







# A WSN Real-Time Monitoring System Approach for Measuring Indoor Air Quality Using the Internet of Things

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**Abstract.** Indoor Air Quality (IAQ) describes the air quality of a room, and it refers to the health and comfort of the occupants. Typically, people spend around 90% of their time in indoor environments where the concentration of air pollutants and, occasionally, more than 100 times higher than outdoor levels. According to the World Health Organization (WHO), indoor air pollution is responsible for the death of 3.8 million people annually. It has been indicated that IAQ in residential areas or buildings is significantly affected by three primary factors, they are outdoor air quality, human activity in buildings, and building and construction materials. In this context, this work consists of a real-time IAQ system to monitor thermal comfort and gas concentration. The system has a data acquisition stage, captured by the WSN with a set of sensors that measures the data and send it to be stored on the InfluxDB database and displayed on Grafana. A Linear Regression (LR) algorithm was used to predict the behavior of the measured parameters, scoring up to 99.7% of precision. Thereafter, prediction data is stored on InfluxDB in a new database and displayed on Grafana. In this way, it is possible to monitor the actual measurement data and prediction data in real-time.

**Keywords:** Indoor Air Quality · Monitoring System · Internet of Things · Wireless Sensor Network

## 1 Introduction

In some cases, people may spend around 90% of their time, mainly at home or in the workplace, indoor environment conditions contribute significantly to human well-being [1]. According to the World Health Organization (WHO), the Indoor

Air Pollution (IAP) is responsible for the death of 3.8 million people annually [2]. Harmful pollutants inside buildings include, but are not limited to, carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), Volatile Organic Compounds (VOC), Particulate Matter (PM), aerosols, and biological pollutants [3].

Some of the reasons behind poor air quality are ventilation, building materials, human activities, and repeated use of chemical-rich products that are responsible for CO, CO<sub>2</sub>, VOCs, O<sub>3</sub>, NO<sub>2</sub> and SO<sub>2</sub> concentration in indoors environments [4]. In a specific case of human activities, the CO<sub>2</sub> concentration in enclosed spaces increases according to the number of people (due to human beings exhaling CO<sub>2</sub>). Higher CO<sub>2</sub> concentrations can cause nausea, dizziness, vomiting, reduction of cognitive function, headaches, and fatigue [4]. Moreover, VOCs' concentrations in indoor environments are at least ten times higher than outdoors, regardless of the building location. Furthermore, VOCs are considered to be harmful risks to human health and potentially cause cancer in long-term exposure [5].

Indoor Air Quality (IAQ) is often not prioritized due to distraction of people during the performance of their activities throughout the day or there may also be a loss of perception/sensitivity of the smell when people get used to the air during breathing, among other factors. However, these indoor environments can become intelligent and alert critical air quality levels. The alert can be obtained by monitoring the gases present in the indoor air compositions through sensors. Spreading sensors in a given internal space can identify possible elevations of the parameters that are distributed in the internal space. In this way, people could be warned that the environment must be aerated, for example, opening a window. This approach could be a possible solution to guarantee the air quality of internal spaces and, consequently, the well-being of the people present in the environment.

Based on air quality and risks that this can cause to people's health if it is not controlled, this work presents a system development capable of monitoring the IAQ using a Wireless Sensor Network (WSN). The developed WSN is comprised by modules with sensor that must measure parameters that influence the air quality. Then, the WSN must send the data to a database that can be accessed by a monitoring platform, showing the air quality during periods such as days, weeks or months.

The rest of the paper is organized as follows. After the introduction, Sect. 2 presents the related work. In Sect. 3, the system architecture is addressed to describe each part (hardware and software) of the proposed approach. An example of the final prototype module and its circuit is exhibited in Sect. 4. After, in Sect. 5, the WSN is stressed with some tests to validate the proposed acquisition data. The last section, Sect. 6, concludes the paper and points out some direction for future work.

## 2 Related Work

Monitoring indoor environments through sensor modules involve many technologies and methodologies because several sensors are capable of operating

indoors to detect parameters for determining the IAQ index. The IAQ monitoring requires a specific selection of sensors and communications protocols. For example, the work in [6] shows that IAQ is dependent on several thermal comfort parameters, especially temperature and humidity. In the same way, some of the gases and substances for IAQ analyses are CO<sub>2</sub>, CO, VOC, and NO<sub>x</sub> and the MQ series sensors are known for cost-effective measurements of gases in the indoor environment [7]. However, MQ135 is highlighted as a multi-gas sensor for IAQ measurements being capable of measuring many different parameters such as CO<sub>2</sub>, benzene (C<sub>6</sub>H<sub>6</sub>), ethanol (C<sub>2</sub>H<sub>5</sub>OH), NO<sub>x</sub>, ammonia (NH<sub>3</sub>), and smoke [8]. According to [9], the BME680 sensor is widely recommended for measuring VOC, atmospheric pressure, humidity, and temperature. To monitor formaldehyde (CH<sub>2</sub>O) levels, the ZE08-CH<sub>2</sub>O sensor is used in some research [10].

When using sensors in monitoring systems, WiFi is one of the most preferred choices [11], because it is available in most buildings (different to systems developed by [12,13]). To transfer data to the dedicated server from the target site, several researchers work with Message Queuing Telemetry Transport (MQTT) protocol for its ability to support easy implementation and low power consumption [14]. For example, the device developed in [15] is a prototype of monitoring system for IAQ designed to use MQTT protocol to send the data, measured by MQ135 and DHT11 sensors, to a cloud data storage. Another example can be seen in [16], where the air quality of a classroom is related to the concentration of O<sub>2</sub>, CO, CO<sub>2</sub> and NH<sub>3</sub> gases with MQ135, MG811, MQ7 and ME2O2 sensors. Other facility monitored by sensor is demonstrated in [17] which developed a low-cost device with BME680 and CCS811 sensors to monitoring some IAQ parameters in a hospital. In the same way, [18] developed a low-cost Internet of Things (IoT) device with BME680 and CCS811 sensors and ESP32 microcontroller equipped with WiFi communication systems that monitors the temperature, humidity, equivalent dioxide carbon (eCO<sub>2</sub>), and TVOC. The collected data is stored on the database platform InfluxDB [19]. The microcontroller ESP32 have been used in a lot of researches for IAQ Monitoring, making available some useful functionalities, such as WiFi and Bluetooth communication, in addition to low-power consumption [20].

### 3 System Architecture

The IAQ monitoring system through a WSN in this work involves combining several hardware and software tools. For a better understanding of the whole system, Fig. 1 illustrates a block diagram representing a high-level integration of the system. The system is separated into two main parts, the first is the hardware architecture, which is responsible for sensing all the gases parameters and executing the communication with the cloud and the second is the software architecture, which stores and processes the data received by the hardware.

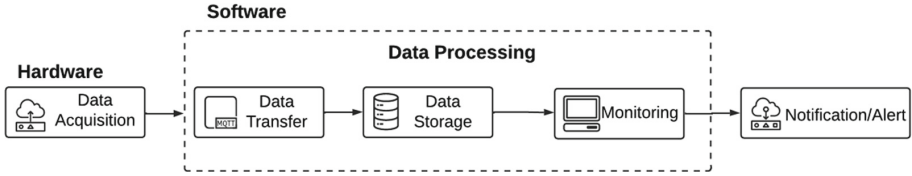


Fig. 1. Phases of implementation process of an IAQ monitoring system.

### 3.1 Hardware

The proposed system has individuals modules to make the data acquisition process, accordingly, it is possible to perform the monitoring at several points in the same environment or even in different spaces. Each module’s hardware contains an ESP32 microcontroller and three gas sensors, the MQ135, the BME680, and the ZE08-CH2O (Fig. 2). The choice of these devices was based on IAQ monitoring studies presented in [15,17,18]. Moreover, the modules’ design is expected to consider the cost-benefit ratio.

The choice of ESP32 was due to the lower power consumption and the WiFi integration allows a large physical range and direct connection to the Internet via a router [21]. Other sensors, such as DHT11, MQ5, MQ7, and CCS811, were tested before obtaining this configuration. On the other hand, all four sensors presented less stability and precision during the breadboard test. Also, they were more expensive than the chosen sensors. In this context, the main characteristics of each sensor of the module responsible to measure the IAQ parameters will be presented below.

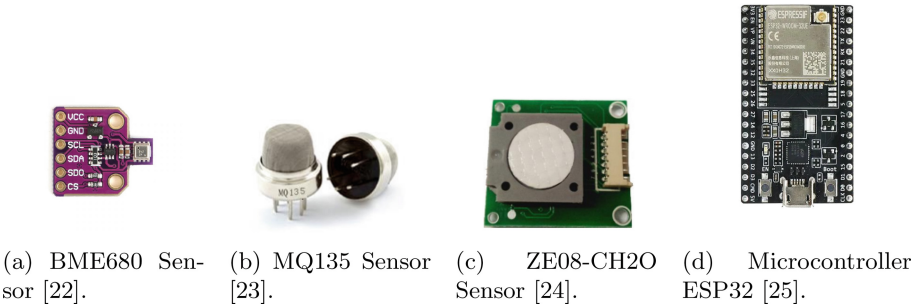


Fig. 2. Set of sensors inserted in each WSN’s module.

**BME680.** It is a digital 4-in-1 sensor with gas, humidity, pressure and temperature measurement based on proven sensing principles [22]. This sensor is widely used in IAQ, IoT, home automation, monitoring systems, and weather forecast

applications. The BME680, presented in Fig. 2a, supports the I<sup>2</sup>C and SPI digital interfaces, where it acts as a slave for both protocols. The interface used in this work is the I<sup>2</sup>C interface, as it supports Standard, Fast and High-Speed modes.

This device is a metal oxide-based sensor that detects VOCs by adsorption (and subsequent oxidation/reduction) on its sensitive layer. Thus, BME680 reacts to the most volatile compounds polluting indoor air. In contrast to the sensor's selectivity for one specific component, this sensor can measure the sum of VOCs/contaminants in the surrounding air. This enables BME680 to detect, e.g., outgassing from paint, furniture, and garbage, high VOC levels due to cooking, food consumption, exhaled breath, and sweating [22]. The signal provided by the BME680 sends resistance values inversely proportional to the VOC concentrations present in the environment, the higher the VOCs concentration, the lower the resistance value and vice versa [22].

**MQ135.** It is a low-cost sensor with tin dioxide (SnO<sub>2</sub>) as a sensitive material (Fig. 2b), which has lower conductivity in clean air. When there is a target polluting gas, the sensor conductivity increases proportionally to the gas concentration, for that reason, it is applicable in air quality control equipment for buildings. This sensor is sensitive to some gases, such as NH<sub>3</sub>, NO<sub>x</sub>, alcohol, C<sub>6</sub>H<sub>6</sub> and CO<sub>2</sub> [23].

**ZE08.** It is a general-purpose and miniaturization electrochemical formaldehyde detection module, demonstrated by Fig. 2c. It utilizes the electrochemical principle to detect methanol (CH<sub>2</sub>O). It is sensitive to alcohol, CO, and smoke in the air with significant stability. Moreover, it has a built-in temperature sensor to make compensation and simultaneously provide a digital and analog voltage output. It combines a mature electrochemical detection principle and sophisticated circuit design.

**ESP32.** This microcontroller is a single 2.4 GHz WiFi-and-Bluetooth combo chip designed for mobile, wearable electronics, and IoT applications. There are two CPU cores that can be individually controlled, and the CPU clock frequency is adjustable from 80 MHz to 240 MHz [26]. ESP32 integrates a rich set of peripherals, ranging from capacitive touch sensors, Hall sensors, SD card interface, Ethernet, high-speed Serial Peripheral Interface (SPI), Inter-IC Sound (I<sup>2</sup>S) and Inter Integrated Circuit (I<sup>2</sup>C) [21].

### 3.2 Software

Data processing is done by a set of tools and software (Arduino IDE, MQTT protocol, Node-RED, InfluxDB, Grafana and PyCharm) commonly used for monitoring systems [15, 27, 28]. Figure 3 shows the phases of this process.



Fig. 3. Software diagram of the system.

The data transfer is responsible to receive the data with Arduino IDE and send to influxDB using MQTT protocol through Node-RED platform. Then, the stored data is sent to Grafana to be monitored and accessed by machine learning algorithm developed on Pycharm.

### 4 Prototype

Once the group of sensors that will be inserted in each module of the WSN is chosen, it is necessary to perform the circuit diagram. Each sensor has their particularities about the inputs and outputs, interface of communication protocol and power supply. The connection of the sensors with ESP32 is presented in Fig. 4.

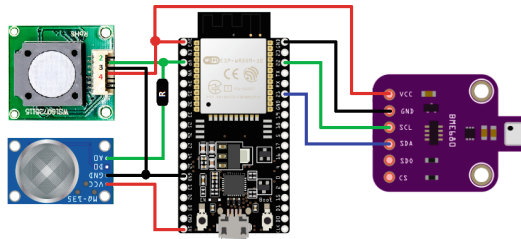


Fig. 4. Circuit connection between ESP32 and each sensor.

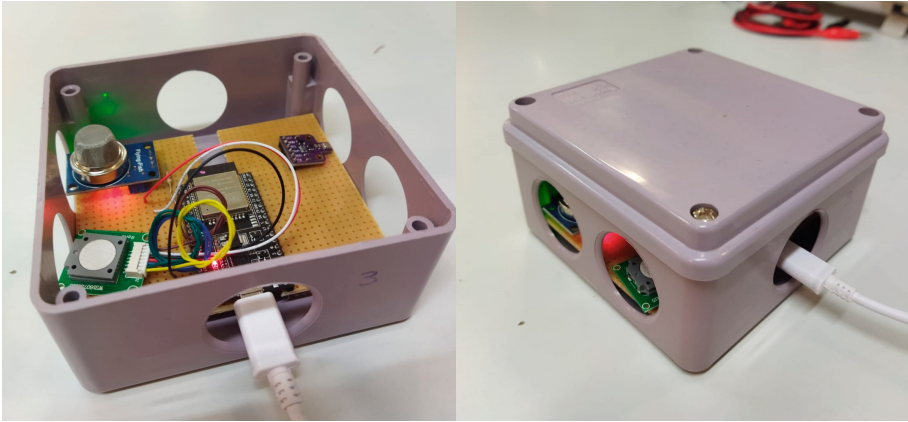
Starting with the connection between ESP32 and MQ135, the Vcc pin is connected to 5V of the ESP32 board, and the ground pin is connected to the ESP32 ground. The analog pin of the MQ135 is connected to the A0 pin of the ESP32 via a resistor. For this sensor, the A0 port is used, this GPIO allows receiving the analog signal from the sensor without WiFi usage interference (WiFi uses analog pins to run). But GPIOs' ESP32 requires a signal with 3.3V (not 5V tolerant). A resistor is added between the MQ135 analog pin and the ESP32 A0 pin to protect the GPIOs port from voltage damage.

BME680 outputs resistance values react according to the gas concentration, which means the output signal variation is inversely proportional to the gas concentration. The sensor is connected to ESP32 via I<sup>2</sup>C communication protocol

that uses two wires to share information. The sensor is powered with 3.3 V, and the SDA and SCL outputs are connected to GPIO21 and GPIO22, respectively, which is the default connection I<sup>2</sup>C using ESP32.

This ZE08 sensor uses only three pins to connect with the microcontroller, and this device gives an output signal in a range of 0 to 5 ppm with high sensitivity (up to 0.01 ppm). Pins 3 and 4 are GND and VCC, respectively, and Pin 2 of ZE08 is connected to the Vcc pin of ESP32. As well as MQ135, this sensor gives measurement through an analog signal.

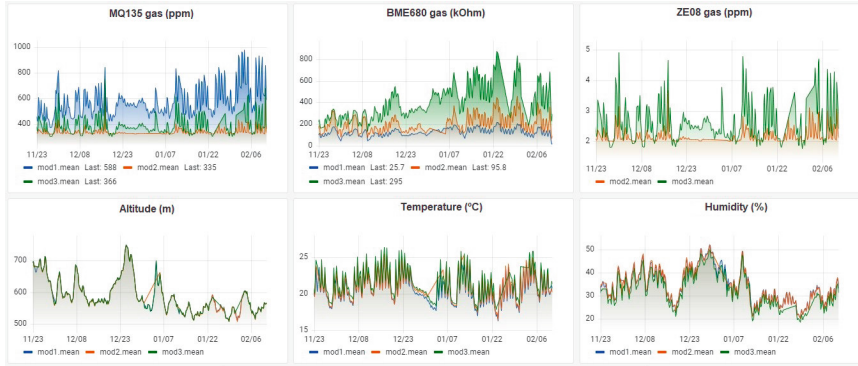
After assembling everything in a printed circuit board (PCB), the circuit was enclosed in a box. Figure 5 shows the final result of the module with the microcontroller and sensors responsible for the system's data acquisition stage. Three modules were assembled (Module 1, Module 2, and Module 3).



**Fig. 5.** Module with microcontroller and sensors used to collect data.

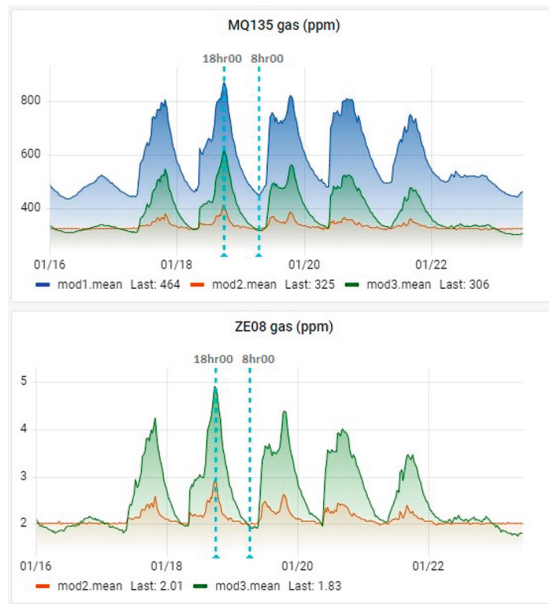
## 5 Results

Each module of Fig. 5 was programmed to collect and store data every two minutes. In Fig. 6, the database of parameters measured in a laboratory of the Institute Polytechnic of Bragança (IPB) is presented graphically. It is noted that from the date 12/20/21 to 01/10/22, the concentration of gases showed levels below average due to the pause in academic activities at the IPB lab due to year-end and new year's period, which reduced human activities in the laboratory.



**Fig. 6.** Temporal graphs of data stored in the database.

After some days, it is possible to understand the behavior of these parameters on regular days during a week of activities at IPB's lab. The data stored from January 16th to 23th is presented in Fig. 7. The top graph shows the gas concentration measured by MQ135 and ZE08 sensors over the week, where Module 1 (mod1) is presented in blue, Module 2 (mod2) is orange and Module 3 (mod3) is the green indicator. In bottom graph, only mod1 is not shown since this module does not have the ZE08 sensor.



**Fig. 7.** Gas measure of MQ135 and ZE08 sensors during a week. (Color figure online)

Starting on Sunday (January 16th) until Saturday (January 22th), the data measured by the sensors showed the same behavior due to some substances, such as CO, alcohol, and smoke. From Monday to Friday, the gas level increased from 8 h 00 morning, when the human activities start on IPB's lab, until 18 h 00. Then the gas concentration decreased because people start leaving the laboratory, marking the lowest gas level between 7 h 00 and 8 h 00 in the morning. After passing the period of dawn without human activity in the environment. Weekend has low gas concentration because it usually does not have activities in the laboratory.

Figure 8 presents the BME680 reading where the gas concentration showed a behavior similar to the MQ135 and ZE08. However, as the BME680's output signal is inversely proportional to gas level, the highest output signal values were stored during the dawn period and on weekends (when the lowest levels of the pollutant in the environment are expected). Still comparing BME680 with MQ135 and ZE08, the opposite happens in the morning and afternoon from Monday to Friday. The higher the registered gas level, the lower the values of the BME680 output signal.

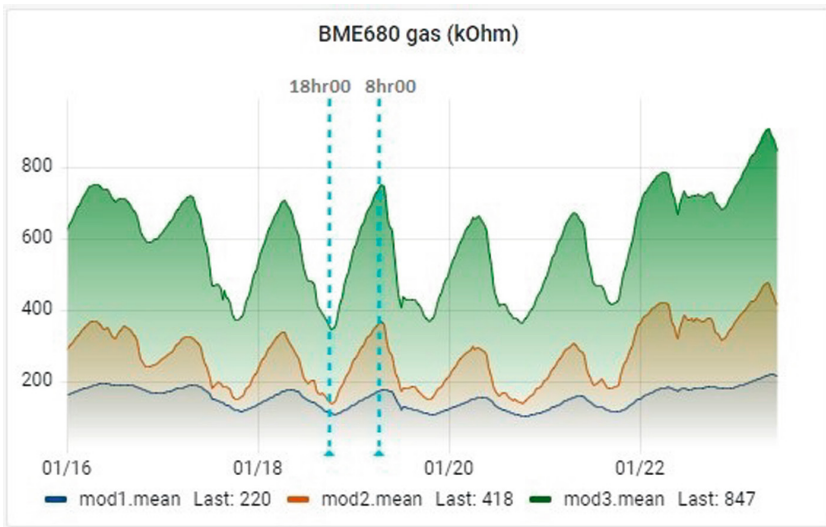
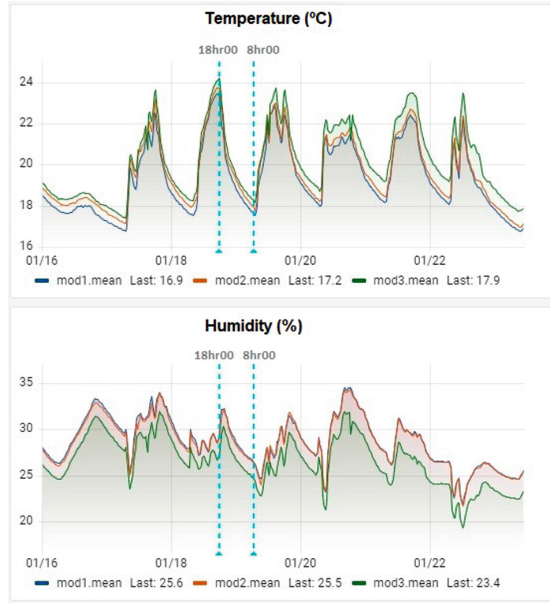


Fig. 8. Gas measure of BME680 sensor during a week.

As expected, the temperature and humidity levels increase during the day and decrease at night. It can be seen in Fig. 9, where the data stored demonstrates the expected behavior throughout the week. This behavior of temperature and humidity did not occur on Sunday (January 16th), when the temperature registered lower than the other days. On Sundays, the laboratory heating system is not turned on.



**Fig. 9.** Temperature and humidity measure of BME680 sensor during a week.

### 5.1 Forecasts Tests

Using data from January 16th to 23th, an LR algorithm was used to predict the parameters values and the results are presented in Fig. 10. The red line is the actual data used to training the model, the blue line the prediction data resulted from LR model and the grey line represents the error between the two values.

When analyzing the test and the prediction, the error value is close to zero for all tested values where the assertively of BME680 gas concentration (Fig. 10.A) was 99.7%, and the mean absolute error to this prediction was about 1.67 k $\Omega$ . Figure 10.B shows the forecast from the gas level registered by MQ135. As well as BME680 gas, LR prediction presented a high assertively degree (95.81%) and about 1.4 ppm of mean error. The prediction of ZE08 gas in Fig. 10.C is similar to MQ135 and scored 95.5% of predict precision and 0.015 ppm of mean error. The score precision of temperature prediction in Fig. 10.D was 99.1%, and the humidity score was 96.7%. In this test, a dataset was used where the parameters did not present changes in behavior to verify the degree of assertiveness of the machine learning model developed. The linear regression model showed a higher degree of precision to predict the data in all cases.

Another test will be presented when changes in gas concentration are disturbed with a combustion simulation. A smoke test was carried out on February 10th so that the sensors could read high concentrations of different gases. In the combustion simulation, a piece of burnt paper was placed next to the modules and they were covered with a box (reducing the air volume to intensify the sen-

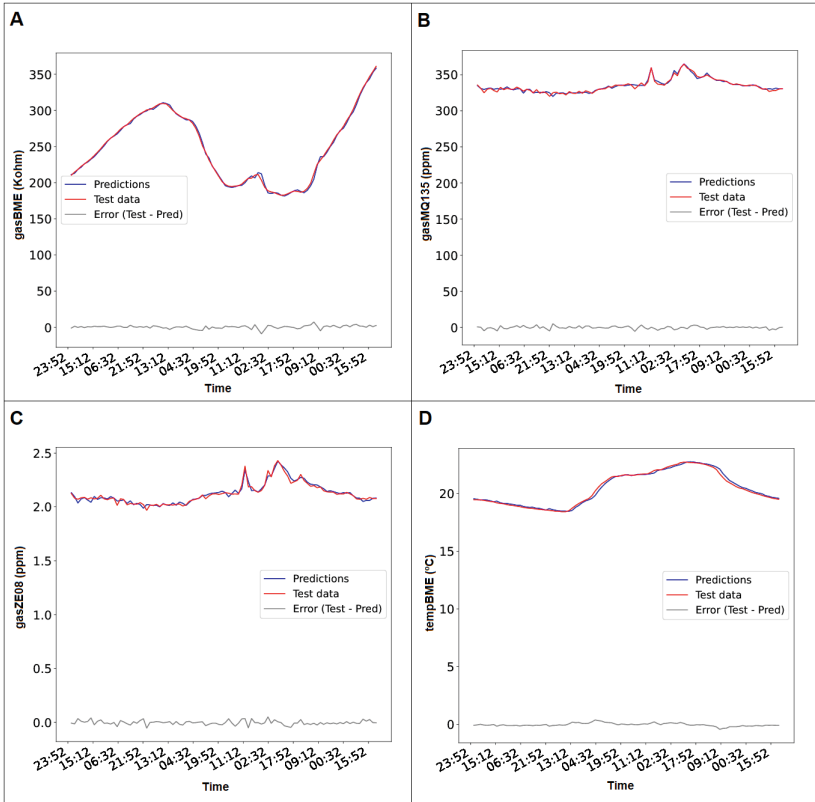


Fig. 10. LR predictions results. (Color figure online)

sor read). The test was carried out for one hour and only the gas levels were changed, while temperature and humidity maintained the same behavior.

The algorithm was run using the test data, as expected, the prediction showed different values from the measured data. Analyzing the Fig. 11.A, the forecast of BME680 gas concentration presents high differences between test and prediction values. The final prediction from LR scored 60.63% and the average error was around 46.33 kΩ. Figure 11.B presents the MQ gas forecast, when analyzing the Error line, it is noted that the measured gas value has values greater than 1500 ppm than the predicted value. The assertively to LR model was 46.61% and the mean absolute error scored around 629.42 ppm. The same behavior happens with ZE08 gas predict, in Fig. 11.C the Error line shows the difference between test and prediction values to the linear regression, the predict in this test was 47.24% and a median error from around 6.5 ppm.

In general, the smoke test presented expected results, given that the learning models were trained to predict the value of gases at normal levels according to the data stored in InfluxDB. This high value of detected error makes it possible

to perceive situations that compromise the IAQ of the environment, thus being able to alert, in real time, about variations in parameters.

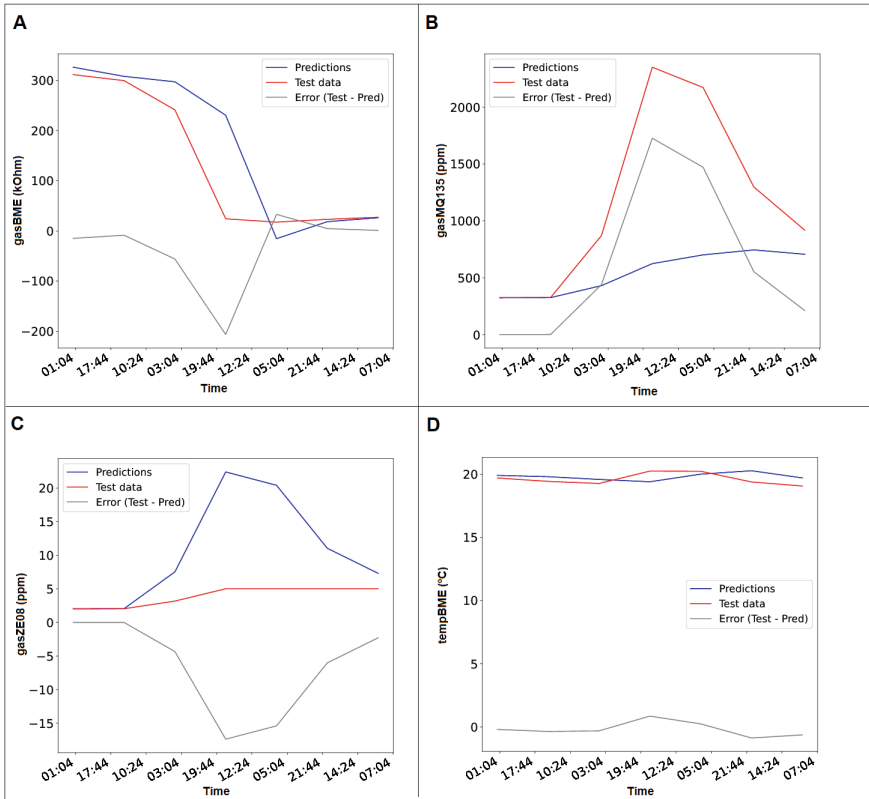
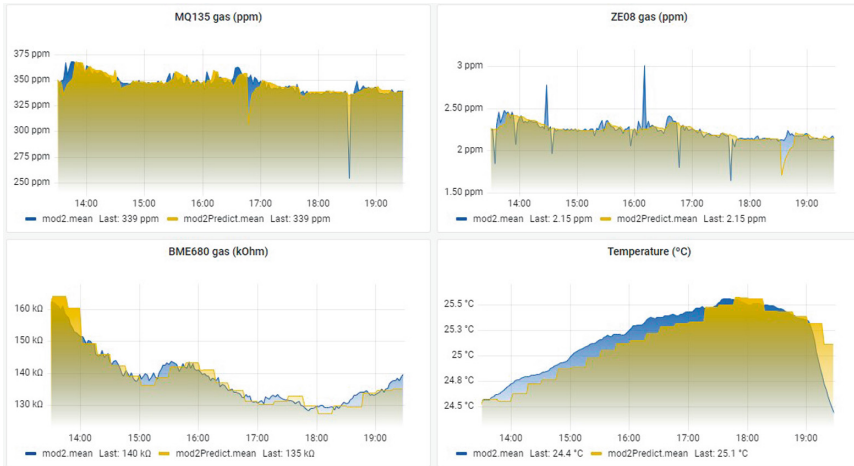


Fig. 11. RL predictions results.

## 5.2 Real-Time Monitoring

With the trained learning models, the real-time monitoring implementation is done in Grafana with a new database to store prediction values resulted from the LR model. Figure 12 is the real-time monitoring in normal conditions done on March 4th, the measured parameters are highlighted in blue are presenting a behavior similar to predictions values in yellow.

The data read by the sensors is sent to the database and automatically loaded into PyCharm IDE to be used in the learning algorithms, then the prediction values are sent to NodeRED and stored in a database. Then the data is displayed on Grafana to verify that the parameters read are as expected. The entire process is repeated every two minutes to keep monitoring as up-to-date as possible for possible data variations.



**Fig. 12.** Real-time monitoring in normal conditions. (Color figure online)

## 6 Conclusions and Future Work

The presented paper addressed the development of IAQ models, based on IoT technology that allows for acquisition, storage, and data analysis. The low cost associated with each module permits replicating it and spreading it in several places to monitor the air quality, which results in creating the WSN. Moreover, the adopted communication methodology (WiFi) is able to add new sensors and modules as required. The obtained results validate the prototype showing the user with the acquisition variables and generating alerts to avoid breath diseases. As future work, the improvement of modules with more data acquisition variables, for example, include particle sensors in modules to improve the quality of data collected. It is expected to develop an application to control any device focused to solve problems given an alert provided by algorithms predictions. In this sense, adding new prediction algorithms (such as Neural Networks, or a comparison between Supervised and Unsupervised algorithms) are promising directions to follow.

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