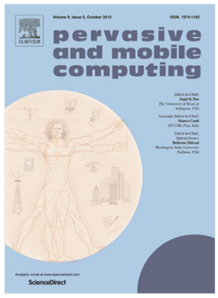

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SYSTEM FOR MONITORING AND SUPPORTING THE TREATMENT OF SLEEP APNEA USING IOT AND BIG DATA

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Abstract

Sleep apnea has become in the sleep disorder that causes greater concern in recent years due to its morbidity and mortality, higher medical care costs and poor people quality of life. Some proposals have addressed sleep apnea disease in elderly people, but they have still some technical limitations. For these reasons, this paper presents an innovative system based on fog and cloud computing technologies which in combination with IoT and big data platforms offers new opportunities to build novel and innovative services for supporting the sleep apnea and to overcome the current limitations. Particularly, the system is built on several low-power wireless networks with heterogeneous smart devices (i.e, sensors and actuators). In the fog, an edge node (Smart IoT Gateway) provides IoT connection and interoperability and pre-processing IoT data to detect events in real-time that might endanger the elderly's health and to act accordingly. In the cloud, a Generic Enabler Context Broker manages, stores and injects data into the big data analyzer for further processing and analyzing. The system's performance and subjective applicability are evaluated using over 30 GB size datasets and a questionnaire fulfilled by medicals specialist, respectively. Results show that the system data analytics improve the health professionals' decision making to monitor and guide sleep apnea treatment, as well as improving elderly people's quality of life.

Keywords: IoT, big data, fog computing, cloud computing, sleep apnea.

1. Introduction

Over the years, human beings experience changes in their bodies and lives. One of those changes is sleep's disruptions that occur with age, making it difficult to sleep. Sleep disorders are affecting the good sleep stages which play a key role in physical and mental health, and in some cases, they can become a serious problem for elderly people. Like so, Obstructive sleep apnea syndrome (OSAS) is one of the most dangerous and common respiratory disorders that produces during sleep. Sleep apnea at any age is a major concern because of the health problems it can lead to, but it's even more problematic in elderly people who are more likely to have issues with breathing at night. These breathing issues are less likely to be diagnosed (over ~80–90%) as OSAS or they are diagnosed simply as snoring in some cases. Research indicates that between 13 and 32% of elderly people (over 65 years old) having some sleep apnea (suffering from it) [1]. Difficulty falling and staying sleep combined with a lack of deep sleep results in a poor quality of life (QoL) and increases health risks for an elderly. For example, sleep apnea generates the risk of traffic accidents caused by the excessive daytime somnolence [2]. Thus, a home-based system to monitor and support OSAS patients will help to reduce the health risks associated with OSAS and improve elderly's QoL.

Promising technologies such as the Internet of things (IoT), fog computing, big data and cloud computing have significant potential for the implementation of home-based solutions to monitor and support the sleep apnea. The IoT paradigm has emerged as a key enabler for the empowerment of the elderly people regarding independent aging, wellness, and disease management [3]. IoT enables the ubiquitous interconnection of a variety of smart objects with sensing, acting, networking, and processing capabilities through the Internet by providing the ability to share information [4]. This interconnection could generate large amounts of data that require scalable computing infrastructure for an efficient real-time processing and analysis. In such context, cloud computing could aid by providing on-demand and scalable storage that enable big data analysis as well as processing services. However, this technology is not especially suited for data pre-processing in time-sensitive solutions such as in healthcare field, where the delay caused by data transfer to the cloud and back to the application is unacceptable. In view of that, fog computing extends cloud computing by providing resources on devices at the edge network overcoming delay limitations. Therefore, fog computing and cloud computing represent two complementary technologies, which in combination with IoT and big data offer new opportunities to build novel and innovative services to support the sleep apnea and Active and Healthy Ageing (AHA) by exploiting the processed and analyzed information.

In this work, we present and discuss an innovative system that supports health professional to monitor sleep apnea and guide its treatment called SA-IoTBigSys, as well as helps elderly people to improve their QoL. Particularly, the system is capable of providing new and innovative services such as remote monitoring, alert notifications and data analysis for supporting the decision-making health professionals. This system performs monitoring sleep apnea by exploiting the potential offered by the joint use of different technologies, components and complementary open standards such as 6LoWPAN, ZigBee, BLE, Smart IoT Gateway, FIWARE [5] and lightweight and secure IoT protocols such as MQTT and CoAP. The system is able to gather, in real time, elderly's physical activities, sleep environment, sleep status and context information, which affect the progressing of sleep apnea treatment. Also, the system uses a Smart IoT Gateway, which enables technical, syntactic and semantic interoperability through the implementation of a fog-computing, capable of allowing real-time processing to detect events and ensure an immediate system response in emergency situations. The data are securely sent to the cloud, where a component of an open platform of the Future Internet (i.e., FIWARE) called GE Orion Context Broker, manages them. Moreover, the system provides data analysis by implementing a big data module to extract information from IoT data coming both from sensor nodes reading in the system and external open data sources using Apache Spark. Finally, the information analyzed is presented into Web User

Interface (Web UI) to support the decision-making of health professionals, caregivers, and emergency centers involved in the care and attention of the treatment of elderly's sleep apnea.

1.1 Contributions:

This paper presents some contributions with the objective to tackle the challenges and limitations of the current literature in the study area. To sum up, the system architecture achieves:

- *IoT Interoperability,* by implementing an IoT Smart Gateway capable of bringing syntactic, semantic and technical interoperability for supporting heterogeneous sensors.
- *Reducing latency to send notifications,* by implementing a fog computing layer to pre-process data with the aim to detect real-time situations that affect the sleep quality.
- *Smart City integration,* by using an integration with smart city services to generate innovative application such as the prediction of the less polluted place in the city to elderly's activities.
- *Monitoring apnea*, by using wearables sensors and Commercial off-the-shelf COTS to measures elderly's sleep quality, sleep environment, and physical activities.
- *Managing apnea,* by exploiting data in the big data analyzer to generate reports for improving medical's decision-making.

The remainder of the paper is structured as follows. Section 2 reviews the motivation behind our research, as well as the current literature concerning to this field of research. Section 3 presents the high-level architecture of the IoT system to that guides health professional in diagnostic sleep apnea and helps elderly people to improve their QoL. In section 4, the implementation of the system is described. In Section 5, the results of the conducted experiments and evaluations applied to a case study are described. And finally, Section 6 presents conclusions and future work.

2. Related Work

The potential use of IoT in different health application areas has been widely discussed in the current literature. Some of them proposed interesting solutions to the health challenges, but there are still some limitations that make possible to exploit the IoT benefits in the health area. The integration between IoT with others developed technologies provide new opportunities to overcome the IoT limitations. For example, cloud computing technologies combined with big data platforms and tools provide more benefits to improve several applications, as it is illustrated in [6]. Also, big data has been widely used in the context of internet search, business, or social networks [7], but it has not been discussed in health applications to improve elderly's quality of life. The integration of IoT, cloud computing, and big data are envisioned to improve services and applications in healthcare areas such as Ambient Assisted Living (AAL), community health care, chronic diseases monitoring, healthcare solutions using smartphones among others [8]. In this paper, the recent advances in chronic diseases monitoring area are analyzed with a particular regarding in obstructive sleep apnea.

Sanino et al. in [9] proposed a real-time mobile system for monitoring patients with obstructive sleep apnea (OSA). The system used a Zephyr BioHarness™ BH3 device for recording the ECG signals. This device used Bluetooth technology to transmit data to a mobile device (Smartphone and PDA), where ECG data along with heart rate variability (HRV) parameter was computed. The collected data by the mobile device were pre-processed to send alerts and notification at the smartphone. Furthermore, the system provided a descriptive data analysis and a rule-based classification model for detecting apnea events. Conversely, the proposal was carried out on a smartphone, which depended on a battery, so the point of failure was maximized.

Similarly, Bsoul et al. in [10] proposed a system for monitoring real-time sleep apnea and recognizing apnea events based on ECG readings. They made use of an off-the-shelf one lead ECG sensor, which was connected to the smartphone via Bluetooth (802.15.1). The features derived from the ECG were widely used to monitor sleep apnea episodes. The system detected apnea event using a support vector classifier in a feature set extracted from ECG and HRV. The results were better than the rule base proposed by [9]. However, these apnea systems did not provided information about sleep quality, nor it used snoring information to complement the apnea information. To overcome these limitations, Nakano et al. in [11] proposed a system to quantify snoring and OSA severity using only a microphone embedded in a smartphone, which was used like a snoring sound monitor operated on an android system. In [12] an automatic sleep monitoring system called "Umemory" was proposed for long-term monitoring sleep quality of residents in nursing homes. The authors used a piezoelectric transducer placed under a mattress to measure elderly's heart pulsation, respiration, and in-bed body movements. The collected data were sent to database servers via the Internet to generate a descriptive data analysis.

On the other hand, some health behaviors tips are necessary to improve the elderly's sleep quality, such as the ones advise proposed (avoid caffeine beverages and high-calorie foods after six o'clock, or reminders to practice physical exercises) in [13]. Also, the authors described a non-invasive sleep-environment monitoring system developed for the detection of environmental factors (temperature, humidity, noise, luminosity), and the sleeper movements that contribute to poor sleep. The system used multimodal technologies such as smart devices (e.g. phones, bands, and watches) and e-health monitors for parameters monitoring. The collected data were forwarded to the middleware (called "Sleep mon") for further analyzing and processing by Wi-Fi technology via a wireless access point. The middleware sent notification about health behaviors tips and generated a descriptive data analysis. Although the authors include another communication technology such as Wi-Fi, there are others low power wireless technologies that can improve the collected stage. Also, neither cloud nor fog computing approach was considering to provide computational resources.

In the same way, Nam et al. in [14] focused on quantifying sleep quality. They described non-intrusive system developed as a multimodality sensor fusion framework using a pressure sensor and a three-axis accelerometer. The multimodal sensors monitored data on sleep pose, body activity, respiration rate and heart rate. Data were transmitted via a ZigBee wireless connection to an external assistive recording mobile device and PC platform. Also, Rofouei et al. in [15] proposed a non-invasive, wearable neck-cuff system for monitoring people's sleep and pre-diagnosis of sleep apnea. The proposal used oximetry sensor, microphone, and accelerometer for monitoring blood oxygen saturation level, breathing sounds and body movements respectively. A Bluetooth module was used for established the connectivity between sensors and cellphone or PC, where the processing was carried out. These proposal systems did not provide an interoperability of wireless technologies to support ZigBee and Bluetooth sensors.

Finally, Kumar et al. in [16] proposed a system to help patients with OSA based on wearables devices and sensors to monitor blood oxygen pressure, saturation, heart rate, temperature, and humidity. The system supported Bluetooth and Zigbee sensors. The collected data by the sensors were sent to the cloud layer via the Internet gateway for a descriptive data analysis. Also, the system was capable of pre-processing data and sending sounds to elderly's smartphone and notifications to emergency services from the cloud. A mechanism to facilitate access in the system to pre-authorized people was also proposed in this system to tackle the privacy and security limitations in this kind of systems. Accordingly, the proposal has not considered effective ways to transmit the data to the cloud such as the proposed in [17], [18] to transfer multimedia data efficiently to the cloud, and an efficient algorithm to encrypt this kind of data in [19].

To sum up, some health monitoring systems have been developed to monitor sleep apnea in elderly people, but these solutions are not focused on supporting the treatment of sleep apnea. Moreover, these solutions still have some technical limitations such as the use of invasive devices and technologies, limited wireless technologies support, a lack of interoperability of them, processing delays, a limited integration with other data sources, and other requirements. For these reasons, the system proposed in this paper overcomes the limitations found in the current literature, and provide more details to monitor, evaluate, and guide the sleep apnea treatment.

3. Proposed System

The proposed system architecture is organized hierarchically. The architecture includes three tiers: collection data tier, fog computing tier, and cloud computing tier, as is delineated in Fig. 1. The collection data tier gathers the data of multiple heterogeneous sources (sensors in elderly homes as well as open datasets) and transfers the data to the fog computing tier. The fog computing tier provides the basics functionalities to offer connectivity and seamless interoperability between the heterogeneous devices involved in the system. This layer is also responsible for a data pre-processing stage to detect in real-time possible adverse events regarding the elderly patient and send alerts or notifications to medical professionals and caregivers for improving the responsive emergency time. The pre-processed data along with open data are stored, processed and analyzed in the cloud tier to guide health professional in the sleep apnea diagnose and treatment decisions. Finally, the web application converts the information analyzed in content, which is an essential tool for continuous monitoring elderly's sleep apnea. The main functions of each tier and their relationships are described below.

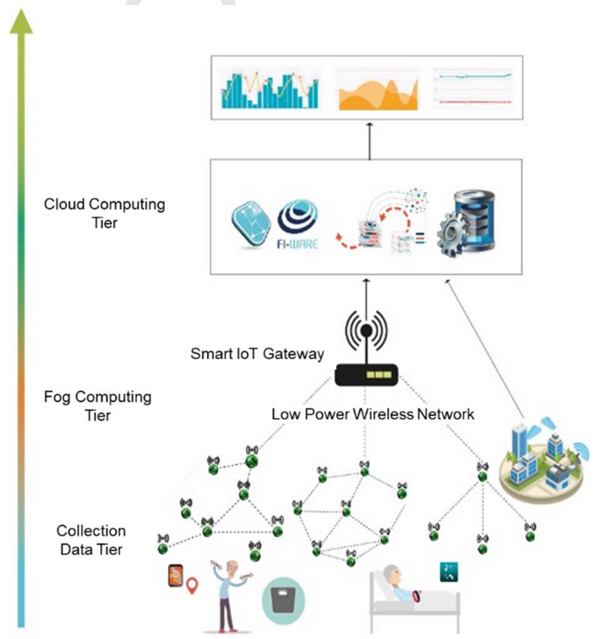

Fig. 1. High-level view of the hierarchical proposed architecture.

3.1 Tier I. Collection Data Tier

The lower layer is mainly used for sensing the physical world, gathering data and reacting accordingly. These data are collected from heterogeneous multisource such as sensor nodes as well as smart city open-data. All of these multisource data are illustrated in Fig. 2 and grouped into the following categories:

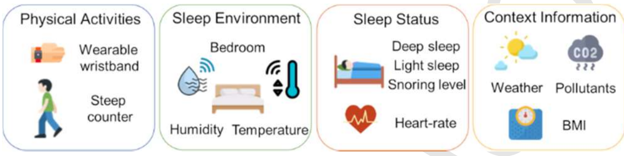

Fig. 2. Sensing physical world categories.

- Physical activities: active and healthy lifestyle are important to enjoy a good QoL. Also, the physical activities provide effective therapy to address sleep apnea and other diseases [22]. In this sense, SA-IoTBigSys is focused on daily monitoring of physical activities to determine whether elderly people are active. Accordingly, a steps counter is used in our system to achieve this aim. A steps counter is chosen because it is the most reliable and easier indicator to control the elderly's daily activities [20]. This measure is gathered by a steps counter sensor integrated into a wearable wristband with a daily frequency at the end of the day.
- Sleep environment: a comfortable environment is beneficial to improve the elderly's health and wellness. Also, a good sleep environment during the different elderly's sleep stages improves sleep apnea conditions and elderly's QoL [21]. Accordingly, controlling and adjusting environment parameters are used in SA-IoTBigSys to achieve a comfortable environment. Sensors and actuators embedded and placed into the elderly´s bedroom are used for monitoring the temperature and humidity parameters and acting accordingly by controlling the surrounding environment. These data are monitoring in a daily frequency in the normal sleep-schedule (22:00 PM – 08:00 AM) [21].

- Sleep status: a sleep quality along with a balanced diet and regular physical activity is vital to keeping a good QoL. In addition, a continuous deep sleep reduces the risk of developing arterial hypertension, obesity, and other diseases. In this manner, SA-IoTBigSys is dedicated to monitoring elderly's snoring level, sleep stages such as light or deep sleep, and heart rate to know their sleep quality and heart rate variability during sleep states respectively. Sleep stage measures are gathered by an embedded sensor in a wearable wristband. These data are recording in a daily frequency in the normal sleep-schedule, considering that 12:00 AM – 06:00 AM is the hour-range with a high risk of a heart attack in sleep apnea [22].
- Context information: the information of elderly's weight and height as well as smart city open-datasets is important to guide of sleep apnea treatment and assist elderly on time when necessary. For example, open data related to city's environment such as pollutant levels and weather conditions allow determining the less-polluted place where elderly could perform their activities. Furthermore, body mass index (BMI) calculated based on weight and height measures can reflect elderly's living habits. Particularly, a health professional may be able to adjust the sleep apnea treatment plan according to the BMI and heart rate variability for the recovering elderly.

Since that proposed system welcomes both real-time and offline data, categories are classified into two types of data, online and offline. On the one hand, physical activities data, sleep status data and context information (open data) are considered as offline data because the system needs to access to these data at the end of the activity or because data are part of historical values. On the other hand, sleep environment, sleep status, context information (elderly's position, weight, and height) are considered as online data because they need to be processed in real time.

3.2 Tier II. Fog Computing Tier

Fog computing tier consists of Smart IoT gateways, which are intelligent enough to transform the raw sensor data to uniform and easily understandable format and pre-process locally these data to detect in real-time possible events that could worsen the elderly's sleep apnea status. These fog computing devices act as bridges between collection tier and cloud computing tier. The fog computing devices are responsible for the communication and seamless interoperability between IoT devices, as well as encrypt sensors data before to send them to the cloud computing tier periodically. Fog computing tier consists of wireless communication and interoperability, event processing, and event handler modules, as is shown in Fig. 3.

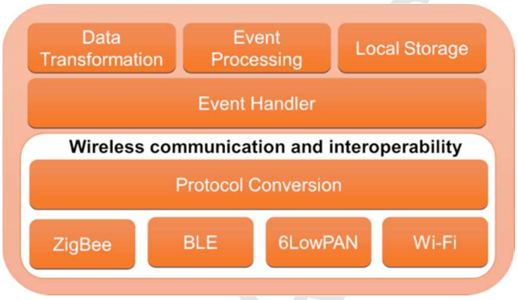

Fig. 3. Fog Computing Tier modules

3.2.1 Wireless communication and interoperability

This module performs protocol conversion for establishing the communication and interoperability of the different devices involved in SA-IoTBigSys, regardless of underlying communication technologies and protocols.

Communication: in SA-IoTBigSys, the communication as in other IoT systems involves intelligent sensor networks that depend on wireless technology due to their inherent advantages. Some of them are greater mobility, easy deployment and maintaining, and support for numerous IoT devices. To support short to medium or long-range communications, the system uses low power technologies such as 6LowPAN, ZigBee, and BLE or Smart Bluetooth. These wireless technologies have been chosen because they are the most popular and widely used to enable any range communications at a very low cost and with very low requirements. Therefore, these technologies are proper to be implemented in IoT environments. The information about the type of sensors along with the technologies communication and protocols used for sensing the different data category are described in section 4.

Interoperability: interoperability in modern healthcare is vital to provide information when and where it is needed, to facilitate faster and more robust healthcare professional's decision-making [23]. Interoperability needs appropriate standards to connect and integrate the heterogeneous IoT devices that belong to different wireless networks, and to share information in a way that meets security needs. The interoperability in SA-IoTBigSys involves getting data, exchanging data, and using the information. SA-IoTBigSys enables different kind of interoperability including technical, syntactic and semantic interoperability.

In order to achieve technical interoperability, the edge fog node performs a coordination of communication tasks, redirecting and forwarding the data through the multiple network interfaces. Particularly, the edge fog node solves protocols incompatibility issue as well as messages conflicts between the different wireless networks by encapsulating the data sent by the source protocol into a compatible format with the destination communication protocol.

Since heterogeneity is also present in the different data formats supported by the IoT devices used in the system, a syntactic interoperability is performed in the edge fog node. To do so, the edge fog node maps the collected data to a system-defined data standard for a format conversion. In addition, the definition of a common structure prior to pre-processing and sending data contributes directly to the lower consumption of resources and bandwidth.

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 sensors data, manage access and extract knowledge of this information. Before forwarding the data to the cloud computing tier (once the data have been pre-processing, detailed below), the edge node provides semantic interoperability by mapping the system-defined data format structure to a

SensorML ontology-based contextualized information model. Similarly, the edge fog node encrypts the pre-processed data to ensure security through a hash algorithm with SSL. Any unauthorized devices cannot decrypt the data package even if they have access to the system.

3.2.2 Event processing

Online data monitoring can reflect elderly health status related to sleep apnea and how comfortable is the atmosphere of the elderly's bedroom for sleeping, in real time. Therefore, these data need to be pre-processed rapidly. In this context, Smart IoT Gateway performs local pre-processing using a rule-based complex event processor (CEP). Several rules have been defined in the CEP to detect events and consequently react quickly to respond to emergency situations with a reduced response time and latency. Table 1 shows the rules established in the CEP.

Table 1. CEP-rules

Parameters	Rules	Threshold	Periodicity	Action
Steps count	sedentary	< 5000	Daily	Notifications to elderly, health professionals and caregivers
	mild active	5000 - 7499		
	moderate active	7500 - 9999		
	active	10000 - 12499		
	high active	>12500		
Temperature and Humidity	low temperature	< 18	22:00 - 08:00	Turn on / off Air Conditioner / Dehumidifier Notifications to caregivers
	high temperature	>22		
	low humidity	< 50%		
	high humidity	>70%		
heart rate	normal	60-100	22:00 - 08:00	Notifications to health professionals and caregivers
snoring level	normal	< 40 db	22:00 - 08:00	Notifications to elderly, health professionals and caregivers
	mild	40 - 50 db		
	moderate	50 - 60 db		
	severe	> 60 db		
BMI (Height and weight)	underweight	<18.5	Daily	Notifications to elderly, health professionals and caregivers
	Normal	18.5 - 24.9		
	overweight	25-29.9		
	Obese	>=30		

3.2.3 Event Handler

This module executes the actions related to an event, as soon as it is detected. To do so, it sends commands to actuators and pushes notifications to the caregivers, healthcare professionals, emergency centers and family members with access to the information, using an MQTT-broker. Notifies information and commands are also encrypted to ensure security through a hash algorithm with SSL.

3.3 Tier III. Cloud Computing Tier

This tier is responsible for efficiently managing, storing and analyzing all the gathered data by the system. Since the system is closely related to the elderly's health, the high availability and high performed analysis of the data are necessary in order to support the development of innovative services while supporting the medical professionals' decision-making. This layer is composed of the data manager, big data analyzer, web application and management entity, as is shown in Fig. 4.

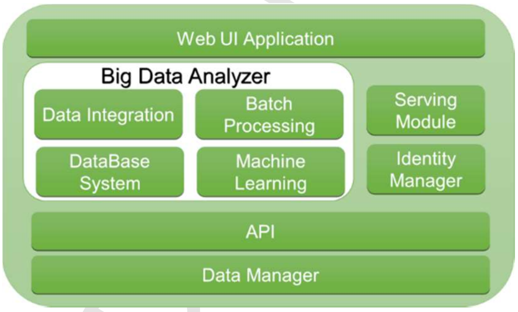

Fig. 4. Cloud Computing Tier modules

3.3.1 Data manager

The data manager is responsible for managing the data context (elements and attributes) coming from the fog computing layer along with data availability. To do so, the data manager offers REST API interfaces, which allow for registering, retrieving and publishing the context data to any interested party (services or applications interested in consuming this information) for subscription operations. This component is transversal to various application domains and can be shared by several of these. In SA-IoTBigSys, the big data analyzer (detailed below) is subscribed to the data manager in order to get online data.

3.3.2 Big Data Analyzer

Big data analyzer is able to process and analyze both online and offline data. To do so, big data analyzer implements data integration, batch processing, machine learning, and serving modules.

Data integration implicates the combination of different sources to provide a uniform view of data for reducing storage expense, and improving data analysis. The data integration module includes an Extracting, Transforming and Loading data stages (ETL). Extraction stage provides the necessary tools to connect to sources system. For example, this module implements the necessary REST API interfaces to subscribe to the data manager for collecting online data as well as to connect to open data sources for collecting offline data. Before the transforming stage, the data are filtered to split online data and offline data. Also, the transforming stage converts data formats as well as check data integrity. The online data do not need to pass through the transformation stage because they accomplished a pre-processing data in the smart IoT gateway and in the data manager, while the offline data is transformed from JSON and CSV open data formats to a tabular data schema (data frame). Finally, loading stage copy the data frame to the batch repository file system in a total load (historical smart city open data) or incremental load (physical day activities and sleep status). The batch repository file is capable of storing large files replicated in multiple machines to provide high availability and scalability.

Batch processing provides an environment to process raw data previously stored in the file system repository by the data integration module. This module executes jobs to process the data in a parallel way. To do so, they provide high-level languages such as Pig, Hive or SparkSQL to make data queries to exploit daily IoT data. This way, high-level languages allow processing data by mean of cleaning and enrichment methods. The cleaning processing activity is executed in order to identify inaccurate, incomplete (null), or unreasonable (outlier) data and replace them with an average value or a linear interpolated value. Meanwhile, the data enrichment consists of merging different data sources in order to provide more information about an event. For example, the raw data about sleep phases, steps counter, weather conditions, pollutant levels and the elderly's location activities track are extracted from the file distributed system, cleaned and merged using as the index the timestamp and the position to provide data enriched with context information to improve data analysis accuracy. The cleaned data are stored in a cache as data frame to be analyzed. The high-level languages are used to execute a statistical data analysis such as mean, median, mode, skewed distribution, symmetric distribution, range, variance, and standard deviation, to understand the data characteristics. Finally, the statistical data results are stored in the serving module to be presented in a dashboard.

Machine learning includes the fundamental libraries to implement data mining models over the data which come from the batch module cache store. The machine learning module allows the development of a predictive analysis using data mining methods and algorithms. First, feature selection, normalization, feature scaling, among other technics are performed over the data before training machine learning models. For example, the module provides the capability of applying automatic feature selection (such as low variance removing features) to choose the variable to generate a predictive model. Also, the machine learning module is capable of generating classification, logistic regression, linear regression, or neural networks models for making a predictive analysis. This way, the pollution levels and weather data are used to predict the hourly pollutant levels and determine the less-polluted place where elderly can perform their activities. The trained models are save in a database to use later for pipelining jobs. Machine learning module provides platform and tools to develop models for making predictions or inferences from data to help to make decisions.

The Serving module provides a temporal store using a publish/subscribe service. This module gathers ad-hoc queries, batch processing views from the different data analysis pipelined jobs using the modules above described and stores them. The publish/subscribe service allows the integration with the applications for supporting the decision-making of the medical professionals.

3.3.3 Web Application

Web application interacts with the big data analyzer for greater data availability and usability. Since the web application is at the top of the system, it makes use of all the data from this module through RESTful interfaces. The web application is targeted towards health professional for continuous monitoring sleep apnea elderly's. Also, the web application focuses on displaying all the data points captured and sleep apnea-general risk statistics in order to support the medical decisions. Considering the privacy and security, HTTPS is established as a secure protocol to display the content by the Web application. This protocol provides data encryption enabling data security. Also, the web application uses authentication access in order to provide access only to pre-authorize people.

3.3.4 Identity Manager

Identity Management is a key component that enables the control of access to the architecture proposed. It covers a number of aspects involving users' access to the system, including user's secure and private authentication, authorization & trust management, user profile management and privacy-preserving. Furthermore, Identity Management is used to securely authorize access to data available data in Data Manager both for application or services external.

4. Testbed Setup

The system implementation is divided into wireless sensor networks, IoT nodes, smart IoT gateway, data manager, identity manager, big data workflows and Web UI interface implementation. Fig. 5 shows the testbed system overview.

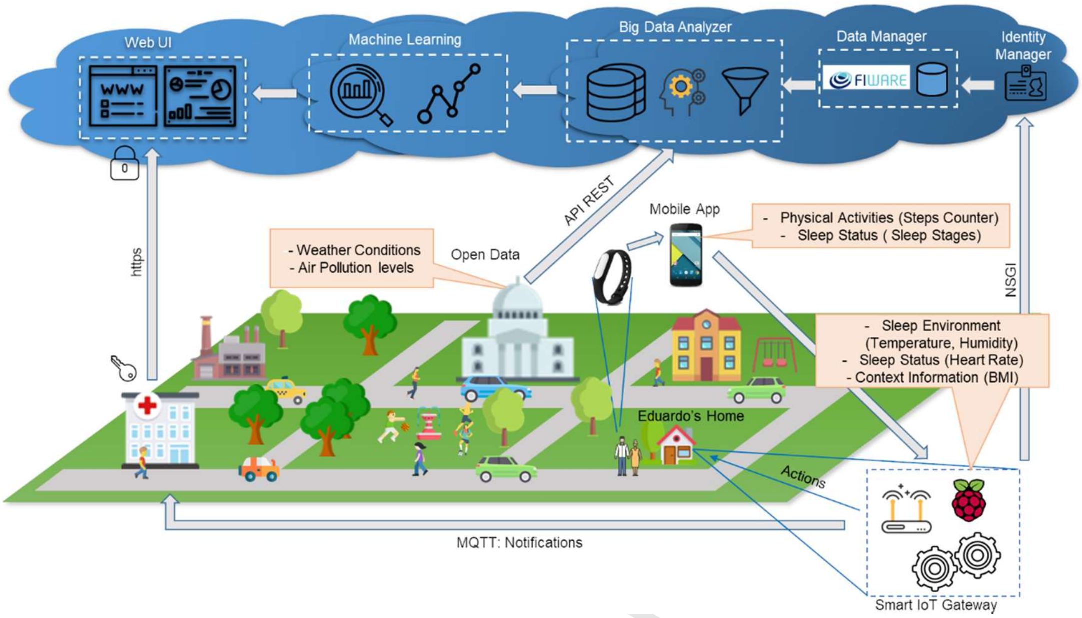

Fig. 5. Testbed system overview

4.1 Communication Networks

At the first stage, three heterogeneous wireless sensor networks (WSNs) are implemented to collect data sensors, using low power technologies such as 6LowPAN, ZigBee, and BLE. These wireless technologies have been chosen because they are the most popular and widely used to enable any range communications at a very low cost and with very low requirements. In addition, these technologies have inherent advantages such as greater mobility, easy deployment, and maintaining, and support for numerous IoT devices, that makes them technologies proper to be used in the IoT-enabled device, especially in resource-constrained devices. A 6LowPAN network is formed by environmental sensors, which record temperature and humidity of the elderly's bedroom. ZigBee network includes pulse and sound sensor to monitor heart rate and elderly's snoring, respectively. Bluetooth network contains activity sensors for recording the total number of daily steps, stage sleep (daily minutes of light and deep sleep), position, and elderly's weight

4.2 IoT nodes

Several IoT nodes have been assembled to enhance the data collection process from the different sensors.

A sensor node for 6LowPAN network is constructed from the combination of three STM32 modular blocks[1]: STM32 Nucleo board microcontroller (NUCLEO-L152RE) plugged with one expansion boards (X-NUCLEO-IDS01A5) with sub-1GHz RF connectivity operating at 868 or 915 MHz and a sensor expansion board (X-NUCLEO-IKS01A1). Next, this sensor node is equipped with environmental sensors (i.e., .temperature and humidity). STM32 Nucleo is based on ARM Cortex-M processor and supported by software modules. The software modules facilitate the rapid innovative IoT applications prototyping, for these modules use STM32 32-bit microcontroller family combined with other ST components connected via expansion boards. The ARM Cortex-M is designed to offer a very high performance, real-time capabilities, digital signal processing, low power and low voltage operation, while it maintains full integration and ease of development. To provide the access to the 6lowPAN sensors resource, a CoAP server is configured using Erbium-CoAP implementation on the top of the Contiki OS [24]. Erbium is a low-power REST engine written in C programming language that provides RESTful access.

Two ZigBee sensor nodes are constructed by the combination of an Xbee wireless S1 module, a mini Arduino, and an analog front end (AFE) device. Xbee modules are configured for operating in an Application Programming Interface (API) mode as end devices (slaves). In one node, 3-pin sound AFE sensor is used to collect the elderly's snoring sound. In another node, a pulse heart rate AFE sensor is used to gather elderly's heart rate. Data are collected while elderly people are sleeping. Also, both nodes send the data to their respective mini Arduino through SPI (Serial Peripheral Interface) connection and then the data are transferred to the Smart IoT Gateway. All operations in arduino were programmed using C++.

[1] http://www.st.com/en/microcontrollers/stm32-32-bit-arm-cortex-mcus.html

An Android application has been developed for retrieving the activity performed by the elderly people such as total number daily steps and daily minutes of each stages sleep, as well as their position. These data are collected from low-power embedded sensors (e.g., gyroscope, accelerometer, GPS, actinometrical) in a smart bracelet attached in the elderly's wrist. Android application is also able to gather elderly's weight from a UC 321PBT precision health scale. The application transfers the data sensors to the Smart IoT Gateway through a Bluetooth connection (smart bracelet uses Bluetooth Low Energy, while the precision health Scale uses Bluetooth ver.2.1 class 1**).**

4.3 Smart IoT Gateway

The smart IoT gateway is formed by the combination of STM32 Nucleo board (NUCLEO-L152RE)1 integrated with one expansion boards (X-NUCLEO-IDS01A5), and a Raspberry Pi 2 Model B by featuring a 900MHz Quad-Core ARM processor, 1GB of RAM, 4 USB ports, 1 HDMI port, 1 RJ-45 port and one power consumption of 700 mA, (3.5 W). Moreover, this gateway supports heterogeneous interfaces such as ZigBee S1, Bluetooth 4.0, USB serial link and 10/100 Ethernet. This gateway uses a 32 GB class 10 SD card powered by Raspbian operating system in order to execute the whole modules functionalities.

STM32 Nucleo board (NUCLEO-L152RE), along with one expansion boards (X-NUCLEO-IDS01A5), forms the 6LoBR node, which collects data from others 6LoWPAN nodes and forwards to the Raspberry Pi through a USB serial link. Similar to the IoT devices, all operations in the 6LoBR node are executed on Contiki OS. For instance, an RPL (IPv6 Routing Protocol for Low-power and Lossy Networks) implementation is used to enable communication between 6LoWPAN nodes and the smart IoT gateway. On the other hand, to translate packages coming 6LoWPAN nodes to IPv6/IPV4 packages and vice versa, a tunneling-virtual network adapter is configured in the Raspberry Pi using tunslip6 tool running on Contiki OS v3.0. Additionally, to retrieve the

6LowPAN resource sensors, a CoAP client is implemented in raspberry pi using CoAP library based on Python 3 asynchronous I/O.

A Bluetooth 4.0 interface module is configured for establishing the connection with the smartphone and acquiring the data from the Android application using the *python-Bluetooth* library. The ZigBee interface module is programmed as a coordinator for receiving data from the ZigBee nodes. The ZigBee coordinator initiates and maintains the nodes on the network.

4.3.1 Functionalities implemented

All gateway functionalities such as data transformation, events processing and events handling are implemented in python using specific libraries and implementations.

- *Data Transformation:* a JSON-data structure is used in the system for mapping sensor data to a standard format. JSON has been chosen because it is a lightweight data exchange format and provides multiple advantages. JSON provides a compact notation and uses a hierarchical data structure that requires minimal resources for its interpretation and generation.
- *Events processing:* Cepheus CEP GE implementation [25] provided by FI-WARE is used for the data pre-processing (online data) based on rules defined in table 1 in real-time. CEP uses REST service for receiving incoming online data and sending derived alarms from the processed data. CEP GE is chosen because it provides and flexible way to define and maintain the event processing logic without taking a toll on system performance.
- *Events handler*: MQTT-broker is implemented using paho MQTT v3.1 library for sending the notifications from the Cepheus CEP GE to the MQTT-client app installed in the health professional's smartphone. Also, actuators have been configured as MQTT-Client to receive actions from the gateway. MQTT is chosen because is a lightweight and security

IoT protocol. MQTT provides end-to-end secured communication and reliability based on SSL. In addition, it incorporates some quality of service levels to confirm the delivery of messages from a non-optimal minimum level (QoS0) to a double-recognition level (QoS2). Since SA-IoTBigSys is closely related to elderly's healthcare, the losses level are minimal or zero. Therefore, the quality of service level QoS 2 has been configured to guarantee the reliability of the message delivery. The smart IoT gateway periodically sends all data to the cloud layer.

4.4 Data Manager

A publish/subscribe Context-Broker GE implementation [26] provided by FI-WARE is used as Management Data. Orion Context Broker is an open specification, which manages the data as virtual entities (each sensor represents an entity) through two REST API interfaces: NGSI9 and NGSI10. NGSI9 is used for registering and updating context information. Meanwhile, NGSI10 is used for subscribing, publishing and querying context information.

At a first stage, the Smart IoT Gateway sends the context data sensors to the Context Broker GE through updating the context operation via NGSI9 for helping in the process of creation of the entity. Secondly, as soon as measurements arrive from the sensors, the Smart IoT Gateway updates the context information value of each sensor (entity) through updating the context operation via NGSI9. A persistent last data storage is necessary so that Orion Context Broker maintains it. In this sense, MongoDB database system is used to store each entity data. MongoDB is chosen because allows a high availability, auto-sharing, and quick updates. In addition, the Context Broker GE can expand its functionalities, so it allows to consult the context information through a SPARQL interface. SPARQL is the standard query language for the semantic web [27], and it provides richer semantic interoperability.

4.5 Identity Manager

The KeyRock2 GE [2] provided by FI-WARE is used as identity manager due to it is an open specification that supports the enforcement policies handling and provides procedures for user registration, user profile management, and user accounts modification.

4.6 Data Analyzer

The big data analyzer is designed by the combination of the Apache Hadoop environment and Apache Spark framework. Apache Hadoop environment is considered as the facto big data framework, and its Hadoop MapReduce module is well known because it is widely used in web searching. However, Hadoop MapReduce module is not suitable for interactive applications as IoT. On the contrary, Apache Spark framework uses Resilient Distributed Dataset (RDD) which is considered as a shorter time execution, so its performance is better than Hadoop MapReduce module. On the other side, Hadoop Distributed File System (HDFS) is one of the most reliable, scalable and flexible distributed file systems, and it is compatible to use with Apache Spark which lacks on a distributed file system. Apache Spark and HDFS integration are possible by using Apache Spark in a standalone mode or in a YARN cluster. For the sake of this testbed, the big data analyzer architecture is implemented on a server FUJITSU with Intel Xeon CPU E3-1220 v5 3.00GHz, 64GB memory and VMware is used as the hypervisor. Apache Spark 2.1.0 in a cluster YARN mode is configured using virtual machine instances based on Ubuntu 14.04 images. As result, a highly scalable, reliable and flexible raw data store and processing platform are implemented to support the development of services and applications.

Furthermore, some others powerful platforms, systems, libraries, and tools are added to the big data analyzer architecture to facilitate the pipelining job's design. A publish/subscribe and a database system is implemented using Apache Kafka and Apache Cassandra. Apache Kafka

[2] https://keyrock.docs.apiary.io/#introduction/preface/acknowledgements

provides flexibility and high availability to interchange data in between the components of the big data analyzer modules. For example, Apache Kafka is used to sharing the raw data from the data integration module to the batch module, and to share the processed data results from the serving module to the application. Also, Apache Cassandra provides fault-tolerance, and scalability, as well as a Query Language, to exploit ad-hoc views and temporary tables which come from the data analysis. The results of data analysis are sent to the serving module and store in Apache Cassandra. Moreover, the Apache SparkSQL, MLlib, and Scikit-learn 0.18.0 libraries are provided to the machine learning module characteristics described in the big data analyzer architecture modules. Apache SparkSQL library is used as a high-level language to implement the batch processing functions such as cleaning and enriching data. SparkSQL provides data frame operations to clean, join and apply statistical methods for a descriptive analysis. Meanwhile, Apache MLlib and Scikit-learn libraries facilitate the implementation of machine learning models to extract useful information from the raw data. Consequently, a complementary big data stack is implemented to provide a powerful environment for the development of services and applications.

To perform the data analysis process five jobs are implemented using Luigi workflow. Luigi is a Python package that facilitates the development of complex pipeline jobs. Fig. 6 illustrates the workflow implemented, and it is described as follows:

1) Retrieving IoT data from the data manager context broker and performing the ETL data integration module task is implemented using Python libraries such as JSON, CSV, requests, and SSL. This job implements a connector to use NGSI10 subscribe operation via API REST for retrieving the IoT data, converting the syntactic data from JSON to a CSV form, and loading to Kafka using the respective topic (a different topic for elderly patient and category).
2) Retrieving Smart city data from the CKAN VLCi platform is implemented using the same Python libraries. In this case, some forms data such as XML, JSON, and CSV are

transforming into a pandas' dataframe for transforming in a uniform data model in a CSV file to be loaded in a Kafka topic.

3) Moving all data (IoT and Smart City) from Kafka to the HDFS is implemented by using an incremental load. The HDFS default factor replication is in charge of distributing the CSV file in the cluster.
4) Descriptive data analysis jobs are implemented to provide daily, weekly, monthly aggregate data statistics for each elderly patient. For example, a job for weekly sleep phases consists of retrieving data from the HDFS, transforming the CSV file to a SparkSQL dataframe defined by a spark context, cleaning the data in the dataframe, performing the statistics mean, median, mode, variance, standard deviation, maximum and minimum value, and saving the results to a temporary Cassandra table.
5) Predictive information jobs are implemented about the less pollutant site. To do so, a previous work describes the implementation of the model to provide this service [28]. The job retrieves information about the pollutant levels and weather Smart City information saved in a CSV file in the HDFS, transforms data into a SparkSQL dataframe, cleans data using SparkSQL functions, makes the next Air Quality Index prediction with the model previously trained, and stores the results in a temporary Cassandra table. The model previously trained was saved in HDFS and it is loaded each time that the prediction job is executed. Consequently, a predictive and a descriptive analysis are performed by using scheduled jobs to process data and make predictions.

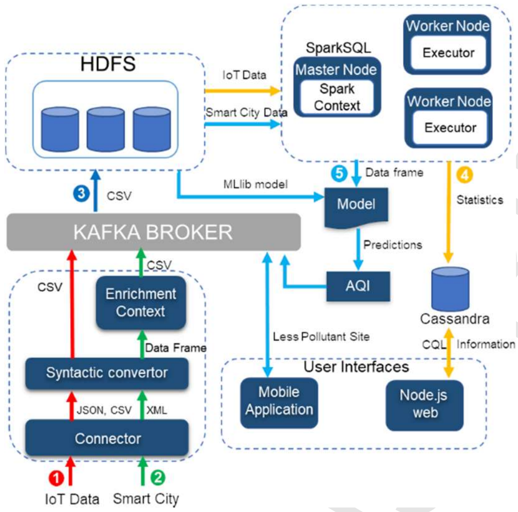

Fig. 6. Workflow pipelining used for the data analysis.

4.7 *Web UI Interface and Mobile Application*

Node.js is used for implement the Web UI interface, which subscribes to Apache Kafka broker for retrieving the results and connecting to Cassandra tables to make queries of the temporary tables and statistical graphs. Finally, Web UI interface displays the analysis results to the health professional for supporting make-decision. Also, a mobile application is developed using Android Studio. This application is used for medical specialists that receive MQTT messages to inform about elderly's risky situations.

5. Results and Experiments Evaluation

5.1 *Dataset Analysis*

To perform a data analysis, four dataset groups were collected according to the categories described in section 3.1. Physical activities, sleep environment, and sleep status data were collected from two volunteers, who live in Valencia City, from 19 February to 13 August in 2017. Volunteers have signed a consent to use their data for research purposes. Volunteers were checked by a medical specialist to diagnose the apnea severity. One of the volunteers was diagnosed with mild apnea severity, while the other one was diagnosed with no apnea disease. Also, context information data were collected from the Valencia Smart City VLCi open data [29]. The dataset details are summarized in Table 2. Overall, more than 30 GB were used to analyze and test the system capabilities to achieve the main proposal's objectives (monitoring and supporting the treatment of sleep apnea).

Table 2. Dataset summary

Category	Feature	Records	Size
Physical activities	Steps counter	185	10 Mb
Sleep status	Snoring	177	24.3 Gb
	Sleep track	185	10 Mb
	Heartrate	13450	4,3 Gb
Sleep environment	Temperature	13450	
	Humidity	13450	
Context Information	Weather	4248	735 Mb
	Pollutants	4248	845 Mb

To monitor the sleep apnea, the SA-IoTBigSys classifies the apnea events. To do so, the CEP detects the apnea events and counts the number of events hourly to determine apnea severity. Table 3 summarizes the volunteer's severity classification analyzed from the dataset snoring recordings. Accordingly, the mild severity was the highest detected in the 93 total-night-records corresponding to the elderly person "A". This severity is the same diagnostic done by the medical specialist. Meanwhile, there was no apnea event detected in the majority of the 84 total-night-records corresponding to the elderly person "B", which corresponds with the same diagnostic of no apnea done by the medical specialist. These results are aggregated every night and shown in a snoring frequency graph on the web page for each elderly people. In this way, the graph helps to doctor to infer a change of the elderly's severity. Also, the elderly's heart rate was monitored by the SA-IoTBigSys to detect heart behavior when apnea events happens. This information is sent to medical specialists and displayed in the smartphone application, as shows the Fig. 7. The heart rate average for the elderly person "A" in the 68 mild severity apnea nights was 71 bpm, which is a typical value for apnea patients [30]. On the other side, the heart rate average for the elderly person B in the 49 no apnea nights records was 57 bpm, which is a typical value for no apnea patients [30]. These data analyses confirm the medical specialist diagnostic, so the system is able to monitor the current status of elderly's sleep apnea and provide information when it changes.

Table 3. Volunteer's severity classification.

Severity	Elderly person **A** [nights]	Elderly person **B** [nights]
No apnea	5	**49**
Mild	**68**	26
Moderate	15	9
Severe	5	0
Total	93	84

Fig. 7. Examples of alerts send to medical specialist

To support the sleep apnea treatment, the SA-IoTBigSys performs a descriptive data analysis to provide information about weekly physical activities, sleep environment, and sleep stages. In this case, the system applies the workflow number 4 described in the section 4.6 to show possible trends in the data. The Web UI displays the results of the descriptive data analysis jobs. Fig. 8 shows the Web UI information about a week evaluation for the elder "B". The physical activity data analysis shows that the elder was active in 6 days and performed on average 8914 steps on the week evaluated. Also, the sleep status analysis shows that the elder slept on average 487.71 minutes, 151.88 minutes on mode deep sleep and 329.88 minutes in mode light sleep. Deep sleep mode is the sleep stage when the person can recover energy, more deep sleep time better rest. In this case, the elder evaluated have slept a good quantity of minutes in deep sleep mode. Similarly, the sleep environment control was evaluated. To do so, the CEP of smart IoT gateway detected the change of temperature and humidity, and the event handler sent an action to the actuators for controlling to air conditioner and dehumidifier. In this case, the system maintained the room temperature on average at 21.7 °C and the room humidity on average at 63.5 %. These values verify the correct function of the rules configured on the CEP. Also, the CEP sends alerts to the CEP In other words, the system guarantees a better sleep environment so that the patient can feel better during the apnea treatment. These data analyses confirm that the system working suitably to provide relevant information to medical specialist and patients to improve the control of sleep apnea.

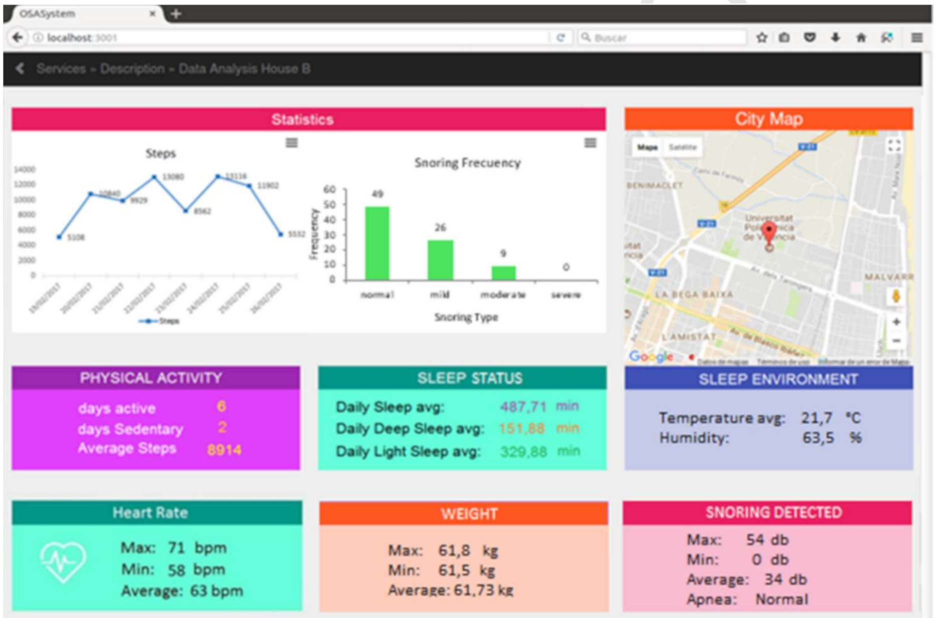

Fig. 8. Web UI application descriptive analysis.

Moreover, the pollution in the city and the snoring were analyzed to provide more information to infer the relation between this variables. This analysis found a correlation between the pollutant levels and the snoring intensity. The Pearson correlation analysis showed that the snoring intensity has a linear correlation to NO2 with ρ = 0.15 and that the snoring intensity has a negative linear correlation to O3 with ρ = -0.22. This means that more NO2 concentration on the city environment higher the elderly snoring intensity. This linear correlation is showed in Fig. 9. Also, this corroborates some studies in which this relationship between apnea and pollutants was described [31] [32]. This result provides more information about the apnea treatment by using the correlation founded in between the pollutants levels and the snoring levels.

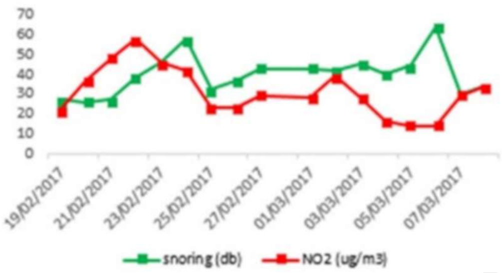

Fig. 9. Relation between snoring intensity and NO, NO2

5.2 Performance System Evaluation

The system was evaluated considering two aspects: the big data analytics performance in term of throughput (Mbps) and the system Web UI helpful information to doctors.

First, the big data analytics performance was evaluated using the dataset described in Table 2. This evaluation provides information about the performance of the big data analyzer when it executes the job number four for data processing described in the testbed section. This job is selected due to it is responsible for computing the descriptive data analysis used to support and monitor the sleep apnea. The datasets were split in various batch sizes (3, 6, 16, 34, 68, 135, 270, 540, 1080, 2150 MB). The throughput is calculated by dividing the batch size by the time to take processing it. Fig. 10 shows the results of the experiment about throughput performance, respectively. The results show that the throughput (Mbps) is increasing according to the data size increment. Also, one can see that from 135 MB to 2150 MB the throughput increases in approximately 2.0 Mbps. This means that the performance does not decrease despite the batch size is increasing. These results is reasonable expected due to the parallel processing using the RDD model provided by Apache Spark. The performance obtained is suitable for this type of system where the performance must not decrease affecting the service provided.

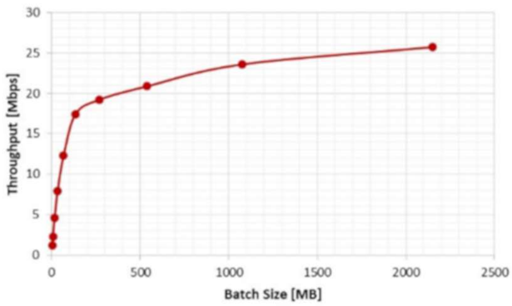

Fig. 10. Big Data Analyzer performance

Finally, the system effectiveness was verified by a questionnaire which was based on P.910 ITU-T recommendation [33] and adapted to this system. The objective of the questionnaire is to evaluate the quality of the information based on four aspects (information to improve the situation awareness, information to support the decision making, the Web UI usability, and data analytics quality). To do so, the questionnaire is composed of 10 questions. The questionnaire was completed by Spanish medical experts such as health professionals, and medical specialists in sleep disorders medicine, in a total of 30 questionnaires were fulfilled. Table 4 presents the punctuation of aspect analyzed with the questionnaire. Accordingly, Web UI usability and data analytics quality provided a subjective satisfaction of the users by an intuitive design and data analytics results details. On the other hand, the improvement of situations awareness information and support for decision-making aspects lacked some relevant information causing few subjective satisfaction of the users. Experts recommend measuring parameters such as breathing rate and oxygen levels in order to improve the situation awareness information and decision making.

Table 4. Questionnaires Punctuation Results

Improvement of situation awareness	3,75/5
Support for decision making	4/5
Web UI usability	4,5/5
Quality of data analytics	4,5/5

6. Conclusion and Future Work

In this paper, an innovative system to monitor and guide sleep apnea treatment has been proposed by combining promises technologies such as IoT, fog computing, cloud computing and big data. These technologies integration offers many advantages that are exploited by the system. First, the system is taking advantages of the fog computing by implemented a smart IoT gateway to provides interoperability (technical, syntactic and semantic) and low latency response time. The smart IoT gateway is capable of interoperating heterogeneous IoT devices deployed in an intelligent environment and operating over several LPWs such as 6LowPAN, ZigBee, and BLE. Also, the smart IoT gateway is capable of pre-processing data on the edge network for a rapid response in emergency situations by sending real-time notifications to the health workers (i.e., caregivers, medical professionals and emergency centers) in charge of the care and attention of elderly people, as well as sending commands to the actuators. In particular, this is achieved through a CEP as well as a scalable MQTT-Broker publishing/subscription architecture. Second, the system is taking advantages of the almost unlimited resources capabilities provided by cloud computing to implement a data manager (Context Broker) and a big data architecture for analyzing the IoT data. The data manager is capable of provides well-defined APIs to connect IoT data and the big data architecture. On the other hand, the big data architecture is capable of analyzing various data sources from both intelligent environments (real-time data) deployed in the elderly's homes and smart city open-datasets through big data platforms for a descriptive and predictive analysis. The big data analytics implemented in the cloud provides scalability, robustness, and flexibility to process IoT data for supporting services and applications. Finally, a Web UI application on the top of system converts the information analyzed in content, which is an essential tool for continuous monitoring elderly's sleep apnea.

In addition to these advantages, the architecture presents the following characteristics: ubiquity, quality of services, security and low resource consumption. A set of experiments has been implemented to validate the applicability and performance of the proposed system. The results show that the system information provided by the IoT data analysis is helpful to the medical specialists to guide sleep apnea treatment. Also, the data analysis performance is not degraded even though the data volume increases. In this way, the system proposed not only provides services that support sleep apnea but also it guides sleep apnea treatment based on integral monitoring of several data categories. Despite this system focus in sleep apnea field, this architecture is flexible and open for use in any application domain.

From a future perspective, more features and services will be added to the system to improve the data analytics. In this way, sensors for measuring breathing rate and oxygen levels will be implemented to improve the applicability of the system, based on the medical specialist recommendation. Also, machine learning models will be implemented to classify the apnea severity and to predict future apnea conditions based on the new data sensors. These models will be modified to be implemented in the smart IoT gateway, to enables the edge analytics. Moreover, system integration with a database storing persistent data such as medical records, disease histories, and patient profile will be implemented to improve the services proposed in this paper. Finally, the system will be implemented in a large scale scenario to evaluate the big data analyzer performance.

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