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A Smart System for Sleep Monitoring by Integrating IoT With Big Data Analytics

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ABSTRACT Obtrusive sleep apnea (OSA) is one of the most important sleep disorders because it has a direct adverse impact on the quality of life. Intellectual deterioration, decreased psychomotor performance, behavior, and personality disorders are some of the consequences of OSA. Therefore, a real-time monitoring of this disorder is a critical need in healthcare solutions. There are several systems for OSA detection. Nevertheless, despite their promising results, these systems not guiding their treatment. For these reasons, this research presents an innovative system for both to detect and support of treatment of OSA of elderly people by monitoring multiple factors such as sleep environment, sleep status, physical activities, and physiological parameters as well as the use of open data available in smart cities. Our system architecture performs two types of processing. On the one hand, a pre-processing based on rules that enables the sending of real-time notifications to responsible for the care of elderly, in the event of an emergency situation. This pre-processing is essentially based on a fog computing approach implemented in a smart device operating at the edge of the network that additionally offers advanced interoperability services: technical, syntactic, and semantic. On the other hand, a batch data processing that enables a descriptive analysis that statistically details the behavior of the data and a predictive analysis for the development of services, such as predicting the least polluted place to perform outdoor activities. This processing uses big data tools on cloud computing. The performed experiments show a 93.3% of effectivity in the air quality index prediction to guide the OSA treatment. The system's performance has been evaluated in terms of latency. The achieved results clearly demonstrate that the pre-processing of data at the edge of the network improves the efficiency of the system.

INDEX TERMS Internet-of-Things, big data, interoperability, sleep monitoring, health monitoring, open data, fog computing, cloud computing.

I. INTRODUCTION

Over the years, we human beings experience changes in our bodies and in our lives. One of these changes is the alteration of sleep that occurs with age. In particular, obstructive sleep apnea syndrome (OSA) is one of the most common and dangerous respiratory disorders that occur during sleep. OSA consists of the obstruction or partial blockage of the upper respiratory tract for at least 10 seconds and that prevents proper oxygenation of the blood [1], even over 20-30 times an hour of sleep. According to number of interruptions per hour and by using the apnea-hypopnea index (AHI), OSA can be classified into 3 categories from higher to lower severity; if these interruptions occur between 5 and 15 times per hour as "mild", if these interruptions occur between 15 and 30 times per hour as "moderate", and if these respiratory interruptions occur more than 30 times per hour as "severe" [2].

The sleep fragmentation produced by these respiratory interruptions have clinical consequences associated including depressive disorders, irritability, intellectual deterioration, decreased psychomotor performance, behavior and personality disorders [3]. As a result, the quality of life (QoL) can be significantly decreased and thereby increase the associated health problems and medical costs. Sleep apnea affects 21% of the US population (~70 million people), and account for an estimated \$16 billion in health care expenses each year [4].

OSA at any age is a major concern due to the health problems it can cause, but it is even more problematic for older people who are more likely to have respiratory problems at night, but are less likely to be diagnosed; (more than ∼80–90%) are not diagnosed or simply diagnosed as snoring. Research reveals that between 13 and 32% of people over 65 suffer from OSA [5] and it is a growing problem in developed countries, which are average life expectancy has increased.

The difficulty or trouble falling asleep, combined with the lack of deep sleep, results in a poor QoL and a greater health risk for elderly people. In addition, the long-term implications of chronic sleep disorders include an association with an increased risk of death [6].

Nowadays, the main reference tool for the diagnosis of OSA is a conventional polysomnography (PSG) study. PSG is an examination that lasts all night in a specialized clinic or in hospitals under constant medical surveillance, which means that the patients must go to a medical facility frequently, which will inevitably increase the burden on hospitals. Additionally, this method incorporates many sensors on a person's body, which is considered intrusive and, in turn, can disturb sleep [7]. In addition, the high cost of PSG makes it a very impractical monitoring method to be implemented in the long term.

On the other hand, there are many approaches available for OSA treatment, including weight loss, sleep hygiene techniques, positional and continuous open airway therapy (COAT), continuous positive airway pressure (CPAP) and surgical interventions. CPAP is an effective treatment for OSA [8], nevertheless adherence to treatment is suboptimal because to low perceived disease risk by the patients. This in turn may bring discomfort to the patients and lead them to interrupt therapy. Therefore, there is a significant need to provide an unobtrusive real-time- systems that not only allows for the detection of the OSA but also supports its treatment at home.

Several researches have proposed a variety of systems to detect OSA episodes, generally using wearable sensors incorporated in smart devices such as bands, bracelets, watches, and telephones. These systems achieve near real-time detecting of the OSA based on especially monitoring of physiological parameters such as the respiratory rate, the heart rate, and the oxygen saturation through wireless technologies such as Bluetooth [9]–[12], Wi-Fi [13], and ZigBee [14] with promising results. Nevertheless, as far as we know, these systems do not support the long-term treatment of this syndrome. In addition, almost all existing systems cannot work without a smartphone, which is used as a receiver and a processor of the data [9], [14]. Therefore, such proposals are unsuitable to monitor OSA patients at home, since the complex tasks of data processing can have a great impact on the daily use of the smartphone and thus in operating the system. The effects of sleep apnea and its complications have heightened the urgency for the patient to have not only a rapid diagnosis but also treatment.

In this work, an architecture of an OSA monitoring system based on the Internet of Things (IoT) and Big Data is proposed. The three-layered architecture integrates Fog and Cloud Computing capabilities to support both diagnosis and treatment of sleep apnea by creating of various services including remote monitoring, real-time alert notifications, data analysis and information visualization. The proposed system envisions assisting health professionals in medical decision-making.

The system performs the monitoring of the OSA harnessing advantage of the combined use of different technologies, components, and complementary open standards such as 6LoWPAN, ZigBee, BLE, Smart IoT Gateway, FIWARE [15] and lightweight and secure IoT protocols such as MQTT and CoAP.

The data related to the physical activities of the elderly, the sleep environment, the sleep status, the physiological parameters, and the context information collected are transmitted directly to a Smart IoT Gateway operating at the Fog Computing level using different Low Power Wireless Networks such as Bluetooth 4.0, ZigBee, and 6LowPAN. The different types of interoperability provided (technical, syntactic, and semantic) by the Smart IoT Gateway allows seamless interoperability between the different networks and communication protocols used.

In order to guarantee an immediate response from the system in emergency situations with low latency, the preprocessing of the data independently is also implemented in the Fog Computing level. The pre-processed data is stored and made available to users at the Cloud Computing level through a generic enabler which can greatly improve the administration and availability of the data.

Additionally, at this level, an analyzer based on Big Data is implemented to support the processing of data by extracting and analyzing the data coming from both the Fog Computing level and the open data catalog available in smart cities, in particular, from the city of Valencia. To do so, the big data architecture is based on Lambda architecture because it provides a fault-tolerance, scalable and reliable system. Using the batch layer described on the lambda architecture, the historical data is stored in a Hadoop Distributed File System (HDFS) cluster and exploited by using the Apache Spark platform. Despite lambda architecture proposes a speed layer to real-time processing, this is not considered in the Big Data architecture proposed because the real-time processing is implemented in the fog layer. In the same level, a web-based graphical user interface (GUI) is also implemented that enables health professionals, caregivers, and emergency medical centers to remotely access the data on elders' physical activity, sleep stage, sleep environment, and medical condition in order to assess whether treatment needs to be changed, as well as to contact them when in need. The proposed system has been successfully implemented and its real feasibility in the monitoring and treatment of OSA has been fully tested.

The rest of the article is structured as follows. Section 2 reviews the current literature related to this field of research, highlighting the key points of the research development. Next, Section 3 presents the high-level architecture of the proposed system, as well as its implementation. Next, Section 4 describes the main components built and used in the experimental Testbed and Section 5 describes the results of the experiments and evaluations conducted in order to validate the functionality of the system. Finally, Section 6 concludes the paper and presents directions for our further work.

II. RELATED WORK

In the literature, there are several works available related to OSA which are mainly focused on detecting OSA through the monitoring of different physiological parameters. For example, Bsoul *et al.* [9] proposed a low-cost system that enables the detection and recognition of OSA episodes in real time, based on the measurements of a single-channel electrocardiogram (ECG) using a support vector machine classifier (SVM) that runs on a smartphone. The communication between the ECG sensor and the Smartphone is done through Bluetooth.

A similar investigation was proposed by Sannino *et al.* [10], the authors proposed a mobile system in real time to detect the OSA based on the automatic extraction of a set of rules (IF ... THEN), which contained typical parameters derived from the analysis of the heart rate variability obtained from an electrocardiogram (ECG). The authors use the Zephyr BioHarness^{TM}BH3 physiological sensor attached to the patient's chest to record the ECG signals. The data were transmitted to a mobile device (for example, a smartphone or PDA) for processing using Bluetooth technology.

Zhu *et al.* [11] proposed an automatic system for the long-term monitoring of the quality of sleep of the elderly in a residence. The system uses a piezoelectric transducer placed under a mattress to measure the heart rate, respiration, and the parameters of the body movement of older adults at the time of sleep. The collected data is transmitted to database servers through the Internet.

Similarly, a non-intrusive system for quantifying sleep quality was proposed by Nam *et al.* [14] The system was equipped with multimodal sensors, which included a three-axis accelerometer and a pressure sensor. Multimodal sensors monitor various physiological parameters, such as the respiratory rate, the heart rate, and the body activity, as well as the posture of older adults during sleep. The data collected from the system is transmitted over a wireless network of sensors based on ZigBee technology to a portable recording device and to a PC.

Finally, Rofouei *et al.* [12] proposed a portable non-invasive ''neck-cuff'' system to monitor several physiological signals related to sleep quality in real time. These signals were generated from various sensors incorporated into a collar used by the patient during sleep: an oximetry sensor to monitor the level of oxygen saturation in the blood, a microphone to capture breath sounds, and an accelerometer to monitor body movements. The sleep data was sent wirelessly via Bluetooth to a cell phone or PC for processing and storage.

Although, several important parameters have been monitored (mostly physiological) to determine sleep quality and detect OSA. Other factors such as, for example, the sleep environment, also have an impact on OSA, since it allows to assess whether the environment is comfortable to sleep. In this context, a non-invasive IoT-based system to improve the well-being of people with sleep disorders was proposed by Lobato *et al.* [13], which allows for the monitoring of several environmental parameters that contribute to the lack of sleep such as temperature, humidity, noise, and luminosity. The system acquires the data through multimodal technologies such as smart devices (telephones, watches) and electronic health monitors. The collected data is sent through a Wi-Fi access point to a ''Sleep mon'' middleware, for analysis and processing. Additionally, the system offers advice throughout the day with health behaviors that can improve the quality of sleep, such as reminders to practice exercises.

Although the aforementioned research shows its advantages in the detection of OSA, there are still many limitations. For example, most systems are not based on IoT and Big Data-based architectures. An IoT system consists of IoT devices (sensors and actuators), communication interfaces, IoT protocols, algorithms and cloud interfaces. In addition, the pre-processing of data is carried out on devices such as smartphones; whose main constraint is relatively high energy consumption, so these systems could only be active for a short period of time. Others studies perform the pre-processing of data on servers located in the cloud using a Cloud Computing approach; where the delay in the latency caused by the transfer of data from the sensors to the cloud is unacceptable in latency-sensitive solutions, as in the case of healthcare solutions.

Additionally, as a consequence, these systems are not able to notify health professionals in real-time in emergency situations which elders might experience. Likewise, the analyzed works do not address the interoperability of heterogeneous devices working and operating with different protocols and communication technologies, which must be guaranteed in any IoT solution.

Unlike the previous works, the main motivation of this work is to propose a system based on IoT and Big Data that not only focuses on the detection of OSA, but also in guiding the treatment of this syndrome, based on the use of open data processing available in smart cities as well as multiple factors that directly affect OSA such as sleep environment, sleep status, physical activities, and physiological parameters. The system performs two types of processing: (*i*) a pre-processing based on rules that enable the sending of real-time notifications to health professionals and emergency services, in the event of an emergency situation relating to OSA that affects the health of the elderly. This pre-processing is essentially based on a Fog Computing approach implemented in a Smart IoT Gateway operating at the edge of the network that additionally offers advanced interoperability services: technical, syntactic, and semantic; and (*ii*) a batch data processing to perform a descriptive analysis that statistically details the behavior of the data and a predictive analysis for the development of services, such as predicting the least polluted place to perform outdoor activities. This processing uses Big Data tools on Cloud Computing to provide a scalable, flexible, secure, and highly available environment.

III. THE ARCHITECTURE OF IoT-BIG BASED SLEEP APNEA MONITORING SYSTEM

Fig. 1 illustrates the architecture of the proposed system consisting of three functional layers: the IoT layer, the Fog layer, and the cloud layer. The different layers are integrated in order to support the OSA to diagnose and treat elderly people in internal environments such as homes or hospitals, in order to improve their QoL.

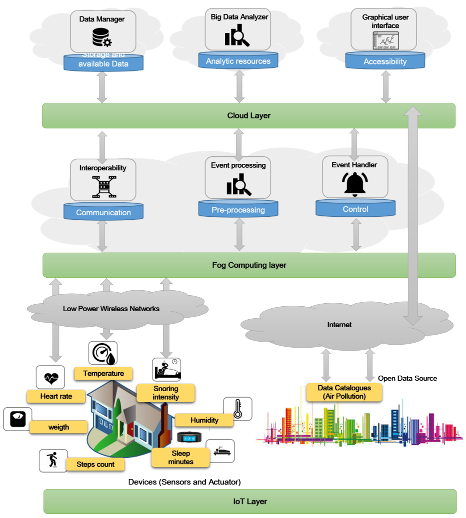


FIGURE 1. **The high-level architecture of an Internet of things and Big Data-based obstructive sleep apnea monitoring system.**

The IoT layer obtains and aggregates the data from multiple heterogeneous sources and transfers them to the fog layer. Fog layer provides the basic functionalities to offer seamless connectivity and interoperability between the different heterogeneous devices involved in the system. This layer is also responsible for the pre-processing of the sensor data necessary for detecting possible adverse events for older adults relating to OSA and to react in real-time by sending notifications to those responsible for the healthcare of the elderly people so that they can receive immediate help. The data from the fog layer is stored, processed, and analyzed at the cloud layer using generic enablers provided by IoT platforms and algorithms based on Big Data, in order to discover new knowledge and thus, support medical decision-making. Finally, the results of the processing can be visualized in a web application through a graphical user interface (GUI), which converts the analyzed information into rich content to guide the treatment of the OSA.

A. IoT LAYER

The IoT layer is the foundation of the entire system since it acquires data from different heterogeneous sources through different wireless networks; IoT nodes located in the elderly person's house, mobile devices worn by the elderly, and open data from smart cities. The IoT nodes and mobile devices are constituted by sensors that measure different parameters such as the sleep environment, the sleep state, physical activities, and physiological parameters. Additionally, the IoT layer uses parameters related to air pollution which are available in the open data catalog of smart cities, taking competitive advantage over previous works [9], [10] that focus exclusively on physiological parameter monitoring. All the parameters have been selected because they have a direct relationship with the OSA and/or a high impact on the progress of the treatment of this syndrome, and they influence the QoL of the elder. On the other hand, wireless networks allow for the transmission of data to the fog layer through low-power wireless technologies. The parameters measurement is described as follows.

1) SLEEP PARAMETERS MEASUREMENT

Sleep is influenced by several factors that directly affect its quality, including the sleep environment and sleep state [16]. The monitoring of these parameters will allow for the estimation of the presence of some type of alteration.

- Sleep environment: one of the general measures to get to sleep is to ensure that the environment in the bedroom is comfortable by avoiding noise, light stimuli, humidity, or extreme temperatures [11]. In our system, environmental sensors are used in order to monitor the temperature and humidity of the sleep environment and determine whether it is comfortable to sleep.
- Sleep status: frequent interruptions of deep sleep often lead to excessive sleepiness during the day and is a clear indicator that a person has had apnea episodes [1], which greatly influences their QoL. In this sense, motion sensors (an accelerometer and a gyroscope) are used to monitor the sleep quality based on the minutes of deep and light sleep of the elderly.

2) PHYSIOLOGICAL PARAMETERS MEASUREMENT

Elderly people suffering from OSA may suffer from various cardiovascular and respiratory problems during sleep [17]. In this context, the heart rate and snoring intensity need to be measured to analyze your health.

- Heart rate: this parameter has a strong link with strokes and heart attacks in people who have OSA because sleep disorders influence the autonomic nervous system and can cause heart rate disturbances [18]. A heart rate monitor placed on the elderly's chest is used to monitor the heart rate during sleep, considering that 12:00 am to 06:00 am is the interval with a high risk of a heart attack [19].
- Snoring intensity: snoring is a major symptom of OSA and its intensity is closely correlated with the severity of this syndrome, that is, the intensity of snoring increases as OSA becomes more severe [20]. Therefore, it is necessary to detect snoring and assess its intensity. To do

this, a 3-pin sound sensor module is used and located in the elderly person's room.

3) PHYSICAL ACTIVITY PARAMETERS MEASUREMENT

A healthy and active lifestyle is essential to mitigate the symptoms of OSA, this includes, among others, avoiding a sedentary lifestyle, performing physical activities, and maintaining a healthy weight.

- Physical activity: active and healthy life habits are considered factors of protection and even treatment of OSA [21]. Monitoring the physical activities in one's daily life can be beneficial to the health and individual sustainability of the elderly person. For example, if a doctor has recommended an elderly person to do exercises to treat OSA, such as walking around the house, or taking different walks outdoors, it is possible to control whether he complies with the care plan. In this work, a pedometer embedded in an intelligent bangle is used to quantify the number of steps taken by the elder during the day.
- Weight: it is directly related to obesity, which constitutes an element of development risk of OSA; a 10% weight gain increases the odds of OSA development by 6-fold [22]. Therefore, it is important to monitor both the elderly person's physical activity and weight. A precision smart scale is used to obtain the weight of the older adult from the comfort of their home.

4) AIR POLLUTION PARAMETERS COLLECTION

Air pollution is associated with higher probabilities of sleep disruption [23]. The available data on this parameter can provide complementary information to guide, in a more precise way, the treatment of OSA. In this sense, the system obtains the contamination levels and climatic conditions provided from the open data catalogs available in smart cities, to suggest to older adults the least polluted places in the city where they can carry out their physical activities without affecting their health. In this work, the open data catalogs of the city of Valencia is used.

All the collected data is transferred to the fog layer for processing through low power wireless networks, except for the air pollution data that is used and processed directly in the cloud layer. Heterogeneous WSNs have been deployed and configured using low-power communication technologies such as ZigBee (IEEE 802.15.4), 6LowPAN (IEEE 802.15.4) and Smart Bluetooth (802.15.1). These communication technologies have been selected due to their inherent advantages such as greater mobility, easy implementation, and easy maintenance; but most importantly, they are characterized by their low-power wireless connectivity, low cost, and lack of infrastructure, which makes them suitable technologies for use in devices with limited resources, paving the way for the implementation of ubiquitous computing in a range of IoT applications.

B. FOG LAYER

The fog layer enables interoperability of the heterogeneous sources of the data and the pre-processing and knowledge generation of them by a fog computing approach. In fog computing, a set of edge devices are placed in between the sensing devices and the cloud in order to extend the cloud resources to the edge of the network with the aim of achieving improved performance by networking, storage, processing capabilities, and so on, close to the end devices [24]. In this work, the fog layer consists of a Smart IoT Gateway where IoT protocols, control, notifications, and data pre-processing services are integrated. The first version of our proposal was presented in [25] and in this work we expanded the contents by adding (i) new discussions on the interoperability of physical devices, (ii) built-in fog computing capabilities, (iii) integration with Cloud IoT platforms, (iv) more details about the architecture developed, and (v) new results obtained as a key component of the proposed system. The Smart IoT Gateway has a double objective. On the one hand, it abstracts the heterogeneity of the data format, of the communication technologies, and of the protocols used by the devices in the IoT layer in order to integrate and make them interoperable. On the other hand, it performs the local pre-processing of the data and transmits it to the cloud layer. The pre-processing of the data is essential to detect in real-time the unusual situations that could worsen the state of OSA in the elderly. The fog layer includes the following main modules: Wireless communication and interoperability, an event processor, and an event handler as shown in Fig. 2.

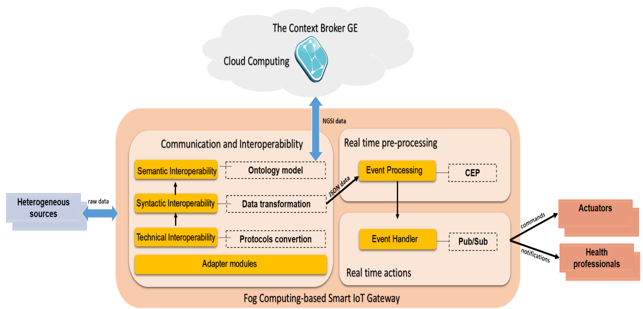


FIGURE 2. The smart IoT gateway architecture.

1) COMMUNICATION AND INTEROPERABILITY

The communication and interoperability in modern medical care are vital to providing information when and where necessary, and to facilitate the health professional's decision-making in a faster and more efficient way. Interoperability needs appropriate standards to connect and integrate heterogeneous IoT devices that operate on different communication technologies and protocols, and to share information in a way that meets the needs of the system. In this work, interoperability is achieved through the Smart IoT Gateway IoT that enables three types of interoperability: technical, syntactic, and semantic.

- Technique Interoperability: To achieve technical interoperability, the Smart IoT Gateway performs the following functions: it coordinates communication tasks through different adapters, resolves the problem of incompatibility of different protocols as well as the conflict of messages between different networks, for this, a hardware abstraction layer is developed, which is responsible for the encapsulation of the data sent by the source protocol in a format compatible with the destination communication protocol. Finally, it redirects and forwards the data through the multiple network interfaces.
- Syntactic Interoperability: Given that heterogeneity is also present in the different data formats supported by the IoT devices used in the system. According to the type of data collected, the Smart IoT Gateway maps this data to a common data standard defined by the system, so that syntactic interoperability is achieved. JSON has been the standard used to format the system data due to its simplicity and compatibility with multiple programming languages. The definition of a common structure before the pre-processing and sending of data contributes directly to the lower consumption of resources and bandwidth.
- Semantic Interoperability: Ensuring the understanding of the data, in a readable and interpretable form, is of vital importance. In this sense, ontologies can facilitate the semantic notation of the collected data, manage access, and extract knowledge of this information. The Smart IoT Gateway provides semantic interoperability by mapping the structure of the data format defined by the system to an NGSI contextualized information model compatibility with ontological vocabulary and sending them, through a REST API, at the cloud layer. Although OMA NGSI does not use a semantic representation of information, it enables the option to use references to ontology concepts (i.e., ontology) to define the types and relationship among these. Therefore, basing the NGSI information on ontological vocabulary (see Fig. 4), NGSI can be used to represent semantic information. In the same way, the Smart IoT Gateway encrypts the pre-processed data to guarantee security through a hash algorithm that uses the SSL protocol. This way, unauthorized devices cannot decipher the data packet, even if they have access to the system.

2) EVENT PROCESSING

The Smart IoT Gateway is also responsible for performing the local pre-processing of the data to detect unusual events that could affect OSA, such as severe snoring, high heart rate whereas the elder sleeps, inadequate comfort in the room, and so forth. To do so, the Smart IoT Gateway incorporates a complex event processor (CEP) based on rules, which receives the data from the syntactic interoperability submodule and processes this data based on the set of rules defined in the system, presented in Table 1. These rules describe the emergency situations related to OSA and the actions that must be executed if the conditions set by the system are met. Each rule refers to a monitored parameter and for each parameter, there is more than one rule.

TABLE 1. The rules configured in the complex event processing.

Parameters	Rules	Threshold	Monitoring interval	Actions
Steps count	sedentary	<5000		NHPC[a]
	mild active	5000–7499		
	moderate active	7500–9999	Daily	
	active	10000–12499		
	high active	>12500		
Temperature	low temperature	<18 °C	22:00 - 08:00	Turn on/off Air - NHPC[a]
	high temperature	>22 °C		Conditioner/ NHPC[a]
Humidity	low humidity	<50%	22:00 - 08:00	Dehumidifier NHPC[a]
	high humidity	>70%	22:00 - 08:00	NHPC[a]
Heart rate	bradycardia	<50 bpm		NHPC[a]
	normal	60–100 bpm	22:00 - 08:00	
	tachycardia	>100 bpm		NHPC[a]
Snoring Level	normal	<40 dB		
	mild	40–50 dB		
	moderate	50–60 dB	22:00 - 08:00	
	severe	>60 dB		NHPC[a]
BMI	underweight	<18,5 kg/m2		NHPC[a]
	normal	18,5–24,9 kg/m2	Daily	
	overweight	25–29,9 kg/m2		NHPC[a]
	obese	>=30 kg/m2		NHPC[a]

[a] NHPC: Notifications to health professionals and caregivers.

This module is the key element for the detection of episodes of OSA. According to [20], the snoring level intensity is sufficient to detect sleep apnea episodes. In this work, an episode of OSA is detected when the snoring level intensity exceeds 60 decibels (i.e., the snoring level is severe) within a window of 10 sec. The CEP checks that this condition is met for three consecutive-time. An example rule analyzing severe apnea episodes is shown in Algorithm 1.

Algorithm 1 Example Rule for CEP

for $(snoring\_level) \in TupleWindow(3)$ **do**
  if $(snoring\_level(t) > snoring\_level_{thr}$
    $AND\ (snoring\_level_{(t+1)} > snoring\_level_{thr}$
    $AND\ (snoring\_level_{(t+2)} > snoring\_level_{thr}$
    then
      Generate event severe apnea
  end if
end for

The Cepheus CEP generic enabler provided by the open Fiware platform [15] is adopted in this system for event processing. The Fiware platform is composed of a set of components referred to as Generic Enablers (GEs) that afford reusable and commonly shared functionalities that enable the development of applications and intelligent services based on the open OpenStack standard.

The direct processing of data at the edge of the network improves the efficiency of the system whilst contributing to the rapid delivery of notifications that are necessary for the immediate assistance of the elderly person, unlike the systems presented in [5]–[8] and [10] that lack this functionality.

3) EVENT HANDLER

If the values of the parameters established activate at least one rule, the Smart IoT Gateway detects the event and takes immediate actions with a reduced response time and latency, sending notifications to the groups responsible for the care of the elder and with access to information, as well as commands to the actuators through an MQTT broker. In this work, the Message Queue Telemetry Transport (MQTT) is chosen because it is a lightweight and secure protocol specially designed for resource-constrained devices and suited for IoT applications. Its implementation follows a publish/subscribe architecture based on ''topics''. In this architecture, publishers connect to the MQTT broker and publish under a certain topic, whilst the subscriber receives only the messages associated with the topic(s) interest, which would be previously registered. MQTT provides end-to-end secured communication and reliability based on SSL (Secure Socket Layer). In addition, it incorporates several QoS levels to confirm the delivery of messages, from a non-optimal minimum level (QoS0) to a double-recognition level (QoS2). Since our system is closely related to the elderly's healthcare, the QoS2 level has been configured to guarantee the reliability of the delivery of the notifications and commands associated with each rule. In order to reduce the bit-error rate over the communication media and improve the packet delivery probability, the QoS2 level delivers the message exactly once. In this work, the MQTT broker is implemented using the paho-mqtt Python library.

C. CLOUD LAYER

Cloud computing is currently the preferred paradigm to undertake large storage, computation-intensive data process and analysis tasks, due to its maturity and scaling capabilities, as they allow services to grow and shrink in-line without degrading, which greatly eases the burden of smart devices.

This layer is responsible for efficiently managing, storing, and analyzing all the data collected by the system. Given that the system is closely related to the health status of elderly persons, the availability and analysis of the data are necessary to support medical decision-making. For this, this layer includes the following functional modules: data manager, Big Data analyzer, and web application.

Data Manager acts as a central repository and is responsible for managing and providing access to information coming from the fog layer. The generic enabler, GE Context Broker Orion, also provided by the Fiware platform, is used as the Data Manager. The GE Context Broker Orion handles context information as ''entities'' which consists of elements and attributes that are represented by NGSI generic data structures shown in Fig. 3. The GE Context Broker provides REST API interfaces that allow for the registration, update, and elimination of these entities, as well as for the retrieval of context data to any authorized party in consuming this information such as services or applications, through Publication/Subscription operations as shown in Fig. 5. In our system, the Big Data analyzer (detailed below) subscribes to the Data Manager to obtain the online information.

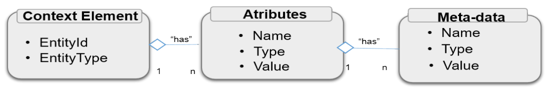


FIGURE 3. The conceptual diagram of data manager entities.

EntityId	ID urn:x-iot:smartsleepmonitoring:1:1	
	Type http://www.semanticweb.org/smartsleepmonitoring/NGSI#ElderlyBedroom	
	isPattern false	
Attribute Domain		
ContextAttribute	Name http://www.semanticweb.org/smartsleepmonitoring/NGSI#hasSoundSensor	
	Type http://www.semanticweb.org/smartsleepmonitoring/NGSI#Sound	
	Value 45	
	Metadata	Name: http://..../NGSI#hasMetadataUnit
		Type: http://..../NGSI#MetadataUnit
		Value: dB

FIGURE 4. NGSI data modelled based on an ontological vocabulary

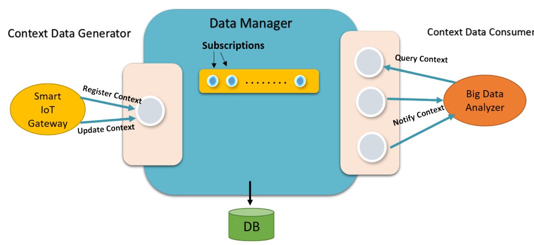


FIGURE 5. The operation of the data manager.

Big Data Analyzer is able to process and analyze the data coming from the fog layer, as well as the open data catalog available in smart cities. To do this, the analyzer implements four modules: data integration, batch processing, machine learning, and services, as shown in Fig. 6.

- The data integration module allows for the data combination, which comes from the fog layer and the smart city open data (conditions of environmental pollution and climatic conditions) using the Python open libraries (csv, json, request). For this, the module implements a data extraction process through connectors which using

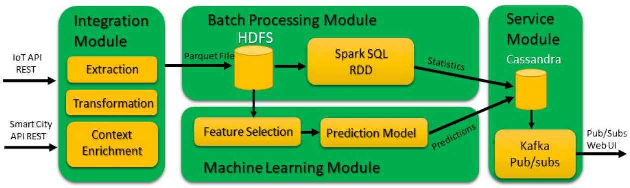


FIGURE 6. The Big Data Analyzer architecture.

the request library to extract the data from the Valencia City Council portal [26] and the Spanish Meteorological Agency AEMET [27], as well as the data manager. Subsequently, the data are transformed from its original format (JSON, CSV) to a tabular data schema, through the Pandas dataframe tool and using the csv and json libraries. The Pandas tool offers some functions that allow the merging of the data of the different sources in a single data model. The data merging is done using the timestamp in which they were generated. These data are transformed into a columnar data representation using Apache Parquet, which provides an efficient compression and encoding schema. The parquet file is stored incrementally in a distribution file system in the batch processing module.

- The batch processing module provides storage and the processing of the data which were merged in the integration module. For this, the module implements a file system distributed through the environment provided by Hadoop. The Hadoop Distributed File System (HDFS) is used as the file system because it provides scalability and redundancy for the support of large files. In addition, the module implements parallel processing tasks exploiting the advantages provided by Apache Spark 2.6. The main characteristic of Apache Spark is the use of Resilient Distributed Dataset (RDD) that allows for the lowering of the execution time in relation to Hadoop. In addition, Apache Spark provides a SparkSQL library to support the usual data query operations of a data storage system through a high-level semantic language. SparkSQL is used to perform a descriptive analysis based on the statistical parameters such as average, maximum, minimum, standard deviation, a histogram of the data collected from monitoring the sleep environment, sleep status, physiological parameters, physical activity, and so forth. In this way, the system obtains the weekly average of the steps traveled, the average hours of deep sleep and/or light sleep, the snoring average and its values in decibels, as well as the statistical distribution data using histograms that allow for the determination of the highest frequency value (mode). These results are stored in a non-relational database in the service module to be presented to the end users through the system's web application.
- The machine learning module exploits the data stored in the batch processing module through pre-processing and prediction tasks in order to provide a prediction service for the places with less pollution in the city. For this, the prediction models are implemented using a historical dataset formed by Valencia City air pollution and weather conditions corresponding to the years 2012–2017. The Valencia City Council provides the hourly information on pollutants present in the atmosphere (nitrogen monoxide NO, nitrogen dioxide NO2, ozone O3, and sulfur dioxide SO2). Meanwhile, the AEMET provides the weather forecast information (temperature, humidity, pressure, wind direction, wind speed, and precipitation) every hour. These data fulfill the pre-processing tasks focused on data cleaning and feature selection. Data cleaning is performed to identify the incomplete, incorrect, and irrelevant data for the system, and replace them with an average value or a linearly interpolated value in order for the model to have more reliable data for training. Meanwhile, feature selection is carried out in order to reduce the resource consumption in the model training process and to increase the model accuracy. Feature selection is done using a Pearson correlation analysis and removing variables with low variance. Subsequently, the data are normalized and adjusted to an adequate scale so that all the data are within the same values range, reducing the computational consumption in the model training process even more. Next, the normalized data are divided into a dataset for model training and testing using a random division 80%–20%, respectively.
  Linear regression models, decision tree, random forest, and artificial neural network (ANN) have been created from the training data in order to predict air pollution levels in Valencia City. Each of these models was previously evaluated using the test dataset in terms of the root mean square error (RMSE) as shown in Table 2.

TABLE 2. The RMSE machine learning models comparison.

Pollutant	Linear Regression	Decision Tree	Random Forest	ANN MLP-tanh	ANN MLP-relu
	RMSE (%)	RMSE (%)	RMSE (%)	RMSE (%)	RMSE (%)
O3	13.45	16.64	15.91	12.69	12.73
NO	15.57	20.38	15.74	14.78	14.56
NO2	15.92	19.90	18.09	14.98	14.96
SO2	2.41	3.52	2.50	2.24	2.23

Scikit-learn 0.18.0 was used for both data pre-processing and models generating. According to the results, the ANN model based on 30 Multilayer Perceptron (MLP) units with Relu activation function was selected because it provides the least RMSE necessary to maximize the prediction accuracies. The ANN predictions provide hourly information about each pollutant levels analyzed. However, the air pollution levels do not provide easy information to infer, therefore, the air quality index (AQI) was used in a complementary manner to provide tags such as excellent, good, improvable, bad, or dangerous, based on the pollution ranges for each pollutant to facilitate the end user's interpretation. The AQI prediction is done for the 6 stations distributed in Valencia City in order to know the station with the best AQI. In this way, the system predicts which place will have the best AQI using the predictions pollutant levels knowledge. Finally, the AQI predictions throughout the day are sent to the service module.

- The service module provides temporary information storage for both the descriptive analysis and the predictions made and a publish/subscribe mechanism for access to this information by the applications. Apache Cassandra was selected as a database system to provide temporary information storage because it provides fault tolerance, scalability, as well as a query language (CQL) to generate queries from the temporary tables resulting from the data analysis. CQL allows us to obtain the necessary information when it is required. Additionally, Apache Kafka was selected for the implementation of the publish/subscribe architecture to facilitate access to the information generated by statistical and predictive analyses because it provides high flexibility and availability.

GRAPHICAL USER INTERFACE (GUI)

The GUI is responsible for converting the analyzed information into rich content and displaying it. In the system, two GUIs are available: the web application and the mobile app. The web application interacts with the Big Data analyzer through the service module for greater data availability and usability. This application makes use of all the data provided by the service module through RESTful API interfaces. The web application is aimed at health professionals for the continuous OSA monitoring of the elderly, focused on showing all the data processed by the Big Data Analyzer to support medical decisions.

Both the web application and mobile app includes authentication mechanisms in order to preserve the data privacy and to provide the secure access to the system data. Health professionals can log onto the web application to check some OSA-related health indicators about elderly people under their care. Apart from visualizing the health indicators, health professionals can log onto the mobile app to receive notifications or warnings regarding their patients in real time, whereas the elderly people can log onto the mobile app to receive suggestions of the least contaminated places in the city.

IV. TESTBED IMPLEMENTATION

In order to evaluate the functionality of the proposed system, in this section, we first detail the implementation of each component used in the different layers of system architecture, then we describe and discussing the obtained results.

A. SYSTEM ARCHITECTURE

A mobile app, smart IoT Gateway, and servers were built and used in the IoT, fog, and the cloud Layer, respectively.

Mobile App developed for the Android operating system consists of several classes built using android studio; the physical activity class to manage the weight and step count readings, the sleep class to manage the minutes of sleep and heart rate readings; and the local database is used to temporally store data in the smartphone. The android application reads the minutes of the sleep/wake state and number of steps, heart rate records and also takes weight records of a wristband Fitbit Flex 2, a Heart Rate Monitor PM235 and an A&D Medical Precision Body Weight Scale, respectively. These wearable devices are wirelessly connected to a smartphone through a Bluetooth connection.

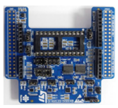
The information gathered by them is transferred automatically to the smart IoT gateway. Furthermore, the mobile application contains an AQI class to subscribe to the service module of the Big Data Analyzer to receive the predictions of pollutant levels in the city. The mobile application uses this information to display the pollutant levels in a map. The best place is determined by identifying the lowest AQI value. All the classes of the mobile app are executed through a data receiver agent. The mobile app is loaded onto the smartphone of the elderly person and it is previously configured with the person's credentials. The mobile application was tested on a Google Nexus 5 smartphone with a Qualcomm Snapdragon 800 processor of 2.30 GHz 4 cores and 2 GB RAM, and with the Android 6.0.1 operating system.

1) SMART IoT GATEWAY

The smart IoT gateway prototype has been implemented using a Raspberry Pi 3 model B as equipped with a 1.2 GHz Quad-Core ARM Cortex processor, 1 GB of RAM, and which is permanently connected to an electrical power supply and located in the elder's room. The Raspberry uses several communication modules to allow the interoperability of heterogeneous devices working with different wireless communication technologies. For instance, XBee 2 mW Wire Antenna S2 ZigBee communication module is configured as a coordinator device in order to acquire sensor data sent by the LM393 sound sensor. In Addition, the gateway integrates a 6LowPAN module (by the combination NUCLEO-L152RE based on ultra-low-power microcontroller and IDS01A5 board) configured as an edge router in order to collect the information from the temperature and humidity sensor HTS221, which is integrated on the IKS01A1 STM32 board. Furthermore, a tunneling-virtual network adapter is configured on the edge router to translate IPv6 packages to IPV4 and vice versa by using the tunslip6 tool running on the Contiki OS. Likewise, the RPL protocol is implemented to route and forward the information inside the 6LoWPAN network. Finally, a CoAP client is configured on the Gateway to retrieve the temperature and humidity values using the aiocoap library based on the

Python 3 asynchronous I/O. The Raspberry Pi 3 model B includes a built-in Bluetooth 4.1 so that there is no need to add an external USB adapter as in previous versions. The library bluez is configured to establish and obtain the information sent by the mobile application. The smart IoT gateway, as well as the mobile app firmware, is executed when sensors are started. Table 3 summarizes the different devices, communication protocols, and the application services supported by them.

TABLE 3. Characteristics of the devices used in the experiments.

Device		Communication Protocol	Application Service
	A&D Medical Precision Body Weight Scale	Bluetooth	Physical Activity monitoring
	Heart Rate PM235	Bluetooth	Physiological monitoring
	MEMS Sensor - HTS221	6LowPAN	Sleep environment monitoring
	LM393	ZigBee	Snoring intensity Monitoring
	Fitbit Flex Bangle	Bluetooth	Physical activity and sleep status monitoring

2) SERVERS

Three types of servers that provide different functionalities were implemented using virtualization technologies running on a private server. The server had the following hardware features: a FUJITSU server with an Intel Xeon E3-1220 v5 3.00 GHz CPU with 64 GB of memory. The server is managed by the vSphere platform, which allows for the deployment of virtual machines. The virtual machines were deployed for each functional module of the cloud layer (Data Manager, Big Data Analyzer, and GUI; 3 virtual machines in total), using the server shared physical resources (for example, memory, CPU, and so forth). Within each virtual machine, the necessary applications, frameworks, and services were deployed so that each module can provide the features described in the architecture design. In this way, the virtual machine assigned to the Data Manager contains the Orion Context Broker GE application provided by FIWARE. The virtual machine destined to the Big Data Analyzer deploys the data analysis pipeline using microservices. The microservices were implemented using docker containers. In this way, this virtual machine contains docker containers of HDFS, Apache Spark, Kafka, and Cassandra, to provide the Big Data Analyzer services. Finally, the application virtual machine deploys a web server that serves as a front-end for the users using Nodejs.

B. RESULTS AND ANALYSIS

The results show how the system works to meet its objective of detecting OSA episodes and supporting its treatment. Several experiments were carried out with 2 adult volunteers who have problems falling asleep and/or sleeping disorders, which have the following characteristics described in Table 4.

TABLE 4. Characteristics of the adults volunteers who participated in the experiments.

	Volunteer A	Volunteer B
Gender	Female	Male
Age	65	60
Height	1.60 cm	1.65 cm
Weight	70 kg	62 kg
OSA Diagnostic	Yes (mild Apnea)	No (but he has problems getting to sleep)

A dataset from the different sources previously specified in Section 3.1 was collected from February 19 to August 13, 2017. Table 5 shows the number of records collected for each monitored parameter.

TABLE 5. Records collected in the experiments.

Parameters	Records
Snoring levels	177
Temperature	13.450
Humidity	13.450
Heart rate	13.450
Steps counter	185
Sleep stages	185

1) APNEA EPISODES DETECTION

The apnea episodes detection is determined as indicated in the events processing subsection according to snoring level rules predefined in the CEP. The location of the sound sensor is very important to detect sleep apnea episodes. Initially, several tests were performed to calibration and tune the sound sensor and detection distance. The calibration was performed in a controlled environment using a sound level meter. Several conditions were conducted, and the correlation between the reference values of the sound level meter and the data of the sound sensor was performed by a linear regression. As a result, a linear equation is defined from which the measurements of snoring level are obtained. These measurements are transmitted to the smart IoT gateway through a ZigBee connection. The CEP processes this data and detects the sleep apnea episodes. In addition, we have verified that the maximum detection distance of the sound sensor is 4 meters. In this work, the sensor has been located at a distance of 0.7 meters from the elderly's bed monitored.

In the Big data Analyzer, the sleep apnea episodes, previously detected, are quantitatively evaluated. The system quantified the sleep apnea episodes in each patient's recordings (i.e., each night evaluated) and detected that in the 93 recordings taken for volunteer "A" there were 5 recordings classified as severity, 15 recordings as moderate, 68 recordings as mild, and 5 recordings as normal, as Fig. 7a shows. These figures help to indicate that the mode or the frequent value is associated with a mild apnea class, which corresponds to the medical diagnosis of patient "A". For patient "B", in the Fig. 7b, there were 9 recordings classified as moderate, 26 as mild, and 49 as normal, without any recording in the severe class. Patient B's mode corresponds to the normal class, with 22 of them that did not present snoring occurrences. These values revealed that patient "B" does not suffer from OSA episodes and his problem of falling asleep was due to other factors. These results were confirmed by a doctor.

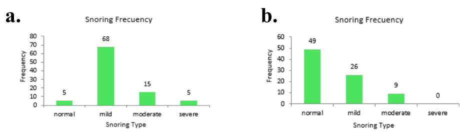


FIGURE 7. **(a) Snoring histogram levels of patient A; (b) snoring histogram levels of patient B.**

The apnea occurrences histogram is presented in the web interface corresponding to each patient as shown in Fig. 8. In this way, if the patients tend to aggravate their apnea situation, the system would show that the mode value rises in rank, so health professionals could infer that the apnea is aggravated and make decisions.

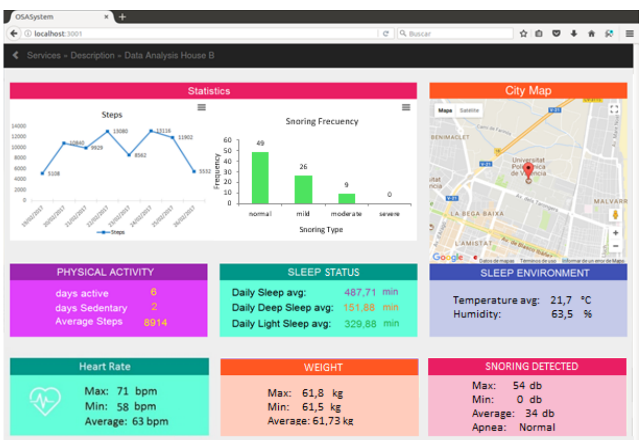


FIGURE 8. **The elderly person's statistics dashboard in web UI application.**

In addition, the system uses the data generated by the sensor that measures the heart rate to evaluate the apnea occurrences. In this case, the system detected that patient A had a 63 bpm heart rate average, measured in the previous night's sleep stage. Also, patient A had 3 maximum peak occurrences up to 71 bpm. This maximum peak up was presented at the same moment that a >60 db-snoring-occurrence was detected, justifying this maximum peak detected. This result is showed in the dashboard web application Fig. 8. On the other hand, the patient B presents with a 57 bpm heart rate average in his sleep stage, which corresponds to normal values in patients without sleep apnea. Along these lines, the system provides more context to infer the OSA occurrences detection with more details.

2) SUPPORTING THE APNEA TREATMENT

The system performs a descriptive analysis of the monitored data (previously specified) in order to know the health evolution of elderly persons who suffer from sleep apnea. The statistical analysis results carried out by the system are presented in the web interface in Fig. 8. The web application shows daily, weekly, and monthly statistical graphs of the elderly person's physical activity performed and sleep stages. The statistics show the steps average value made by the person, the deep sleep average values, the light sleep average values, the sleep environment temperature, and the humidity average. In addition, the web application shows graphs on the sleep stages and steps value evolution in the previous week. With these statistics, the system provides information to infer whether the elderly person had high or sedentary activity, or whether the tendency is to maintain moderate activity, and its influence on their sleep quality. For example, Fig. 8 shows the weekly steps and sleep stage statistics for the patient B. The statistics in this example show that, on average, patient B walked 8914 steps and that in the last week he was very active, with only 2 days being considered as barely active because his steps did not exceed the corresponding threshold. In addition, the graphs help infer that the elderly B is highly active but that his stage of deep sleep is very low, due to his problems of falling asleep. In Fig. 8, one can also observe that the average temperature inside the elderly person's bedroom is among the recommended values for people suffering from these types of diseases, so this verifies that the parameters through actuators in order to keep the elderly person's bedroom environment comfortable.

In addition to the web user interface, the system displays notifications in the smart mobile phone application through the mobile app when some monitored parameter exceeds the thresholds established in the CEP. Fig. 9a shows the sending of notifications to health professionals.

Complementing the functionalities, the system provides information to the elderly to help avoid contaminated places. To do this, the system makes a prediction of the city's air quality and provides a city map indicating the place where there is less environmental pollution. The service uses the ANN with 30 MLP units with a RELU function, previously trained by the system in the Big Data Analyzer machine learning module, to predict the daily the environmental pollution levels in the city. This information is sent to the smart mobile phone

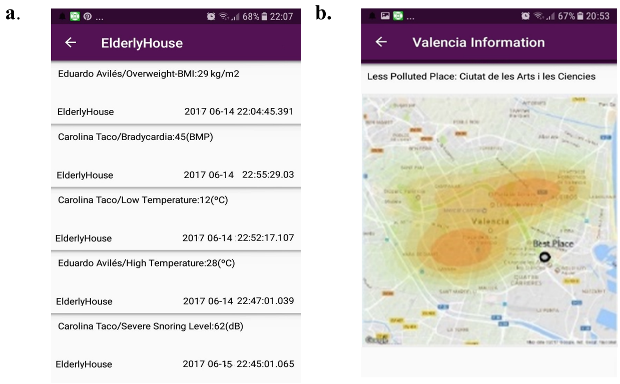


FIGURE 9. **(a) Notifications for the healthcare professionals; (b) Notifications of Valencia City polluted places.**

of each elder, each time they request the service. In Fig. 9b, the city pollution zones are visualized graphically and act as information that serves as support to the elderly person's decision to choose the least contaminated place to carry out their activities without putting their health at risk. The ANN predictions effectiveness was evaluated by performing an experiment executing the prediction service in 15 different days at a different time. The system consults the weather forecast data from the AEMET, with each test execution. The AEMET provides 25 values corresponding to the weather forecast for the test day (00:00–24:00). At the same time, the system consults the pollutants data provided by the Valencia City Council, which are published three hours late. The three-hours-ago pollutants information, together with the weather forecast, allows the system to predict the pollutant levels requested at the test execution time. The prediction accuracy evaluation is made three hours later when the Valencia City Council issues the official air quality index value. By evaluating the correct answers number in relation to the total data number, we determined that the system is on average 93.55% accurate in the AQI prediction in Valencia City. The value is acceptable for this type of service but is still considered improvable.

The overall value of AQI prediction in treating OSA patients is prevent that the condition of a patient's sleep apnea become more serious. The findings of epidemiological studies reveals that people living or conducting activities in places with high levels of air pollution were 60% more likely to suffer from a sleep disorder, compared with those living in areas with better air quality. This is due to a greater exposure to circulating nitrogen dioxide (NO_2) , nitric oxide (NO) and particles (PM 2.5s).

3) PERFORMANCE EVALUATION OF THE PROPOSED SYSTEM

In order to evaluate the performance of the proposed system, we present the latency measurements for the sense-act loop. The results of the measurements presented in Table 6 show that the detection of sleep apnea episodes as well as the pre-processing of all monitored parameters at Fog layer improve the efficiency of the system by reducing the latency on the communication infrastructure. The 6lowPAN, Bluetooth and ZigBee protocols were used during the latency measurements.

TABLE 6. **Latency measurements.**

Latency from sensing to acting via gateway	6LowPAN(ms)	ZigBee (ms)	BLE (ms)
Fog layer	**132**	**42**	**62**
Cloud layer	177	63	138

The long latency introduced by Cloud layer could prevent patients from being assisted in real-time. In addition, the results show that the highest latency occurs when using the 6LowPAN protocol compared with Bluetooth and ZigBee protocols. This is because the processing time largely depends on the complexity of protocol integration. For example, when used ZigBee device, a reading to the serial port connected to ZigBee coordinator is sufficient to get the sensor value for subsequently processing. However, when using 6LowPAN device, a GET request to the CoAP Server embedded in this device is required to retrieve the sensor value.

4) USABILITY EVALUATION OF THE PROPOSED SYSTEM

The system usability was verified by a questionnaire based on the ISO 92411 standard. The system was demonstrated to a group of volunteer doctors and caregivers. The usability of the system aims at determine, to a certain degree, what are the attenders' perceptions regarding the system's user interfaces (both of web application and of mobile app) and the devices used in the system. The UIs were assessed on the following usability criteria: (a) easy to use, (b) visually attractive, (c) intuitive, (d) with a terminology easy to understand, (e) with information well structured, (f) in accord with the notifications, (g) in accord with the monitored parameters and (h) provide clear messages to support the medical decision-making. The devices were assessed on satisfaction criteria (pleasure in use, physical comfort trust, non- intrusive) All the usability criteria were graded from 1 (Disagree) to 5 (Agree).

The results obtained indicated that the attenders agreed, in greater, with the usability of the UIs and with the monitored parameters by the system. They consider that the parameters are suitable for dealing with diagnostic and that the sensors used are not obtrusive for the patients. In fact, they indicated that devices could improve adherence of treatment of sleep apnea. They also agree that the information provided by the notifications supports medical decision-making and may be especially helpful to assist patients on time. Moreover, the doctors agree that the visualization of the least polluted place as a good way to support the treatment of sleep apnea and improve the patient's QoL. The doctors recommend monitoring the oxygen level in blood for improving OSA diagnosis, and including a score in the Web UI according to the number of parameters that exceeded the corresponding thresholds.

V. CONCLUSIONS

QoL has become a need in society that will continue to be even more important if we consider that in the future the number of older adults will represent more than 14% of the world's population. OSA is one of the diseases that most compromises the QoL of the adults who suffer from it and causes important complications that can affect their health. The continuous monitoring and the processing of multiple parameters related to OSA will lead to the alerting of health professionals, emergency centers, caregivers, and relatives of adults at the right time so as to be assisted on time, in order to improve their QoL, and in some cases, even preserve their lives.

Innovative technologies such as IoT and Big Data have been gradually developed to create intelligent and pervasive systems focused on the healthcare of adults and, in general, on medical care. More precisely, IoT can be used as a tool to support the monitoring and control within a health ecosystem, whereas data analysis technologies can be used to support decision-making.

A system based on a 3-level architecture for supporting real-time monitoring of OSA in elderly people and guiding their treatment has been proposed and implemented. The system is implemented using heterogeneous and non-intrusive devices, IoT protocols, components of standard platforms, low-power technologies, big data technologies, and fog and Cloud computing approaches.

At the fog layer, an efficient processing on a smart IoT gateway has been implemented and evaluated for processing the snoring level and data of the of multiple factors that directly affect OSA (sleep environment, sleep status, physical activities, and physiological parameters), detect the episodes of the OSA and unusual events, and alert the health professionals and caregivers in time. With the IoT vision in mind, at the fog layer also the technical, syntactic and semantic interoperability has been implemented, so as to allow the communication and data sharing among heterogeneous IoT devices as well as the transfer of data from the IoT layer to the Cloud layer.

Taking advantage of the Big Data tools, a batch data processing at the Cloud layer has been implemented. It is able to perform a descriptive analysis that statistically details the behavior of the data from the smart IoT gateway and predict the least polluted place based on the pollutant's data available in smart cities in order to guide the treatment of OSA. The analyzed data are delivered to a server, which display the information in a Web IU, so the healthcare professionals involved in the care of the elderly people can easily access from anywhere at any time and from any device.

Several experiments were conducted to validate the proposed system. The usability evaluation of the system showed that the UIs of the system provides suitable information to help to the healthcare professionals to infer OSA context-awareness and support the medical decision-making on their treatment. In addition, the results demonstrate that the non-intrusive devices used to monitor and the predictions of the less polluted places on the city could lead to facilitate adherence to the prescribed medical treatment. The prediction of the AQI provides a 93.3% effectiveness. Given that the AQI prediction error is 6.7%, it is concluded that such AQI prediction provides an acceptable level of confidence and that the machine learning model can be used for supporting the OSA treatment. The performance evaluation of the proposed system is evaluated in terms of latency. The results demonstrate that the detection of apnea episodes making at the Fog layer reduces the latency on the communication infrastructure compared to at the Cloud layer. In the future, we will focus on integrating the system with other solutions applied to the healthcare domain derived from Inter-IoT project with the aim of facilitate the delivery of elderly smart healthcare services. In addition, a future evaluation with more patients will provide both useful lessons learned and results to be used to further enhance the proposed system.

REFERENCES

[1] K. P. Strohl and S. Redline, "Recognition of obstructive sleep apnea," *Amer. J. Respiratory Critical Care Med.*, vol. 154, no. 2, pp. 279–289, 1996.

[2] E. J. Olson, W. R. Moore, T. I. Morgenthaler, P. C. Gay, and B. A. Staats, "Obstructive sleep apnea-hypopnea syndrome," *Mayo Clin. Proc.*, vol. 78, no. 12, pp. 1545–1552, 2003.

[3] M. H. Bonnet and D. L. Arand, "Clinical effects of sleep fragmentation versus sleep deprivation," *Sleep Med. Rev.*, vol. 7, no. 4, pp. 297–310, 2003.

[4] *National Institutes of Health Sleep Disorders Research Plan*, Nat. Inst. Health, Bethesda, MD, USA, 2011.

[5] M. Glasser, N. Bailey, A. McMillan, E. Goff, and M. J. Morrell, "Sleep apnoea in older people," *Breathe*, vol. 7, no. 3, pp. 248–256, 2011.

[6] H. K. Yaggi, J. Concato, W. N. Kernan, J. H. Lichtman, L. M. Brass, and V. Mohsenin, "Obstructive sleep apnea as a risk factor for stroke and death," *New England J. Med.*, vol. 353, no. 19, pp. 2034–2041, 2005.

[7] A. S. Karunajeewa, U. R. Abeyratne, and C. Hukins, "Multi-feature snore sound analysis in obstructive sleep apnea–hypopnea syndrome," *Physiol. Meas.*, vol. 32, no. 1, p. 83, 2011.

[8] A. Cartwright *et al.*, "0510 use of a personalized video to enhance PAP adherence: Preliminary report from a randomized clinical trial," *Sleep*, vol. 40, no. 1, p. A190, Apr. 2017, doi: 10.1093/sleepj/zsx050.509.

[9] M. Bsoul, H. Minn, and L. Tamil, "Apnea MedAssist: Real-time sleep apnea monitor using single-lead ECG," *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 3, pp. 416–427, May 2011.

[10] G. Sannino, I. De Falco, and G. De Pietro, "Monitoring Obstructive Sleep Apnea by means of a real-time mobile system based on the automatic extraction of sets of rules through Differential Evolution," *J. Biomed. Inform.*, vol. 49, pp. 84–100, Jun. 2014.

[11] X. Zhu, X. Zhou, W. Chen, K.-I. Kitamura, and T. Nemoto, "Estimation of sleep quality of residents in nursing homes using an Internet-based automatic monitoring system," in *Proc. IEEE 11th Int. Conf. Ubiquitous Intell. Comput., IEEE 11th Int. Conf. Autonomic Trusted Comput., IEEE 14th Int. Conf. Scalable Comput. Commun. Associated Workshops*, Dec. 2014, pp. 659–665.

[12] M. Rofouei *et al.*, "A non-invasive wearable neck-cuff system for real-time sleep monitoring," in *Proc. Int. Conf. Body Sensor Netw.*, 2011, pp. 156–161.

[13] F. M. F. Lobato, D. C. O. de Resende, R. P. do Nascimento, A. L. C. Siqueira, A. F. L. Jacob, Jr., and A. L. de Santana, "Multimodal low-invasive system for sleep quality monitoring and improvement," in *Beyond the Internet of Things: Everything Interconnected*, J. M. Batalla, G. Mastorakis, C. Mavromoustakis, and E. Pallis, Eds. Cham, Switzerland: Springer, 2017, pp. 223–242.

[14] Y. Nam, Y. Kim, and J. Lee, "Sleep monitoring based on a tri-axial accelerometer and a pressure sensor," *Sensors*, vol. 16, no. 5, p. 750, May 2016.

[15] (2017). *FIWARE*. Accessed: May 1, 2017. [Online]. Available: https://www.fiware.org/tag/iot/

[16] M. Kay *et al.*, "Lullaby: A capture & access system for understanding the sleep environment," in *Proc. ACM Conf. Ubiquitous Comput.*, 2012, pp. 226–234.

[17] M.-A. Martínez-García *et al.*, "Cardiovascular mortality in obstructive sleep apnea in the elderly: Role of long-term continuous positive airway pressure treatment: A prospective observational study," *Amer. J. Respiratory Critical Care Med.*, vol. 186, no. 9, pp. 909–916, 2012.

[18] T. Penzel, J. W. Kantelhardt, L. Grote, J. H. Peter, and A. Bunde, "Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 10, pp. 1143–1151, Oct. 2003.

[19] A. S. Gami, D. E. Howard, E. J. Olson, and V. K. Somers, "Day–night pattern of sudden death in obstructive sleep apnea," *New England J. Med.*, vol. 352, no. 12, pp. 1206–1214, Mar. 2005.

[20] N. Maimon and P. J. Hanly, "Does snoring intensity correlate with the severity of obstructive sleep apnea?" *J. Clin. Sleep Med.*, vol. 6, no. 5, pp. 475–478, Oct. 2010.

[21] H. Igelström *et al.*, "Improvement in obstructive sleep apnea after a tailored behavioural sleep medicine intervention targeting healthy eating and physical activity: A randomised controlled trial," *Sleep Breathing*, pp. 1–9, Dec. 2017. doi: 10.1007/s11325-017-1597-z.

[22] R. Wolk, A. S. M. Shamsuzzaman, and V. K. Somers, "Obesity, sleep apnea, and hypertension," *Hypertension*, vol. 42, no. 6, pp. 1067–1074, 2003.

[23] E. B. Martha *et al.*, "Relationship of air pollution to sleep disruption: The multi-ethnic study of atherosclerosis (MESA) sleep and MESA-air studies," *B20 Big Data Comes Sleep Med.*, p. A2930, May 2017.

[24] A. V. Dastjerdi and R. Buyya, "Fog computing: Helping the Internet of Things realize its potential," *Computer*, vol. 49, no. 8, pp. 112–116, Aug. 2016.

[25] D. C. Yacchirema and C. Palau, "Smart IoT gateway for heterogeneous devices interoperability," *IEEE Latin Amer. Trans.*, vol. 14, no. 8, pp. 3900–3906, Aug. 2016.

[26] Valencia SmartCity. *Plataforma Valencia*. Accessed: Sep. 27, 2017. [Online]. Available: https://portal.vlci.valencia.es/#/

[27] A. E. de Meteorología. *Agencia Estatal de Meteorología- AEMET. Gobierno de España*. Accessed: Oct. 16, 2017. [Online]. Available: http://www.aemet.es/es/portada

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