annoyance every second, and every 30 s, send the average value to the webserver. In the case of Sigfox connectivity, the acoustic sensor node calculates the subjective noise annoyance every second, but in this case, the average value is sent every 10 min to the webserver. This is because the Sigfox network only permits sending 140 messages per day. More details about the protocols, network topology, and technologies used in the WASN can be found in our previous work [29].

As the experiments were performed by giving real measurement inputs to the FRBS, we can compare the evolution of the SPL (used as the objective noise level) with the progress of the subjective noise annoyance on different days or situations. Each acoustic sensor node provides the temporal evolution of the SPL (in dBA) during a selected time interval, the degree of subjective noise annoyance, and the $L_{Aeq,T}$ (in dBA). Figure 7 shows the temporal evolution of the SPL throughout the day from 00:00 to 23:59 h at Isaac Peral Street. The $L_{Aeq,T}$ for that day was 70.9 dBA.

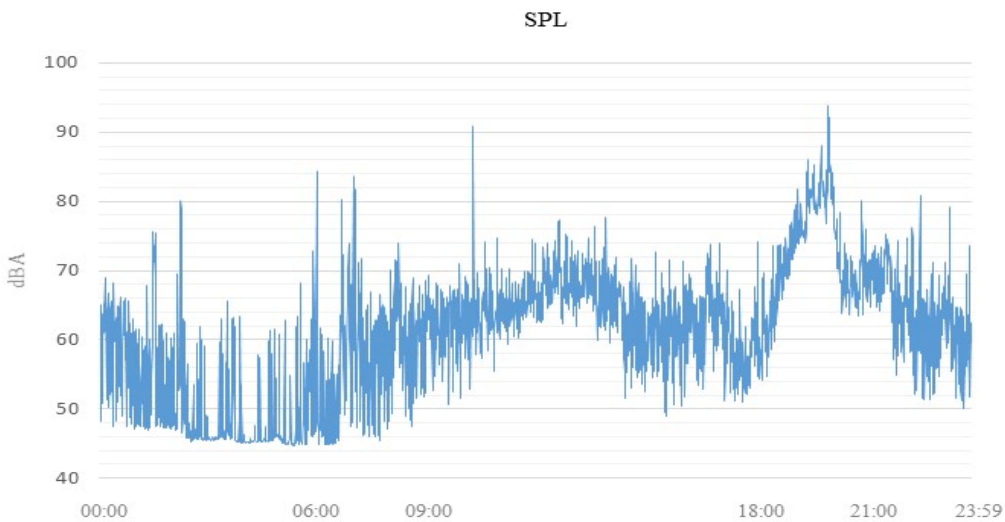


Figure 7. The temporal evolution of the SPL over the whole day at Isaac Peral Street.

Figure 8 shows the progress of the subjective noise annoyance as the output of the FRBS during the same day. The noise annoyance values are in the range {0, 1}, where value 0 means no annoyance and value 1 means maximum annoyance.

As can be observed, the system can correctly detect situations that can be considered more annoying by humans. For example, the subjective noise level increases during the night with respect to SPL, and during the day, the differences are smaller. Nevertheless, we can observe that from 6:00 h onwards, although the SPL starts to increase slowly as the city starts to wake up, the subjective noise level slowly decreases.

Figures 9 and 10 show the temporal evolution of the SPL and the subjective noise annoyance of another whole day in a different location. In this case, we can see that the subjective noise is the greatest at night. During the day, noise peaks are detected, however, their impact is less on annoyance, and during the transition from evening to night, although the SPL starts to decrease, the annoyance starts to increase slowly.

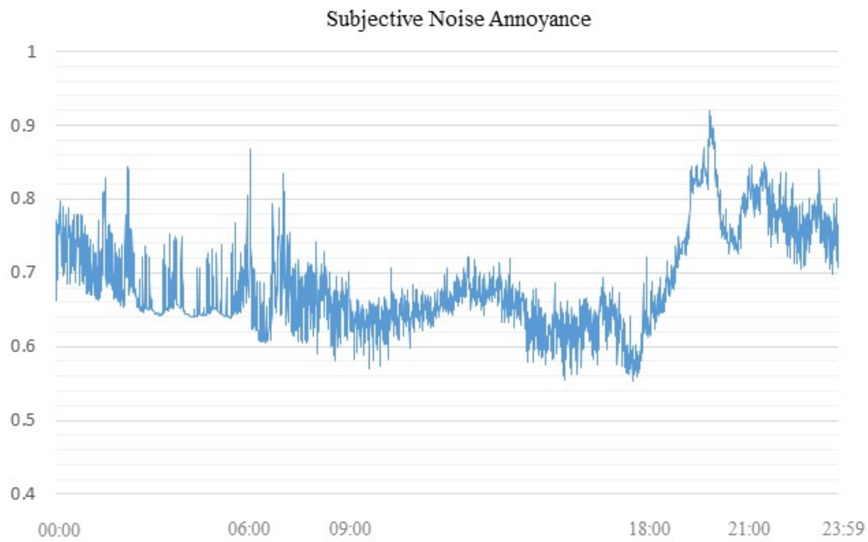


Figure 8. Progress of the subjective noise annoyance as an output of the FRBS.

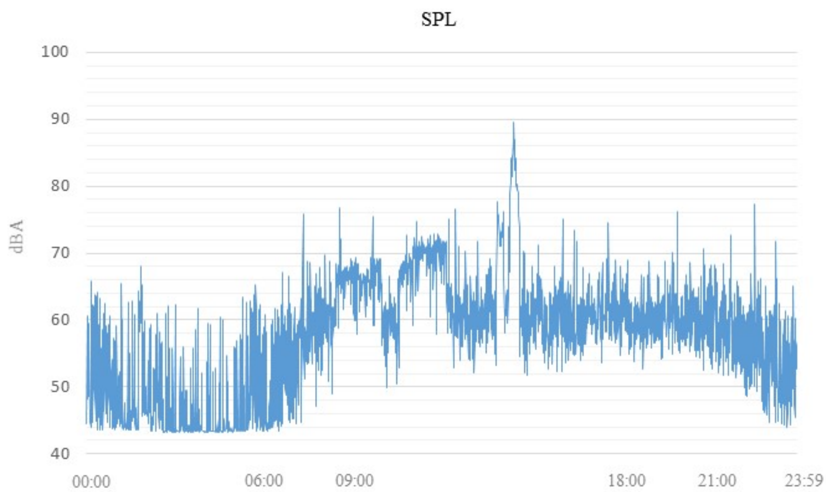


Figure 9. The temporal evolution of the SPL over a whole day at Julio Burel Street.

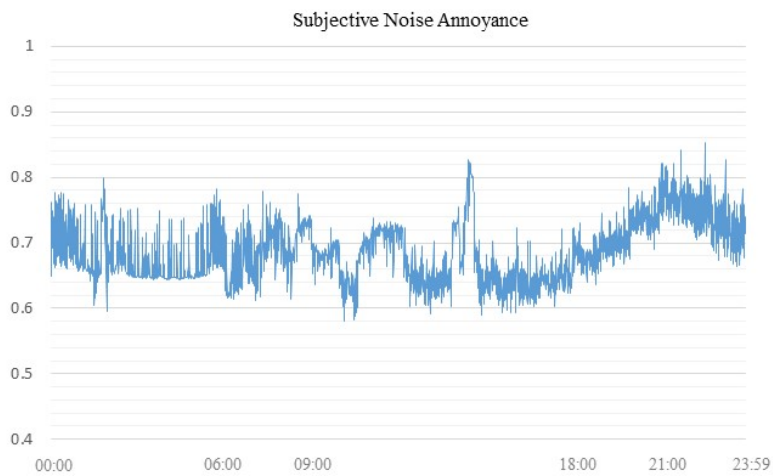


Figure 10. Progress of the subjective noise annoyance as an output of the FRBS at Julio Burel Street.

Appendix A contains one result in a whole day for each node of the implemented system.

5. Conclusions and Future Works

We present the design and implementation of an FRBS, which has been executed into the acoustic sensor nodes of a real WASN deployed in the city of Linares (Jaén), Spain, to provide the degree of subjective noise annoyance in humans in real-time. The FRBS has four input variables as the most representative described in the literature: SPL, frequency, persistence, and time of the day; and one output variable: the grade of subjective noise annoyance. The hardware used for the acoustic sensor nodes was a commercial model, Arduino Due. The system can correctly detect situations that can be considered more annoying by humans. Results show that the subjective noise level increases during the night with respect to SPL, and during the day, the differences are smaller. During the day, noise peaks are detected but their impact is less on annoyance. In most of the locations, from 6:00–7:00 h onwards, although the SPL starts to increase as the city starts to wake up, the subjective noise level slowly decreases. During the transition from evening to night, although the SPL starts to decrease, the annoyance starts to increase slowly. In non-noisy locations, where the values of SPL do not exceed 55–60 dB, noise annoyance is observed to be lower and its temporal evolution is practically flat, with a slight increase in the evening hours.

The results demonstrate that the performance of the Arduino Due is very good. It has sufficient processing capacity and memory to infer the output values using a KB composed of 5 variables and 48 fuzzy rules. The device computes approximately 150 inferences per second, which is equivalent to a reaction time of 6.5 ms. Therefore, both the number of input variables and the number of rules can be increased, as the reaction time is very small for this use case. In addition, the device is able to calculate the SPL (in dBA, applying the A-weighting filter) every 1 s, which allows us to know the variability of the noise in a specific place. It was not possible to execute the FRBS and the algorithm to calculate the SPL on other devices of the Arduino platform, i.e., MKR Family or MEGA. However, any other device with similar or better characteristics to Arduino Due can be used.

In addition, a real WASN was deployed in the city of Linares (Jaén), Spain, in which each acoustic sensor node of the network executed the FRBS to obtain the subjective noise annoyance every 1 s. The system has been working continuously for three months without any problems except for occasional power outages and the consequent restart of the devices. Therefore, we consider that FRBS integrated into the acoustic sensor nodes of a WASN is a valid approach to providing information about the subjective impact of noise pollution and generating annoyance maps.

The system can be integrated into the authority's decision processes and help to reduce noise impact. The system proposed allows continuous measurements over long periods of time (weeks/months), providing information based on the objective noise indicators included in the END regulation [3] as well as on the subjective noise annoyance. This allows preventive and corrective actions to be taken, for example, installation of noise barriers, the establishment of hourly traffic restrictions, setting speed limits, transport infrastructure planning, new urban area planning where people are going to live, changing the noisiest street pavements to more porous and quieter ones, etc. In addition, as the system provides information in real-time, corrective actions can be taken in real-time, for example, reorganization of vehicular traffic on the streets or the detection of situations where the noise derived from a leisure activity (i.e., a bar) is too high.

Regarding future research, as we demonstrate that the acoustic sensor node has enough processing capacity and memory, it should aim to improve the KB, increasing the number of input variables and the number of fuzzy rules. In addition, due to the occasional loss of connection from the Wi-Fi and 3G network to the internet, some data were lost. To solve this problem, we are currently working on the implementation of a fog-computing platform between the sensor nodes and the webserver. The fog server will only be in charge of data storage and retransmission to the webserver.

Author Contributions: Conceptualization, J.-A.F.-P., J.C.-B. and U.B.; methodology, J.-A.F.-P. and J.C.-B.; software, J.-A.F.-P. and J.C.-B.; validation, J.-A.F.-P. and J.C.-B.; formal analysis, J.C.-B.; investigation, J.-A.F.-P., J.C.-B. and U.B.; resources, J.-A.F.-P. and J.C.-B.; data curation, J.-A.F.-P. and J.C.-B.; writing—original draft preparation, J.-A.F.-P.; writing—review and editing, J.-A.F.-P. and U.B.; visualization, J.-A.F.-P.; supervision, J.-A.F.-P. and J.C.-B.; project administration, J.-A.F.-P.; funding acquisition, J.-A.F.-P. and J.C.-B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Programa Operativo FEDER and Consejería de Economía y Conocimiento de la JUNTA de ANDALUCIA (Spain), Project Ref. 1380677, and the APC was completely funded by the same Program.

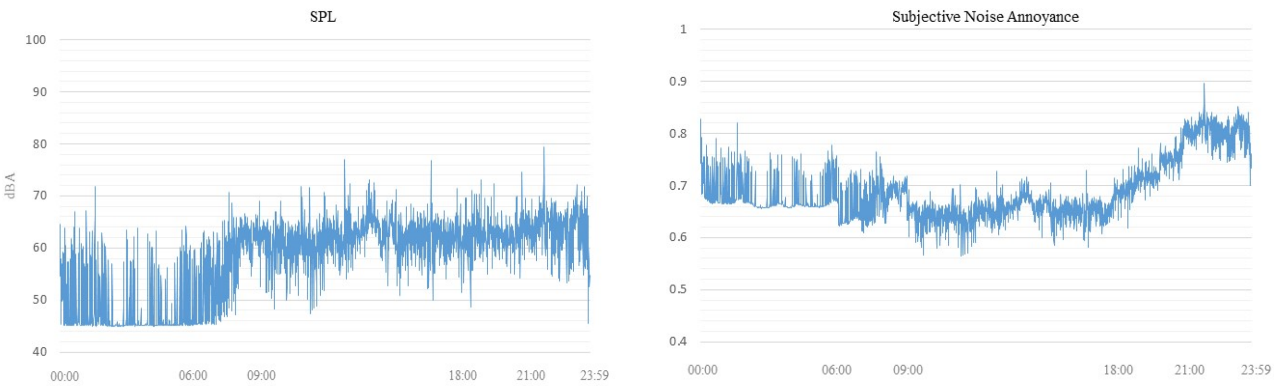
Data Availability Statement: Restrictions apply to the availability of these data. Data were collected from urban residential areas of the city of Linares and are available from the authors with the permission of Excmo. Ayuntamiento de Linares and Junta de Andalucía.

Acknowledgments: We would like to thank the support provided by Excmo, Ayuntamiento de Linares, especially for the technical support given by the ICT department.

Conflicts of Interest: The authors declare no conflict of interest.

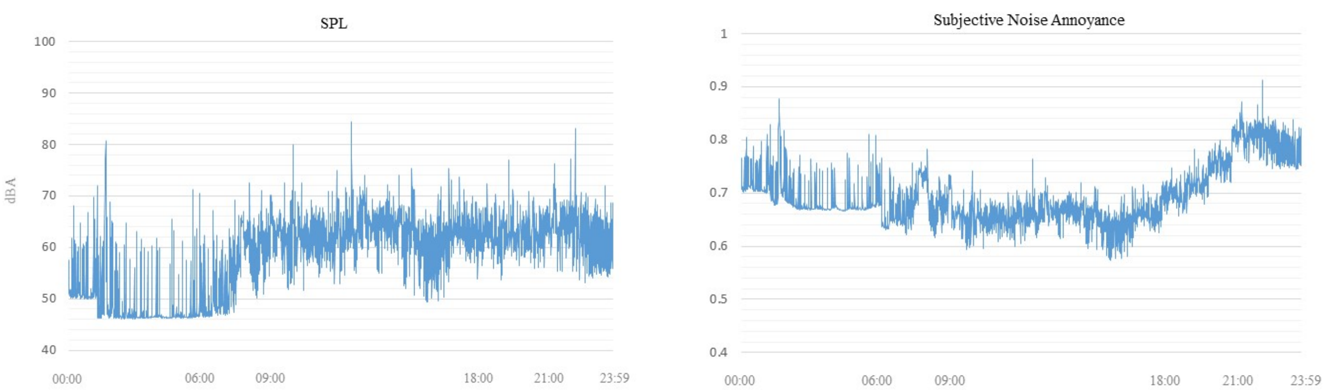
Appendix A

This Appendix A, Figures A1–A7, contains the measurements for a whole day for each node of the implemented system.



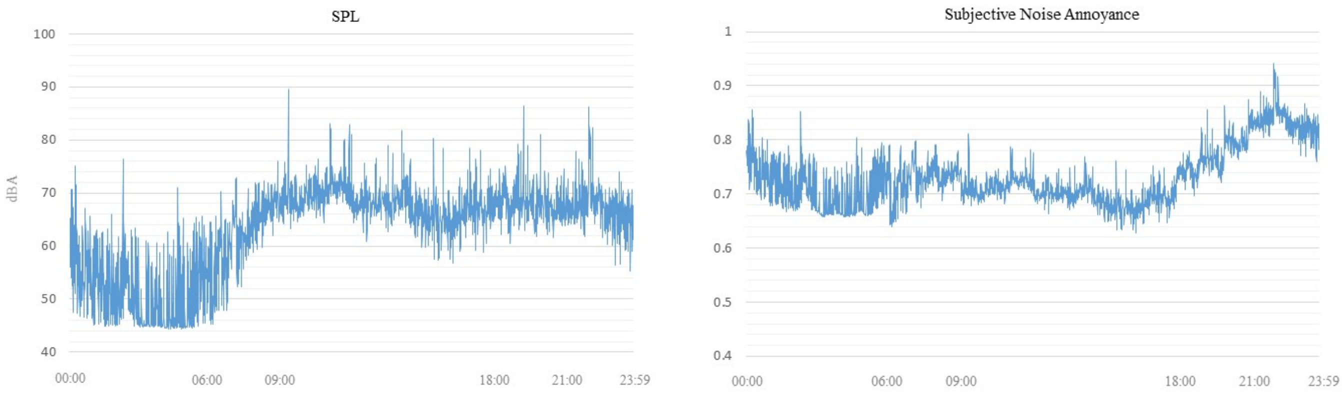
(**a**) (**b**)

Figure A1. Ubeda Street: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



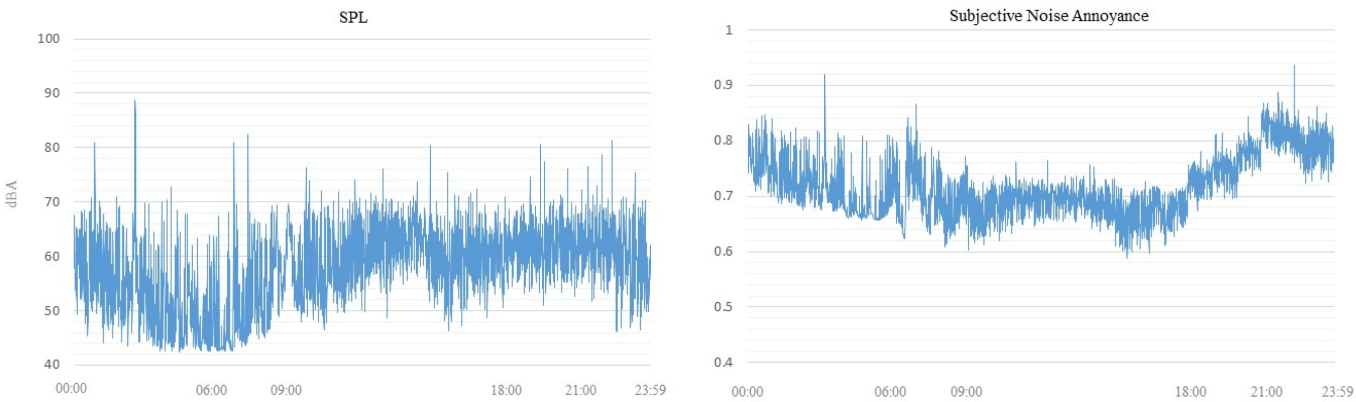
(**a**) (**b**)

Figure A2. San Francisco Square: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



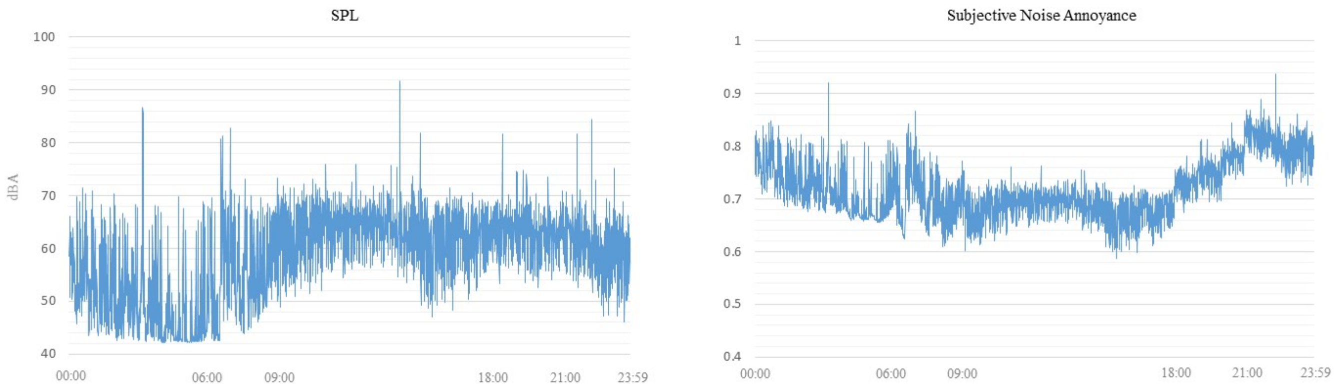
(**a**) (**b**)

Figure A3. Santa Margarita Square: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



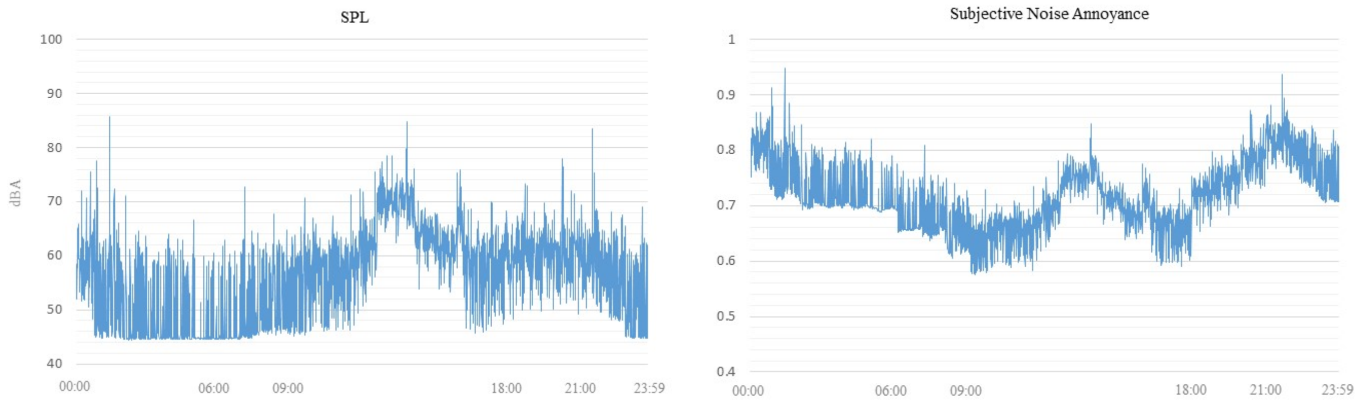
(**a**) (**b**)

Figure A4. Cervantes Street: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



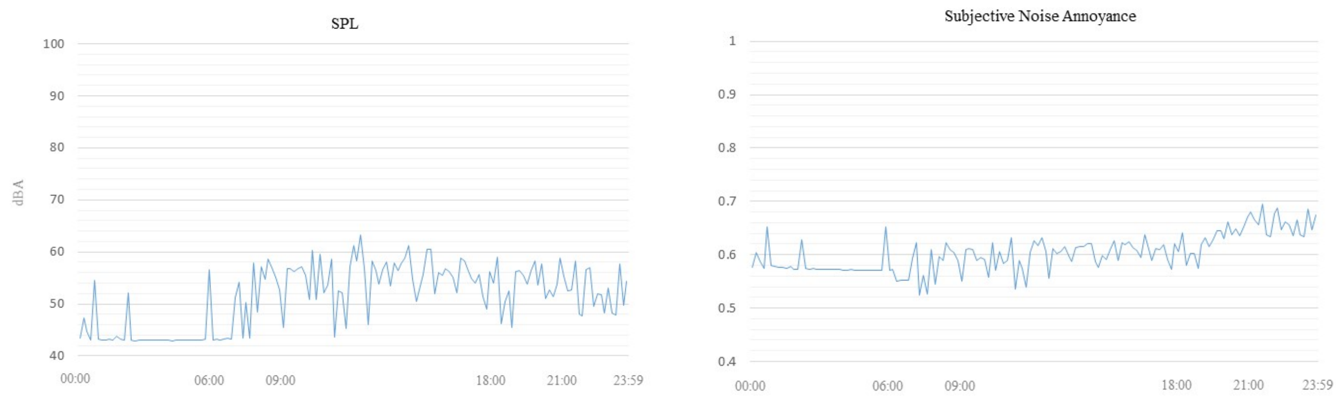
(**a**) (**b**)

Figure A5. Andalucia Avenue: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



(**a**) (**b**)

Figure A6. Ayuntamiento Square: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.



(**a**) (**b**)

Figure A7. Noruega Street-Sigfox network: (**a**) The temporal evolution of the SPL over a whole day; (**b**) subjective noise annoyance as an output of the FRBS.

References

1. European Environment Agency. *Health Risks Caused by Environmental Noise in Europe*; Publications Office of the European Union: Luxembourg, 2020. Available online: https://data.europa.eu/doi/10.2800/524975 (accessed on 10 October 2022).
2. World Health Organization Regional Office for Europe and the Joint Research Centre of the European Commission. *Burden of Disease from Environmental Noise: Quantification of Healthy Life Years Lost in Europe*; World Health Organization Regional Office for Europe and the Joint Research Centre of the European Commission: København, Denmark, 2011; ISBN 9789289002295. Available online: https://www.euro.who.int/_data/assets/pdf_file/0008/136466/e94888.pdf (accessed on 10 October 2022).
3. Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the Assessment and Management of Environmental Noise. *Off. J. Eur. Communities* **2002**, *189*, 12–25.
4. European Commission Working Group Assessment of Exposure to Noise. Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure, Version 2, January 2006. Available online: https://sicaweb.cedex.es/wp-content/uploads/2021/08/Good-Practice-Guide-for-Strategic-Noise-Mapping.pdf (accessed on 10 October 2022).
5. Bertrand, A. Applications and trends in wireless acoustic sensor networks: A signal processing perspective. In Proceedings of the 18th IEEE Symposium on Communications and Vehicular Technology in the Benelux, Ghent, Belgium, 22–23 November 2011.
6. Ouni, R.; Saleem, K. Framework for Sustainable Wireless Sensor Network Based Environmental Monitoring. *Sustainability* **2022**, *14*, 8356. [CrossRef]
7. Cafiso, S.; Di Graziano, A.; Fedele, R.; Marchetta, V.; Praticò, F. Sensor-based pavement diagnostic using acoustic signature for moduli estimation. *Int. J. Pavement Res. Technol.* **2020**, *13*, 573–580. [CrossRef]
8. *IEC 61672*; Electroacoustic—Sound Level Meters. International Electrotechnical Commission: Geneva, Switzerland, 2003.
9. Raimbault, M.; Dubois, D. Urban soundscapes: Experiences and knowledge. *Cities* **2005**, *22*, 339–350. [CrossRef]
10. Rychtáriková, M.; Vermeir, G. Soundscape categorization on the basis of objective acoustical parameters. *Appl. Acoust.* **2013**, *74*, 240–247. [CrossRef]

11. Segura-Garcia, J.; Felici-Castell, S.; Perez-Solano, J.J.; Cobos, M.; Navarro, J.M. Low-Cost Alternatives for Urban Noise Nuisance Monitoring Using Wireless Sensor Networks. *IEEE Sens. J.* **2015**, *15*, 836–844. [CrossRef]
12. Alías, F.; Alsina-Pagès, R.M. Review of Wireless Acoustic Sensor Networks for Environmental Noise Monitoring in Smart Cities. *J. Sens.* **2019**, *2019*, 7634860. [CrossRef]
13. Botteldooren, D.; Verkeyn, A.; Lercher, P. A fuzzy rule based framework for noise annoyance modeling. *J. Acoust. Soc. Am.* **2003**, *114*, 1487–1498. [CrossRef]
14. Nouri, J.; Zare, R.; Alavi, M. A fuzzy approach for modeling noise annoyance in urban environment. *Arch. Des. Sci.* **2012**, *65*, 294–305.
15. Zadeh, A. Fuzzy Sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
16. Aluclu, I.; Dalgic, A.; Toprak, Z.F. A Fuzzy logic-based model for noise control at industrial workplaces. *Appl. Ergon.* **2008**, *39*, 368–378. [CrossRef] [PubMed]
17. Golmohammadi, R.; Eshaghi, M.; Reyahi-Khoram, M. Fuzzy Logic Method for Assessment of Noise Exposure Risk in an Industrial Workplace. *Int. J. Occup. Hyg.* **2011**, *3*, 49–55.
18. Cordón, O.; Herrera, F.; Hoffmann, F.; Magdalena, L. *Genetic Fuzzy Systems: Evolutionary Tunning and Learning of Fuzzy Knowledge Bases*; World Scientific: Singapore, 2001.
19. Bhusari, P.; Asutkar, G.M.; Tech, M. Design of Noise Pollution Monitoring System Using Wireless Sensor Network. *Int. J. Softw. Web Sci.* **2013**, *220*, 55–58.
20. Granda, J.; Solórzano, S.; Clairand, J.M. Noise Pollution Measurement System Using Wireless Sensor Network and BAN Sensors. In Proceedings of the Fourth International Conference on eDemocracy & eGovernment, Quito, Ecuador, 19–21 April 2017. [CrossRef]
21. Nencini, L.; De Rosa, P.; Ascari, E.; Vinci, B.; Alexeeva, N. SENSEable Pisa: A wireless sensor network for real-time noise mapping. In Proceedings of the EuroNoise, Prague, Czech Republic, 10–14 June 2012.
22. Peckens, C.; Porter, C.; Rink, T. Wireless sensor networks for long-term monitoring of urban noise. *Sensors* **2018**, *9*, 3161. [CrossRef]
23. Santini, S.; Vitaletti, A. Wireless Sensor Networks for Noise Pollution Monitoring. In Proceedings of the 6th GI/ITG Workshop on Sensor Networks, Aachen, Germany, 16–17 July 2007.
24. Santini, S.; Ostermaier, B.; Vitaletti, A. First Experiences Using Wireless Sensor Networks for Noise Pollution Monitoring. In Proceedings of the ACM Workshop on Real-World Wireless Sensor Networks, Glasgow, UK, 1 April 2008.
25. Bartalucci, C.; Borchi, F.; Carfagnim, M. The smart noise monitoring system implemented in the frame of the Life MONZA project. In Proceedings of the EuroNoise, Crete, Greece, 27–31 May 2018.
26. Benocci, R.; Bellucci, P.; Peruzzi, L.; Bisceglie, A.; Angelini, F.; Confalonieri, C.; Zambon, G. Dynamic Noise Mapping in the Suburban Area of Rome (Italy). *Environments* **2019**, *6*, 79. [CrossRef]
27. Mydlarz, C.; Sharma, M.; Lockerman, Y.; Steers, B.; Silva, C.; Bello, J.P. The Life of a New York City Noise Sensor Network. *Sensors* **2019**, *19*, 1415. [CrossRef]
28. Mietlicki, F.; Mietlicki, C.; Sineau, M. An innovative approach for long-term environmental noise measurement: RUMEUR network. In Proceedings of the EuroNoise, Maastrich, The Netherlands, 31 May–3 June 2015.
29. Fernandez-Prieto, J.A.; Cañada-Bago, J.; Gadeo-Martos, M.A. Wireless Acoustic Sensor Nodes for Noise Monitoring in the City of Linares (Jaén). *Sensors* **2020**, *20*, 124. [CrossRef]
30. Ouis, D. Annoyance from road traffic noise: A review. *J. Environ. Psychol.* **2001**, *21*, 101–120. [CrossRef]
31. Zare, R.; Alavi, M. A Fuzzy Rule-Based Engine to Predict Noise. *Theory Approx. Appl.* **2021**, *15*, 9–21.
32. Mariscal-Ramirez, J.A.; Fernandez-Prieto, J.A.; Gadeo-Martos, M.A.; Canada-Bago, J. Knowledge-based wireless sensors using sound pressure level for noise pollution monitoring. In Proceedings of the 11th International Conference on Intelligent Systems Design and Applications, Córdoba, Spain, 22–24 November 2011. [CrossRef]
33. Mamdani, E.H. Application of fuzzy algorithms for control of simple dynamic plant. *Proc. Inst. Electr. Eng.* **1974**, *121*, 1585–1588. [CrossRef]
34. Mamdani, E.H.; Assilian, S. An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man-Mach. Stud.* **1975**, *7*, 1–13. [CrossRef]
35. Takagi, T.; Sugeno, M. Fuzzy Identification of Systems and Its Applications to Modeling and Control. *IEEE Trans. Syst. Man Cybern.* **1985**, *15*, 116–132. [CrossRef]
36. Alves, J.A.; Silva, L.T.; Remoaldo, P.C.C. The Influence of Low-Frequency Noise Pollution on the Quality of Life and Place in Sustainable Cities: A Case Study from Northern Portugal. *Sustainability* **2015**, *7*, 13920–13946. [CrossRef]
37. Pawlaczyk-Luszczynska, M.; Dudarewicz, A.; Waszkowska, M.; Sliwinska-Kowalska, M. Annoyance Related to Low Frequency Noise in Subjective Assessment of Workers. *J. Low Freq. Noise Vib. Act. Control* **2009**, *28*, 1–17. [CrossRef]
38. Arduino Due. Available online: https://store.arduino.cc/products/arduino-due (accessed on 10 October 2022).
39. Adafruit Electret Microphone. Available online: https://www.adafruit.com/products/1063 (accessed on 10 October 2022).