

# IoT-based indoor environmental monitoring and CO<sub>2</sub> prediction using FIWARE and Sigfox for smart laboratory environments

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*This paper presents an Internet of Things–based system for continuous monitoring of carbon dioxide (CO<sub>2</sub>), temperature, relative humidity, atmospheric pressure, and illuminance in a laboratory, together with a 15-min-ahead warning function for elevated CO<sub>2</sub> conditions. Sigfox-enabled sensors transmit measurements to ThingSpeak, while FIWARE Orion, QuantumLeap, CrateDB, and Grafana provide context management, time-series storage, and visualization. MATLAB retrieves the measurements, generates lagged CO<sub>2</sub> and recent-change features, and applies regression and ensemble classification models. Because high-CO<sub>2</sub> observations were infrequent, cost-sensitive learning and decision-threshold adjustment were employed. On the evaluated dataset, the threshold classifier achieved an accuracy of 62.63%, a precision of 0.09, a recall of 0.33, and an area under the receiver operating characteristic curve of 0.61. These results demonstrate the feasibility of the proposed end-to-end monitoring architecture, although the model exhibited only modest predictive discrimination. Consequently, larger and more diverse datasets are required before the model can be considered for automatic ventilation control.*

**Keywords** – CO<sub>2</sub> prediction, FIWARE, indoor air quality, machine learning, Sigfox.

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## Introduction

Indoor environmental conditions affect occupant comfort, work performance, and laboratory safety. Carbon dioxide (CO<sub>2</sub>) is commonly monitored as an indicator of occupancy-related ventilation conditions, although acceptable indoor air quality depends on multiple contaminants and building operational factors. Internet of Things (IoT)-based monitoring systems integrate multiple low-cost sensors, wireless communication, cloud storage, and visualization to provide continuous data at a finer temporal resolution than periodic manual measurements [1]. Ventilation design and operation should also be interpreted in accordance with current indoor air quality guidelines, such as ANSI/ASHRAE Standard 62.1-2025 [2].

Although monitoring provides information on current conditions, it does not offer advance warning of a rapid increase in CO<sub>2</sub> concentration. Short-term forecasting enables laboratory personnel to assess occupancy and ventilation conditions before a predefined operational threshold is exceeded. However, accurate forecasting is challenging because indoor CO<sub>2</sub> concentrations are influenced by occupancy, air

exchange, sensor noise, and sampling intervals, while high-CO<sub>2</sub> observations are typically much less frequent than normal observations.

This study develops an end-to-end monitoring and prediction framework that integrates Sigfox-enabled environmental sensors, ThingSpeak, FIWARE context management, time-series services, visualization, and MATLAB-based prediction. Rather than replacing a ventilation controller, the framework provides real-time monitoring and a 15-min-ahead decision-support signal that can be evaluated before implementing automatic control.

The main contributions of this study are as follows:

- an integrated IoT architecture for laboratory environmental monitoring;
- the use of lagged CO<sub>2</sub> and recent-change features for short-term prediction;
- cost-sensitive event classification and decision-threshold adjustment to address data imbalance; and
- a transparent evaluation based on precision, recall, the confusion matrix, and the receiver operating characteristic (ROC) curve.

## Related work

Recent studies have combined indoor environmental sensing and machine learning for CO<sub>2</sub> forecasting. Kallio et al. compared regression and tree-based methods using a one-year office dataset and demonstrated the value of historical CO<sub>2</sub> and occupancy-related information [3]. Taheri and Razban compared several machine learning algorithms for demand-controlled ventilation and highlighted the relationship between prediction horizon and control performance [4]. Deep recurrent models have also been applied to IoT-enabled forecasting. Zhu et al. employed a long short-term memory (LSTM)-based approach [5], whereas Marquez-Zepeda et al. combined low-cost monitoring with short- and long-horizon CO<sub>2</sub> prediction [6].

The communication and data management layers are equally important for deployable systems. Low-power wide-area network technologies, such as Sigfox, enable long-range, low-power communication for sensor deployments, albeit with trade-offs in data rate, payload size, and network operation [7]. For indoor air quality applications, Anto et al. demonstrated a structured platform for collecting and managing heterogeneous data [8]. FIWARE Orion supports context updates, queries, and subscriptions [9], whereas ThingSpeak provides cloud-based data channels and MATLAB-integrated access to live data streams [10].

The present work differs from studies that focus solely on prediction models by evaluating an end-to-end framework encompassing sensing, context management, data storage, visualization, and operational warning generation. In addition, it explicitly examines the effects of class imbalance rather than relying solely on accuracy as a performance metric.

## Methodology

### System architecture

The proposed system comprises a sensing and data transmission pipeline, a prediction pipeline, and a FIWARE-based monitoring pipeline (Fig. 1). Sensor nodes measure CO<sub>2</sub> concentration, temperature, relative humidity, atmospheric pressure, and illuminance. The measurements are transmitted via the Sigfox network and backend to a ThingSpeak channel. MATLAB retrieves the channel data for feature generation, model inference, and estimation of the probability that the CO<sub>2</sub> concentration will exceed a predefined threshold 15 min ahead.

In parallel, a REST-based forwarding process

updates entities in the FIWARE Orion Context Broker. Orion maintains the latest context information and sends subscription notifications to QuantumLeap, which stores the time-series data in CrateDB. Grafana queries the stored data to generate monitoring dashboards. This architecture enables the prediction pipeline and the context management/time-series services to evolve independently while using the same sensor measurements.

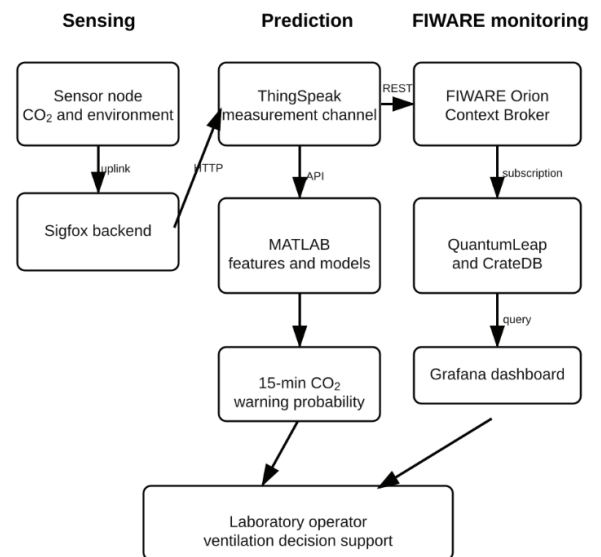


Fig.1. Architecture and data flow of the proposed monitoring and prediction system.

### Data preparation and temporal features

The model inputs consist of the measured environmental variables. Sensor measurements are scaled in MATLAB before model training. To capture short-term temporal dynamics, the feature set includes lagged CO<sub>2</sub> values and the recent change in CO<sub>2</sub> concentration, calculated as the difference between consecutive measurements. These features characterize both the current CO<sub>2</sub> level and its temporal trend without requiring a complex physical model.

### Prediction models

Two prediction formulations were evaluated. The regression formulation estimates the future CO<sub>2</sub> concentration using linear and ensemble regression models. The event-classification formulation predicts whether the CO<sub>2</sub> concentration 15 min ahead will exceed an application-defined operational threshold. Accordingly, the positive class represents a future high-CO<sub>2</sub> event, whereas the negative class represents a future CO<sub>2</sub> concentration at or below the threshold.

Because high-CO<sub>2</sub> events were infrequent in the evaluated dataset, cost-sensitive learning was used to increase the penalty for misclassifying positive

instances. The classifier output probability was subsequently converted into a class label using an operating threshold of 0.15. Lowering the operating threshold increases the number of warnings and may improve event detection but can also increase the false-alarm rate.

### Evaluation procedure

The threshold classifier is evaluated using accuracy, precision, recall, and the area under the ROC curve (AUC). Precision represents the proportion of predicted high-CO<sub>2</sub> warnings that are correct, whereas recall represents the proportion of actual high-CO<sub>2</sub> events that are correctly identified. The confusion matrix is also reported because the evaluated dataset comprises 90 normal cases and only 9 high-CO<sub>2</sub> cases. Under this class imbalance, accuracy alone can obscure poor performance on the positive class.

### Results and discussion

Table 1 summarizes the classifier performance at the selected probability threshold. The classifier achieved an accuracy of 62.63%, a precision of 0.09, a recall of 0.33, and an area under the AUC of 0.61. The AUC indicates modest discrimination between the two future threshold states, while the low precision suggests that most predicted high-CO<sub>2</sub> warnings were false positives.

**Table 1**  
*Performance of the threshold classifier.*

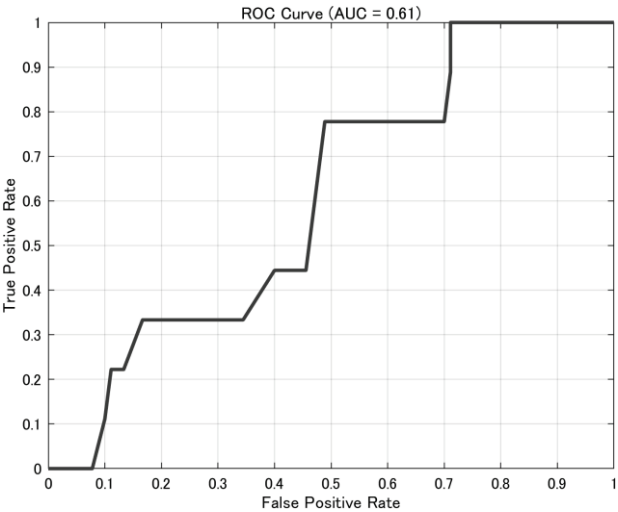
| Metric                | Value  |
|-----------------------|--------|
| Accuracy              | 62.63% |
| Precision             | 0.09   |
| Recall                | 0.33   |
| ROC AUC               | 0.61   |
| Probability threshold | 0.15   |

The confusion matrix (Table 2) provides a more direct assessment of classifier performance. Of the nine high-CO<sub>2</sub> cases, three were correctly detected, whereas six were missed. Among the 90 normal cases, 59 were correctly classified and 31 were incorrectly identified as high-CO<sub>2</sub> events. Thus, the operating threshold of 0.15 increased sensitivity compared with a more conservative decision threshold, albeit at the cost of a high false-positive rate, making it less suitable for unattended automatic control.

**Table 2**  
*Confusion matrix at a probability threshold of 0.15.*

|                             | Predicted normal | Predicted high CO <sub>2</sub> |
|-----------------------------|------------------|--------------------------------|
| Actual normal               | 59               | 31                             |
| Actual high CO <sub>2</sub> | 6                | 3                              |

The ROC curve (Fig. 2) confirms that the model possesses some predictive capability, although its performance is insufficient to support direct ventilation actuation. Accordingly, the proposed platform is better regarded as a monitoring and decision-support prototype. Laboratory personnel can use the generated warnings in conjunction with dashboard history and current occupancy information to support operational decisions.



*Fig.2. ROC curve for the threshold classifier (AUC = 0.61).*

The results also highlight the limitations of the current evaluation. The positive class comprises only nine cases, the dataset represents a single environment over a limited data-collection period, and no independent multi-site validation was performed. Although lagged and change-rate features provide temporal context, an ablation study is required to quantify the contribution of each feature. Furthermore, the regression analysis did not include a complete set of comparable error metrics; therefore, the present discussion focuses on the threshold classifier, for which the confusion matrix and ROC-based evaluation are available.

### Conclusion

An IoT-based framework for indoor environmental monitoring and 15-min-ahead CO<sub>2</sub> warning was developed using Sigfox, ThingSpeak, FIWARE Orion, QuantumLeap, CrateDB, Grafana, and MATLAB. The proposed architecture provides an end-to-end pipeline from sensor data acquisition to context management,

time-series visualization, and predictive decision support.

At the selected operating threshold, the classifier detected three of the nine high-CO<sub>2</sub> events, achieving a precision of 0.09, a recall of 0.33, and an AUC of 0.61. These results demonstrate the technical feasibility of the proposed framework but also indicate that the current model is not suitable for autonomous ventilation control. Future work should increase the number and diversity of high-CO<sub>2</sub> observations, validate the system across multiple rooms and seasons, compare regression models using a comprehensive set of error metrics, perform feature ablation and probability calibration, and evaluate warning strategies with laboratory users.

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