Sensing and Imaging (2023) 24:7
https://doi.org/10.1007/s11220-023-00412-x

ORIGINAL PAPER

Indoor Air Sensing: A Study in Cost, Energy, Reliability and Fidelity in Sensing

Praveen Kumar Sharma[1,5] · **Bidyut Dalal**[1] · **Ananya Mondal**[2] · **Argha Sen**[3] · **Amartya Banerjee**[4] · **Sandip Mondal**[1] · **Tanmay De**[1] · **Sujoy Saha**[1]

Received: 1 May 2022 / Revised: 8 November 2022 / Accepted: 24 December 2022 /
Published online: 20 February 2023

Abstract
The rise in environmental pollution and degradation of air quality worldwide has dragged researchers' attention due to its direct societal impact. Studies reveal that the indoor environment is more polluted than the outdoors. In this paper, a framework for indoor air quality monitoring has been presented. We have developed a portable and cost-effective air quality monitoring device. The device generates fine-grained data for a combination of different pollutants and meteorological sensors (humidity and temperature). In this work, an energy-aware Environment Monitoring Device (EMD) has been developed with an adaptive sampling rate. Different aspects of the EMD have been presented with an analysis of their power consumption. The proposed technique has reduced more than 45% of energy consumption. A proposed energy reduction technique has discussed a trade-off between the cost-effectiveness of developed EMD and its reliability. We proposed the calibration of the sensor to ensure the reliability of the sensed data. A soft-calibration technique has been proposed considering the classrooms' Spatio-temporal nature to ensure the sensed data's reliability by mitigating the sensor errors due to spatial factors and achieved $\approx 6\%$ of error reduction compared to the baselines. Moreover, an energy-aware calibration technique has been proposed by providing a scheduling algorithm for re-calibration. The overall system significantly improves the lifetime and energy consumption of the sensors compared to that of normal conditions.

Keywords Indoor air quality · Air quality monitoring device · Energy aware system · Hard calibration · Soft calibration

✉ Praveen Kumar Sharma
praveencs54@gmail.com

1 National Institute Technology Durgapur, Durgapur, West Bengal, India

2 Indian Institute of Technology, Jodhpur, Jodhpur, Rajasthan, India

3 Indian Institute of Technology, Kharagpur, Kharagpur, West Bengal, India

4 Ramkrishna Mahato Government Engineering College, Purulia, Purulia, West Bengal, India

5 ITER, Siksha 'O' Anusandhan, Bhubaneswar, India

1 Introduction

The deterioration of air quality is a major challenge to humankind, especially in urban regions. The source of most of the pollutants is fuel emission and industrial emission. Over the past quarter-century, there has been an exponential increase in industries. These industries have caused complex and severe problems for the environment and the sustainability of humankind, especially in urban cities. The indoor environments could not remain untouched from the effect of these problems. In indoor, these pollutants are even higher than outdoor environmental pollutants. The pollutants like carbon dioxide (CO_2) and suspended particulate matters ($PM_{2.5}$, PM_{10}) affect the indoor environment severely. A survey by [30] discussed the different aspects of $PM_{2.5}$ indoors as well as outdoors with their sources and impacts. The authors also described the causal effect of $PM_{2.5}$ in terms of cardiovascular and respiratory diseases, which affect the occupants. Indoor pollutants affect the occupants physically as well as cognitively. The sources of these indoor pollutants are the exhalation process of humans, smoking, nearby sources of pollution like traffic, highways, etc. Besides, stationary and mobile sources release various chemical pollutants, including suspended particulate matter (SPM), carbon monoxide (CO), oxides of nitrogen (NO), lead aerosol, volatile organic compounds (VOC), and other toxins, which might also affect the indoor air quality. A report by European Commission depicts that we spend 90% of our time indoors [22] and the indoor environment can be five times more polluted than that of the outdoors [18]. European countries have reduced the emission of pollutants/particles by adopting some policies and measures [14]. In a developing country, to assess such problems, the measurement of the pollutants would be the foremost objective. The studies conducted by [4, 19, 41] show the effects of indoor pollutants on the health of occupants, especially children. It is also observed that the children residing indoors, including classrooms, might suffer from asthma due to the high presence of airborne particle concentrations [6, 36]. Measuring/monitoring the air quality indoors is the foremost step towards reducing exposure to the concentration of pollutants. The government deployed Air Quality Monitoring Station (AQMS) has solved the issue by sensing the air quality in different regions of a city. The AQMSs are very costly to deploy and maintain, so they can not be deployed densely. These devices are deployed sparsely in the city at some locations. Nowadays, sensor-based environment monitoring devices have become a popular solution for air quality monitoring indoors and outdoors. There are some issues regarding the development of such devices, which are mentioned below.

Recently, environment monitoring using pollutant sensors are attracting the attention of the researchers. In recent past, [1, 29, 45, 50] have developed environment monitoring devices using either low or high cost sensors. From the literature, we have observed the unavailability of portable EMDs at a reasonable cost. Besides, these devices are not competent enough due to their size, data sampling rate, and measuring parameters (like $PM_{2.5}$, CO_2, VOC, etc.) Hence, the requirement of developing a cost-effective and portable environment monitoring device equipped with some sensors (PM_{10}, $PM_{2.5}$, CO_2, VOC, Humidity, and Temperature) has been emerged for the indoor environment monitoring. An article by [37] shows that urban buildings consume up to 40% of the total energy. Several studies have been cited [51] in the literature towards the energy saving of a building to maintain the requirement of energy by a nation [23]. However, to provide a clean and healthy environment, the dependency upon the sensor-based EMDs is increased. Deploying an EMD in different rooms of a building increases energy consumption. Several works have been investigated, and some work [28] has been observed discussing the relationship between the occupancy and energy consumption by the building. The adaptive EMD can help reducing energy consumption by occupancy detection and perform accordingly. Although, it has been observed by Eranna et al. [11] that low-cost sensors lose their sensitivity and precision with time. Hence, different types of calibration techniques like zero air calibration, external calibration, etc. must be used. Calibration is the process of minimizing the error in measurement by the sensor. Calibration can be broadly categorized as hard and soft calibration techniques depending upon their calibration methods. Hard calibration requires hardware components or, human intervention such as external and zero air calibration whereas, soft calibration uses machine learning techniques to calibrate the sensors. It has been observed that, even if the system successfully qualifies the external and zero air calibration tests, the sensitivity of the sensors may vary in different ambient conditions. Therefore, different learning models are required to maintain the sensitivity of low-cost sensors. The sensors are calibrated using the learning mechanism but, due to the continuous monitoring, the sensors lose their sensitivity which further needs to be monitored and then calibrated. The correlated features are not the same at different classrooms, so calibration becomes tedious for different classrooms, which needs further analysis.

1.1 Contribution

Our key contribution in this paper is the development of a reliable air quality monitoring system for indoor air quality monitoring. The objectives of this work can be categorised as follows,

- Design and development of a moderate cost device that can capture the pollutants (CO_2, CO, and NO_2), particles (PM_{10}, $PM_{2.5}$, and PM_1) with meteorological parameters (Humidity, and Temperature) used to monitor the air quality of institutional buildings.
- To make the system energy aware by injecting a simple intelligence to the system and making the system adaptive to sample accordingly. This will improve the system efficiency as well as the lifetime of the sensors. This reduces the power consumption by 45% as in the normal condition.
- Hard calibration as well as soft calibration of the device are performed in order to ensure the reliability of the system. A generalised indoor calibration technique

is proposed considering the spatio-temporal parameters, irrespective of its actual correlation coefficient.

- We have designed an energy aware soft-calibration technique. The frequency of calibration reduces the power efficiency of the system which has been managed using the proposed energy aware calibration technique. This technique works for indoor as well as outdoor monitoring devices.

The rest of the paper has been organized as follows,

In Sect. 2 the motivation behind the proposed framework has been discussed. Section 3 presents the overall idea about the development of a cost-effective portable device to monitor pollutant concentration and provides an insight into the sensors with their properties. The energy awareness of our proposed system is described in Sect. 4. We have proposed a spatio-temporal calibration technique for ensuring the reliability as well as robustness of EMD irrespective of its deployment location in Sect. 5. Section 6 provides the energy-aware calibration to improve the efficiency of the system. In Sect. 7, the related studies in the field of air quality monitoring have been described in details. Finally, through Sect. 8 we conclude the paper.

2 Motivation Behind Our Proposed Work

Nowadays pollution is one of the major challenges especially in developing countries. We spend most of our time indoors and indoor environment can be 5 times worse than outdoors. Indoor Air Quality (IAQ) depends upon the ambient conditions which are directly affected by the outdoor environmental conditions [32]. So, we need outdoor environment monitoring as well to measure the indoor air quality. Most of the cities are lacking in suitable number of Air Quality Monitoring Stations (AQMSs). As an instance, in India, there are 37 AQMSs in Delhi, 4 in Kolkata and only one in Durgapur in active state. Such small number of monitoring stations are incapable of monitoring the complete citywide fine grained AQI.

The AQMS placed especially in Durgapur is capable of measuring the concentration of some of the pollutants and contaminants. But, only one AQMS is not enough to measure the air quality of the whole city as the city has a variety of sources of generation of pollutants like, power plants, brick industries, National highway, etc. Moreover, the AQMS provides very less data granularity (Samples per unit time) and deployment of such AQMS indoors is not feasible due to its high cost of deployment and maintenance. Hence, there is a requirement of devices which can measure the air quality. There are devices to measure the concentration of pollutants using inbuilt sensors of different types and different working. Such devices can be categorised depending upon their costs as follows:

Devices with low cost Airveda [29]: India's first app-enabled air quality monitor device designed and manufactured in India. The device has been designed considering the the measurement of the pollutants in Indian context i.e. CO_2, $PM_{2.5}$, PM_{10}, temperature and humidity. AirBeam [2]: an Arduino-powered, portable, palm-sized

Table 1 Comparative analysis of various market available devices with their measuring parameters, cost and granularity which signifies the trade-off among the cost, measuring parameters, and granularity

Name of the device	Measuring parameters	Cost ($)	Granularity (sample(s) per minute)
Aeroqual outdoor starter kit	$PM_{2.5}/PM_{10}$, NO_2, O_3, Temp, Hum	2680	1
Aeroqual indoor starter kit	$PM_{2.5}/PM_{10}$, CO_2, VOC, Temp, Hum	2850	1
Aeroqual outdoor kit (Pro)	$PM_{2.5}/PM_{10}$, NO_2, O_3, CO, VOC, Temp, Hum	4810	1
Aeroqual indoor kit (Pro)	$PM_{2.5}/PM_{10}$, CO_2, CO, VOC, Temp, Hum	4545	1
Flow	$PM_{2.5}$, PM_{10}, CO_2, VOC	300	4
AirBeam	$PM_{2.5}$, Temp, Hum	45	60
Airveda	$PM_{2.5}$, PM_{10}, CO_2, Temp, Hum	300	3

It emerges the requirement of an environment monitoring device which balances the aforementioned parameters i.e., with reasonable cost, desirable measuring parameters, and relatively high granularity

air quality monitor capable of measuring fine particulate matter $PM_{2.5}$, **Flow** [39]: Flow maps air pollution variations around us in real time by measuring real-time concentrations of NO_2, VOC, $PM_{2.5}$ and PM_{10}.

Devices with high cost Aeroqual [1]: There are two versions of Aeroqual. One is **Indoor Air Quality Kit**:[1] The kit is used to measure indoor pollutants, including the following sensors: particulate matter ($PM_{2.5}/PM_{10}$), two indoor pollutant gas sensors (CO_2, VOC), and a combined temperature and relative humidity. The other version of Aeroqual is **Outdoor Air Quality Kit**:[2] The kit is used for outdoor monitoring, including the following sensors: particulate matter ($PM_{2.5}/PM_{10}$), pollutant gas (NO_2, O_3), and a combined temperature and relative humidity.

The summary of the available systems is listed in Table 1. Aeroqual, Airveda and Flow provide less granular data which results insufficient data. Airbeam and Flow are not suitable for detection of all the required pollutants as the sources of pollutants are different in different regions. Moreover, the sensors are inbuilt and can not be modified or, calibrated, so these devices are not reliable.

A comparative study of these different AQMSs has been depicted in Table 1, with respect to the cost and the number of measuring parameters. It can be observed that, the monitoring capability of Aeroqual: (OutdoorKit(Pro)) is high compared to other monitoring devices. But, the cost is also very high. In this paper, we primarily analyse the classroom environment as children are more susceptible to erroneous data. Note, a device with a greater number of measuring parameter is required but at the same time cost of the device should be less so that normal schools and colleges can afford it. Hence, the requirement of a system is desirable that can monitor the desired pollutants with high granularity and low cost. Therefore, we can summarize the problem as,

[1] https://www.aeroqual.com/product/indoor-portable-monitor-starter-kit.

[2] https://www.aeroqual.com/product/outdoor-portable-monitor-starter-kit.

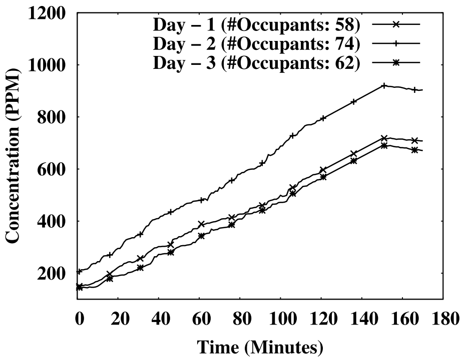


Fig. 1 Variation of CO_2 concentration during the classes, in three random days during the 2nd and 3rd period (between 10:50 am to 12:30 pm) of different classrooms consisting of different number of occupants depicting the sharp rise in CO_2 concentration

Problem Statement-1 Designing and developing a cost effective environmental monitoring device with high granularity.

Though the devices of high granularity is required to monitor the environment with greater accuracy and helps in monitoring the minor fluctuations, it draws an ample amount of energy. The power consumption increases linearly with number of monitoring devices as well as the duration of the deployment. In our study [44], the variation of pollutants concentration in a classroom with varying number of occupants and time, has been shown. The same experiment has been carried out in different scenarios such as in different classrooms, for different duration etc.

It has been observed that the same characteristics have been followed by the pollutants in different set-ups as depicted in Fig. 1. Due to the rapid increase in the population throughout the urban and sub-urban city, the power consumption increases to 20% to 40% in developing countries [37]. It has been observed that whenever a classroom becomes empty the level of the pollutants starts decreasing. So, monitoring of the empty classrooms with such a high frequency is not required as a classroom with occupants. As per the increase in the level of pollutant (specifically, CO_2) signifies the presence of occupants and further continuous increase in CO_2 reveals the duration of presence of occupants. So, controlling the granularity of the EMD can be triggered as per the occupancy and it can solve the problem of energy consumption i.e. the adaptive system is required. Eventually, it increases the lifetime of the sensors through reduced sampling rate. We can summarize our problem as,

Problem Statement-2 Improving the energy efficiency of the developed environment monitoring device by controlling the granularity of the system in real-time by incorporating the intelligence of occupancy detection and self adaptive nature without any extra overhead

Each environment sensor has a lifetime i.e. sensors loose their sensitivity and precision with time - this problem is termed as Sensor Drift [12]. Low-cost sensors are also prone to have cross-sensitivity issues but, assuming this problem as a relative issue in all the sensors, we are not concern about this issue. It has been observed that, the sensitivity of the sensors decreases with time while they are placed in the same environmental condition for a long time. Due to sensor drift, the aforementioned devices are prone to be decayed in sensitivity with time. To use these devices effectively they must be calibrated using different calibration techniques. Some of the calibration techniques viz. external and zero volume calibration require human intervention to calibrate. But at the time of real world deployment these techniques will not help as they require some static and costly set-ups. Hence a soft calibration technique is desirable in such situation. These calibration technique generally follows regression technique, and it requires feature analysis which can be done using correlation coefficient. But, it is observed that the for different classrooms the feature set is different which is undesirable. Hence, a soft-calibration technique has been proposed considering the spatio-temporal behaviour of a classroom irrespective of its actual correlated factors. Hence, the problem can be stated as,

Problem Statement-3 If n no. of EMDs are deployed in different classrooms, some of them provide incorrect measurement although the sensitivity of the sensors is acceptable. Can we enhance the system reliability by improving the sensor precision through a spatio-temporal soft-calibration process, irrespective of its measuring location?

Due to the problem of sensor drift the sensors need to be calibrated in a periodic basis. The period after which the calibration is required is the key to achieve an energy-aware calibration system. The importance of re-calibrating the system depends on the application area, and children are very susceptible to air pollutants. There are works describing the hazardous impact of pollutants [8, 31] such as sick building syndrome (SBS) [13, 52]. Most air quality monitoring devices are equipped with low-cost sensors, and these sensors lose their sensitivity with time. If such calibration and re-calibration are not used, these devices provide erroneous air quality, affecting the occupants. Hence, the problem can be stated as,

Problem Statement-4 Is it possible to make the system intelligent such that it would calibrate the system periodically, and the period for re-calibration can be set through an energy aware calibration system?

3 Development of Cost Effective, Portable Environment Monitoring Device

We have developed a low cost (costs $\approx$ 100\$−200) Environment monitoring device (EMD) as shown in Fig. 2 comprising of environmental as well as meteorological sensors as mentioned in Table 2. The sensors are connected to Arduino, which reads the changes in voltage through its input pin, maps it accordingly and stores the sensed data. Here, we use the Arduino for easy prototyping. The connection of sensors with the controller is shown in Fig. 2. At the very initial stage, some problems arose such as proper voltage supply and its' proper distribution among the sensors. On considering such underlying issues, the moderate cost (costs $\approx$ 300\$ − 450) EMD has been developed. We can evaluate the accuracy of a sensor using the EQ 1.

$$\left(\frac{Actual\ Value - Measured\ Value}{Actual\ Value}\right) \times 100\% \tag{1}$$

Table 2 List of sensors used for the development of the EMD with their specification viz

Sensor name	Type of sensor	Detecting concentration scope	Cost (in \$)	Operating Temp/Hum	Remarks
Low cost EMD					
Sharp GP2Y1010AU0F	Optical	Greater than 0.5 m size bins	16	55	Low cost used in initial EMD, less granularity, less life time low energy consumption
MQ7	Semiconductor	CO	8	-20 to 50/Less than 95%	
DHT11		Temperature, humidity	9.33	0–50/20–80%	
MQ135	Semiconductor	CO_2: 500–2000 ppm, NH_3: 10–300 ppm, Benzene: 10–1000 ppm, Alcohol: 10–300 ppm	8.62	28/65%	
Moderate cost EMD					
TH02		Temperature, humidity	21.52	– 40 to 80/5–99%	Medium cost used in modified EMD, high granularity, relatively more lifetime relatively more energy consumption
PMS1003	Laser based	PM1, PM2.5, PM10	68	–20 to 50/0–99%	
MiCS-6814	Metal oxide semiconductor	CO: 1–1000 ppm, NO_2: 0.05–10 ppm, C_2H_{6OH}: 10–500 ppm, H_2: 1–1000 ppm, NH_3: 1-500 ppm, CH_4: 1–1000 ppm	66	25/50%	
MH-Z16	Electrolyte	0–2000 ppm CO_2	142	0–50/0–90%	
MG811	Electrolyte	350–10,000 ppm CO_2	81.79	28/65%	

The cost of acquisition, types of the sensor, scope of detecting pollutants, the operating temperature and relative humidity along with an overall remarks for the low-cost as well as moderate cost EMDs

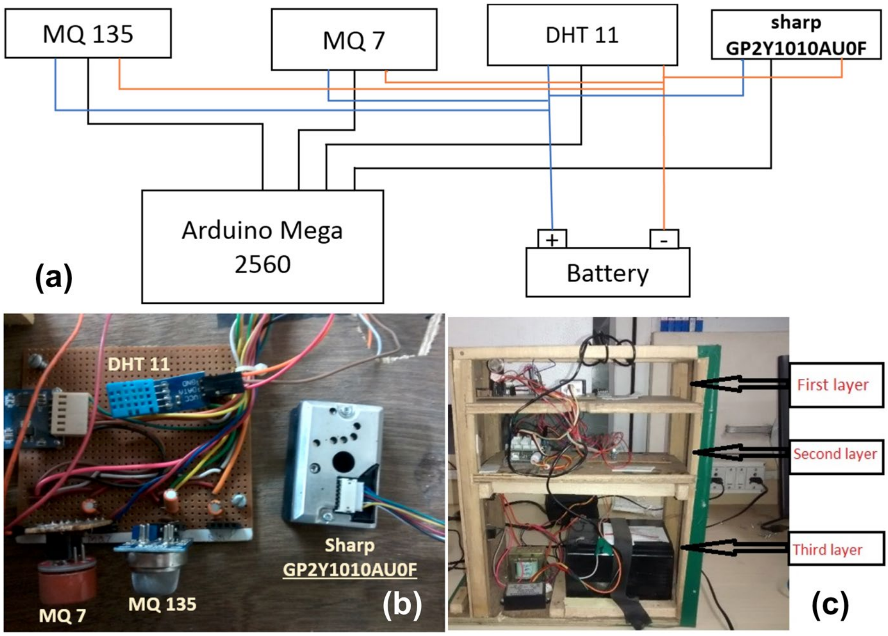


Fig. 2 **a** Architecture of the device consisting of sensors, micro-controller and power module assuming that the power to the micro-controller has been given separately; **b** Pin-out of sensors with micro controller (Arduino Mega 2560); **c** Layer-wise view of the developed EMD consisting all the sensors where, First layer: Sensing layer consisting of sensors, Second Layer: Controller unit consisting of micro-controller, Third Layer: Power module consisting of battery and other electric components

3.1 Low-Cost EMD

On comparing the low cost EMD with the AQMS placed by Central Pollution Control Board (CPCB), Durgapur, India, we have got an accuracy of 60% to 70%. The first design/implementation of the EMD revealed to have some issues at the time of testing it, which are further required to be revised for the enhancement of the system. The issues to be revised are, **(a) Life-Time** of the sensors used in the EMD was poor on average it was 10-11 Months, **(b) Sensitivity** of the sensor was weak, for critical conditions it would reduce up to 40%, **(c) Granularity** of the system was low to 3 data samples per minutes, **(d) Accuracy** provided by the system was 70% to 75% which is satisfactory.

3.2 Moderate Cost EMD

Our objective is to design and develop a GPS enabled cost effective environment monitoring device for monitoring the criteria pollutants i.e. NO_2, PM_{10}, CO_2, etc. and meteorological parameters like temperature, humidity with real time data processing and transmitting feature. We require the GPS to validate the system as

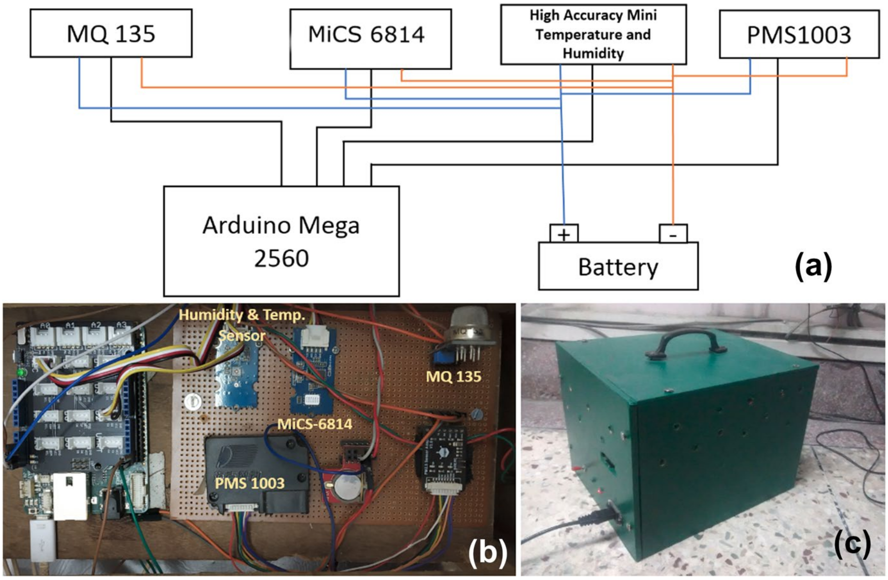


Fig. 3 Layout of the EMD **a** Architecture of the device consisting of sensors, controller and power distribution among sensors assuming that the power to the micro-controller has been given separately, **b** Sensor connectivity with UDOO NEO, **c** EMD with small size and easily portable consists two layers: (i) sensing layer and controller unit and (ii) power module

if the EMD at outside is in the close proximity. We need the system to be portable as to validate and calibrate the system in a timely manner.

After applying the necessary modifications step by step the device has been evolved. The system architecture of the complete system is shown in Fig. 3 in which we have used UDOO NEO for better performance. The sensors used in the moderate cost EMD is mentioned in Table 2 with their features. The end device has the following *Advantages:*

- **Accuracy** On comparing the EMD with the AQMS by CPCB, Durgapur, India, we have got an accuracy from 80% to 85%.
- **Portable & Cost effective** The modified EMD is equipped with two layers with a Power bank which makes it easily portable. The weight of the EMD was reduced to 600 gms. Due to a slight change in the price of the moderate sensors and reduction of size, the EMD remains low cost slightly more than the previous version of EMD.
- **Long battery backup** We use a Power bank of 20000 mAh for power supply which provides 48 hrs backup, so the device can continuously work for the long term without any interruption.
- **High Granularity** The granularity of the EMD are controlled and increased up to 60 data samples per minute.

Table 3 Comparison between the two versions of EMDs i.e., low-cost EMD and moderate-cost EMD developed with respect to some performance parameters such as accuracy of the EMDs, measuring parameters, precision, dimension, weight, their battery running time along with the approximate cost of the EMDs

	Accuracy	Measuring parameters	Precision	Dimension	Weight	Running capacity	Cost (in $)
Low-cost EMD	60%	NO_2, CO_2, CO, $PM_{2.5}$, Humidity, temperature	±10%	$30 \times 25 \times 10$ cm	2.5 kg	10–12 h	180
Moderate cost EMD	80%	NO_2, CO_2, CO, PM_1, $PM_{2.5}$, PM_{10}, Humidity, temperature	±5%	$15 \times 15 \times 12$ cm	0.8 kg	32–36 h	400

- **Connectivity** The sensed data is stored continuously in SD card storage as well as it has the bluetooth and Wi-Fi connectivity which can also supply the data for web storage.

A comparative analysis of the low as well as moderate cost EMD has been made and depicted in Table 3.

The cost-effective EMD has been developed but the energy consumption by the EMD increases the overall cost of deployment. So, for a feasible system an energy aware EMD is desirable which is presented in the next section.

Key Observations: The cost−effective EMD has been developed which can sense the pollutants (NO2, CO2, CO), particles (PM1, PM2.5, PM10), and meteorological parameters(Temperature and Humidity) with acceptable granularity.

4 Energy Aware System

The developed EMD is dependent on lead acid battery which has certain backup depending upon the the number of data samples generated per unit time.

$$EnergyConsumption(E) \propto SamplingRate(S) \tag{2}$$

We have proposed an energy aware system to increase the run time of the EMD by controlling the energy consumption of the system. Eq. 2, says that Energy Consumption (E) is directly proportional to the Sampling Rate (S) i.e. E can be controlled by controlling S. Here our objective is to control S without affecting the accuracy of the system i.e. minimize S over a given time units subject to the constraint that, accuracy will not be reduced. We propose an energy aware system using the fact that, in the absence of the students we do not need to measure the pollutants concentration with high granularity. To make our system energy aware, we have incorporated some intelligence to the EMD. Using this intelligence the EMD can detect if students are present in the classroom or not. Here two factors are underlying which depend upon the occupancy of the target classroom. First factor defines the method of occupancy detection without adding any extra module and the second factor tells about the occupancy of the classroom during the time duration. The Real Time Clock (RTC) provides the information of time of the day and day of the week. These information helps in realizing the time in which classes go on. On the other hand, the occupancy detection is done depending upon the level of concentration of CO_2 as the level of CO_2 increases with increase in the number of occupants [44]. But, here the challenge lies in detecting the occupancy irrespective of the other factors such as size of the classroom, air exchange rate of the classroom etc. Moreover, each time the

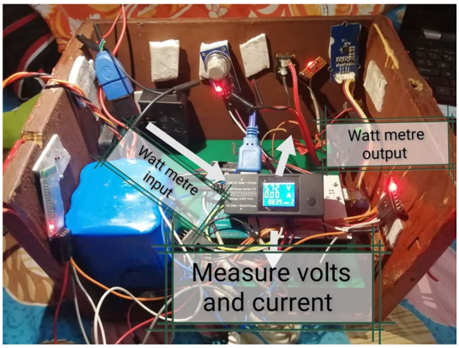


Fig. 4 Measurement of energy consumption by EMD using a power meter with input and output ports which measures the voltage as well as the current through the circuitry which are connected with the input and output of the power meter

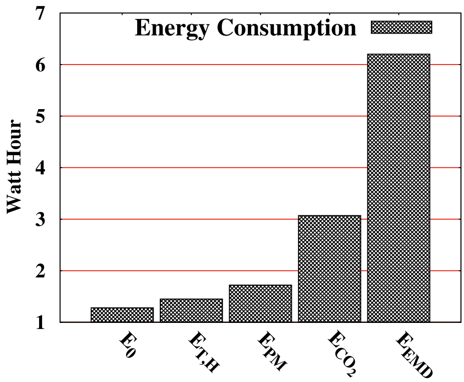


Fig. 5 Energy consumption by the EMD at initial state of the EMD (E_0) with different stages of component integration; on integrating the temperature and humidity sensor ($E_{T,H}$), the particle (PM_1, $PM_{2.5}$, PM_{10}) sensor (E_{PM}), CO_2 sensor (E_{CO_2}), and the complete EMD (E_{EMD})

presence of occupants is detected after some duration (d) of time. This duration d is not fixed as the number of occupants and their age group are not same all the time in different classrooms even in the same classroom. This is not the issue as the impact of the pollutants up to the duration d is not significant as it does not crosses the prescribed limit. But, by using this incomplete data the prediction or other processing of the air quality gets hampered.

Both the aforementioned issue can be resolved using the periodic triggering of the EMD. This period is small enough to capture the essential data for predicting the air quality. Suppose at time t, the concentration of CO_2 is C_t and after the periodic interval p, the concentration of CO_2 is C_{t+p}. Now, if (C_{t+p} - C_t) > Th, where Th is the threshold value, then, it implies that there is a rise in concentration. Hence, the interval time is reduced to p': $p > p'$. This p is very large in case of weekends, the recess duration, and the night duration.

Energy calculation The proposed system is validated by using a power meter[3] consisting of Voltmeter, and Ammeter. We measure the energy consumption of the EMD in different scenarios with different set of integrated devices as shown in Fig. 4. We have calculated the energy consumption with no sensor connected to the

[3] https://www.amazon.in/PortaPow-Monitor-SmartCharge-Chargers-Panels/dp/B0713MTPHX.

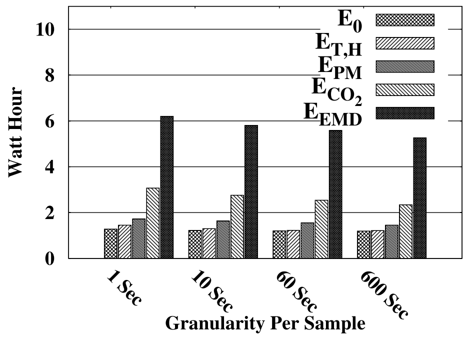


Fig. 6 Energy consumption at each step of integrating the components of EMD with different granularity such as samples per second, samples per 10 s, granularity of 1 min, and the sampling rate of 10 min; it shows the inverse relationship of granularity and energy consumption

Table 4 Energy consumption by normal EMD and the proposed intelligent energy aware EMD for different duration of time such as on running the EMD for 1 h, a day, a week, and for a month

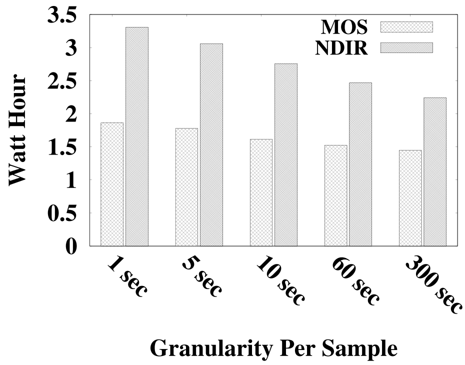
	Total energy consumption (Watt Hour)	
	Normal condition	Energy aware
1 Hour	11.696	10.771
1 Day	280.699	167.13
1 Week	1964.89	1078.528
1 Month	7859.56	4314.112

The overall energy consumption is reduced with respect to the normal EMD

micro-controller to measure the energy consumption at initial condition (E_0) of without any sensor. Then we integrate the sensors one by one and measure their impact over energy consumption. We have used 3 sensors for our experiment viz., TH02, PMS1003, and MQ135 and measured the energy consumption of these sensors as $E_{T,H}$, E_{PM} and E_{CO_2} respectively. Finally the energy consumption by integrating all the sensors together we calculate the energy consumption by the EMD as E_{EMD}. The energy consumption in each scenario has been depicted in Fig. 5. It justifies that energy consumption increases with number of components in the target device. In this work, we have proposed the energy efficient and intelligent system development with variable sampling rate. We have estimated the energy consumption of the system with some variants of sampling rate and with different components. The Fig. 6 depicts the energy consumption in watt hour with different sampling rate and different components integration. It also depicts that the energy consumption is decreasing by decreasing the granularity. This observation has been introduced in our developed EMD as mentioned above. More than 45 % of energy consumption has been reduced by using the proposed energy aware system.

A comparative study has been made between the proposed energy aware system with normal or, previous version of the EMD. We have emulated the proposed system and tested in the real life data-set of our institution and we have calculated the energy consumption by the system. We have estimated the energy consumption by the EMD in 1 h, 1 day, 1 week, and 1 month as shown in Table 4. It has been observed that the energy aware EMD reduces the energy consumption

Fig. 7 Energy consumption by different types of sensors used for measuring the concentration of CO_2 for different sampling rate; 1 sample per second, per 5 s, 10 s, 60 s, and 300 s



due to the intelligence that the EMD is not required to sample the pollutants data with high frequency in the rest of the times when classes are off and even in the weekends. The requirement of the sampling in low frequency even in the vacant classes is required as to model the other predictive or machine learning algorithms. Hence, the proposed system is an efficient system to monitor the air quality of an indoor environment specifically the classrooms of any organization or institution.

Energy vs. Cost based sensor selection: Most of the time, we have options to select sensors from multiple option of available sensors. The sensors with same working principle can be selected based on their sensitivity. Selecting a sensor with similar sensitivity and different type such as, to measure concentration of CO_2 we have two options, one is Metal Oxide Semiconductor(MOS) based, and other is Non-Dispersive Infrared Sensor (NDIR) based. We know that the MOS type sensor consumes more energy but, due to the cost constraint we have selected it. The NDIR sensor consumes less power relatively, but these are generally costly sensors due to its costly arrangements. A comparison between MOS and NDIR type sensor for CO_2 sensing is depicted in Fig. 7. Hence, the selection of the sensors are completely personal choice, this work aims in reducing the power consumption based on the given scenario.

Hence, the proposed system has the following features compared to the market available devices.

- The developed EMD is easily portable, robust, and reliable.
- EMD is made energy aware.
- The cost of development of the EMD is moderate and less than the market available devices.
- It can measure the concentration of the pollutants, and meteorological parameters

After the development of the cost-effective and energy aware EMD, the system is about to investigate and test the pollutants at different locations. But, without verifying the value of EMD, it can not be used, and the verification process is accomplished using calibration.

Key Observations: The energy-aware EMD has been developed with adaptive granularity according to the presence of the occupants, which reduces the energy consumption by 45% as compared to the normal EMD.

5 Calibration of the EMD

Sensor calibration is a method of ameliorating sensor performance by abstracting structural errors in the sensor outputs. Structural errors are distinctions between a sensor's expected output and its quantified output, which emerge consistently every time an incipient quantification is taken up. Any of these errors that are repeatable can be calculated during calibration. Calibration provides a means of providing enhanced performance by improving the overall accuracy of the underlying sensors. Over time, sensors have a tendency to drift and it can be zero-point (baseline) drift or output (sensitivity) drift. For an error-free system, it must be validated through soft as well as hard calibration. Soft calibration is the method of calibrating the sensors using any kind of learning mechanism without human or, hardware intervention. Hard calibration is the technique which requires human intervention, and/or hardware involvement is required to calibrate the sensors.

- Hard Calibration: This technique deals with the calibration where human intervention is required with extra hardware set-ups. We have used two hard calibration technique as mentioned below.
  - Zero Air Calibration: This calibration technique is used to compensate the zero shift error by measuring the output of the sensor in inert condition.
  - External Calibration: This technique uses a reference for comparing the measurements and compensating the errors.
- Soft Calibration: In this technique Machine learning model is used to reduce the error in measurements.

5.1 Zero Air Calibration

We have used pure nitrogen in vacuum gas chamber to calibrate the zero point for "Zero Air" calibration. The calibration procedure is carried out when the temperature is in the range of 24–28°C, while the relative humidity is in the range of 50–60%. The EMD is then put into a chamber made of acrylic sheet, and after 50 min the chamber is evacuated by filling it with nitrogen gas. After 150 min from the start of the experiment, we open the chamber. The result of our experiment is shown in Fig. 8. Here, initially the EMD is kept in the air tight closed chamber so the concentration of pollutant increases. The concentration of the pollutant sharply

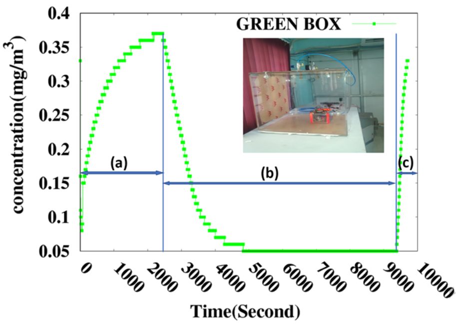


Fig. 8 Calibrating the device using vacuum chamber, the curve is touching the lowest point on purging N_2 gas which denotes the zero of the sensor. During, *a* The EMD (named green box) is kept inside the chamber and closed, *b* N_2 purging has been started, *c* N_2 purging has been stopped and chamber is opened

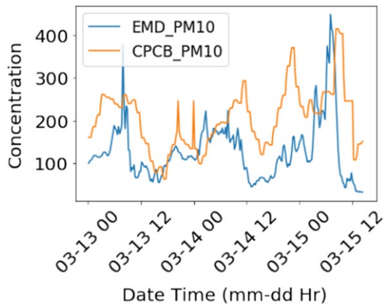


Fig. 9 Concentration of PM_{10} measured by AQMS, Central Pollution Control Board (CPCB), Durgapur, India, and Our Environment Monitoring Device (EMD) placed at Pinnacle Infotech in Durgapur at some distance

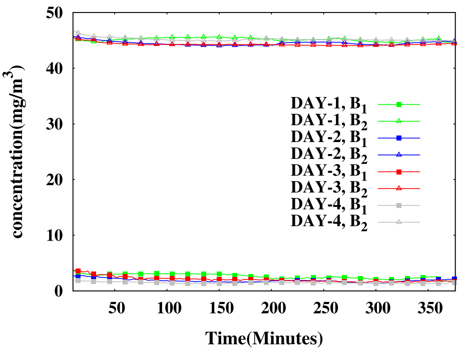


Fig. 10 Concentration of CO using multichannel gas sensors of two EMDs viz, B_1 and B_2; showing the similar behaviour even in different days

decreases to zero on making the air tight chamber as inert by purging pure nitrogen gas into the chamber. Inside the chamber the pollutant concentration remains zero until the chamber is opened. Then the pollutant regains its original concentration in open environment.

5.2 External Reference Calibration

In this method, the sensors have been calibrated using external reference. The Air Quality Monitoring Station (AQMS) placed by Central Pollution Control Board

(CPCB) situated at Sidhu Kanu indoor stadium, city center, Durgapur, India, is taken as a reference and our developed EMD is placed at Pinnacle Infotech, Durgapur, India, at a distance of 200 meters and above 14 meters height from the stadium. The data collected by both the sources has been analysed and it has been verified that the EMD is having a similar behaviour with small deviation as shown in Fig. 9, which ensures the correctness of the EMD and said to be calibrated EMD. The other EMDs are then calibrated using the already calibrated EMD.

After all the EMDs are calibrated, we tested the EMD and find that the measurements are not satisfactory in case of all the pollutants, e.g. *CO* as shown in Fig. 10.

To resolve this problem, a soft calibration with regression technique is used.

5.3 Soft Calibration

In our study, it has been observed that two similar sensors measure two different values for the same parameter. In most of the cases, it is quite obvious, as two electronic devices may not be 100% same. Variation of sensors must be tolerable but this is not the case in our system. This may affect both the complete environment monitoring system and it's data analysis. On applying a machine learning technique, the error can be reduced. In our experiment, it has been seen that, calibrating the device once at one place may not guarantee the correctness of the device at spatially different locations. On analysing the problem it can be formulated as, Given, n no. of devices, consisting of the same type of sensors (S_t), to measure same parameter (P). If one device among the n devices is calibrated, is it possible to calibrate all other $n - 1$ devices such that, those can measure correctly with good precision in almost every spatial variation?

To achieve the solution of the problem, we have done a survey which is summarized in Table 5. The Table 5 shows that most of the works in literature have used the regression technique with its variants. They also used RF and ANN in a few scenarios. Most of these works have not analyzed the correlation among the different pollutants or the other parameters. They have mostly used the available parameter without analyzing the correlation factor. Here, in this work, we have analyzed the correlation coefficient of each of the available parameters for each room. It has been found that, even if the structure of two rooms of an institution is similar, they might not have similar correlated parameters. Further, we have proposed a calibration algorithm using simple linear regression which uses the features having Spatio-temporal correlation. We have considered Temperature and Humidity as the Spatio-temporal parameters, irrespective of their actual Pearson correlation coefficient. Most of the works in the literature have used either temperature or humidity as features. Others have also used similar features with a complex model but, in our scenario, the model should be lightweight for a low cost as we are primarily concerned about the cost.

In this paper, we have proposed a solution that satisfies the spatial variation and fit into most of the scenarios. We have done a comparative study of different regression techniques to analyse the accuracy of the system. The regression techniques we have used are Linear regression, Multiple regression, Support vector regression, Regression tree and Gaussian Process regression.

Table 5 State-of-the-art methods with corresponding features and used parameters

Reference	Target variable	Model	Meteorological data (inputs)			Pollutants (inputs)
			Temperature	Humidity	Others	
[46]	CO	LR, MLR, ANN	Y	Y	Wind and pressure	NOx, O_3, CO, SO_2, CO_2
[9]	NO_2	MLR, RF, SVM, ANN	Y	N	N	NO_2, NO, O_3
[55]	CO, NO_2, CO_2, and O_3	MLR, RF	Y	Y	N	CO, NO_2, CO_2, and O_3
[48]	CO_2, O_3	LR, MLR	N	N	N	CO_2, O_3
[5]	NO, NO_2	MLR, SVR, RF	Y	Y	N	NO, NO_2
[21]	CO, NO_2, O_3	SLR, MLR, RF, Gaussian Process Regression	Y	Y	Pressure	CO, NO_2, NO, O_3, SO_2, CO_2, PM_{10}, $PM_{2.5}$, PM_1
Proposed	$PM_{2.5}$, CO_2	SLR	Y	Y	N	$PM_{2.5}$, CO_2, CO, NO_2

Table 6 Correlation table: pearson correlation coefficient between each pair of pollutants and particles to select the features for the calibration process

	NO_2	CO_2	CO	PM_1	$PM_{2.5}$	PM_{10}	RH	T
NO_2	1							
CO_2	– 0.61	1						
CO	– 0.76	0.86	1					
PM_1	0.05	– 0.02	– 0.00	1				
$PM_{2.5}$	– 0.05	0.01	0.04	– 0.12	1			
PM_{10}	0.01	– 0.03	0.01	0.55	0.49	1		
RH	– 0.65	0.62	0.67	0.08	0.13	0.14	1	
T	0.64	– 0.66	– 0.70	– 0.07	– 0.11	– 0.12	– 0.99	1

Table 7 Overall Correlation of CO with others in different environment

	NO_2	CO_2	PM_1	$PM_{2.5}$	PM_{10}	Humidity	Temperature
EC-1	High	High	Low	Low	Low	High	High
EC-2	High	Med	Low	Low	Low	High	High
EC-3	High	High	Low	Low	Low	High	Med
NEC-1	High	Med	Low	Low	Low	Low	Low
NEC-2	High	High	Low	Low	Med	High	High
NEC-3	Med	High	Med	Med	Med	Med	Med

The Correlation coefficient are mentioned as High (0.51–0.99), Med (0.31–0.50) and Low (0.01–0.30); No any parameters are consistently correlated with *CO*

For the processing of our data collected by the EMDs, the correlation among all the pollutants has been analysed as shown in Table 6. In previous works, it is seen that the application of the machine learning algorithms not only depends on the other pollutants but also on different types of meteorological information, structural information, spatial data, etc. These extra information increase the data acquisition cost, the complexity of the system as well as the computational cost. In our system, there is no such extra ad-ons used for analysis. The data used for processing and developing the complete system requires only the data collected by the developed EMDs. Correlation method is used to select the features required for applying the aforementioned regression techniques.

We have selected six different classrooms for analysis of which three are Empty Classroom (EC) and three are Non-Empty Classroom (NEC). We have analysed the empty as well non-empty classrooms to understand the characteristics of empty classrooms for calibrating a device kept in either an empty or non-empty classroom.

We work with gas sensors which measure carbon monoxide (CO), Particulate Matter ($PM_{2.5}$) and CO_2 concentration. To understand the features upon which the concentration of the aforementioned pollutants and particles depend, we analyse the correlation of all parameters among themselves. The correlation between the same parameters are not identical in different cases, but for generalization, we describe the features in some ranges viz. the coefficient value of 0.51 to 0.99 is mentioned as high, the coefficient value between 0.31 to 0.50 is mentioned as medium, and

Table 8 Overall correlation of $PM_{2.5}$ with others in different environment

	NO_2	CO_2	CO	PM_1	PM_{10}	Humidity	Temperature
EC-1	Low	Low	Low	High	High	Low	Low
EC-2	Low	Low	Low	High	High	Low	Low
EC-3	Low	Low	Low	High	High	Low	Med
NEC-1	High	High	Low	High	High	High	High
NEC-2	Low	Med	Low	High	High	High	High
NEC-3	High	High	Med	High	High	High	High

The Correlation coefficient are mentioned as High (0.51–0.99), Med (0.31–0.50) and Low (0.01–0.30); Humidity is the only consistent correlated parameter separately with empty and non-empty classrooms

Table 9 Overall correlation of CO_2 with others in different environment

	NO_2	CO	PM_1	$PM_{2.5}$	PM_{10}	Humidity	Temperature
EC-1	High	High	Low	Low	Low	High	High
EC-2	Low	Low	Low	Low	Low	Low	Low
EC-3	High	High	Low	Low	Low	High	Low
NEC-1	High	Low	Low	Low	Low	High	High
NEC-2	Med	High	Med	Med	Med	High	High
NEC-3	Med	High	High	High	High	High	High

The correlation coefficient are mentioned as High (0.51–0.99), Med (0.31–0.50) and Low (0.01–0.30); Here also no parameters are consistently correlated

the coefficient value of 0.10 to 0.30 is termed as low. We have selected the range on the basis of theoretical and experimental data. Correlation matrices among all the simultaneously collected particles, pollutants and meteorological information are calculated as shown in Tables 6, 7, 8 and 9.

The result of the correlation analysis depicted in Table 7 shows the correlation of CO with other pollutants and particles. It shows that the correlation of *CO* is High with Humidity and NO2 in empty condition, but the behaviour of the Non-empty room is varying. Table 8 shows the correlation of $PM_{2.5}$ with other pollutants and particles. Here, it can be observed that except PM_1 and PM_{10}, only *Humidity* is showing similar behaviour in similar type of rooms i.e., low correlation in empty classrooms and high correlation in non-empty classrooms.

Table 9 shows the correlation of CO_2 with other pollutants and particles. Most of the parameters are inconsistently correlated and the *Humidity* is highly correlated with CO_2 of five classrooms except the one with different characteristics.

For our experiment, we have selected six classrooms with different parameters as shown in the Table 10. The faulty sensor is calibrated by modelling the error using a machine learning technique. The error is then rectified and a calibrated result is obtained. The result is satisfactory but it is not suitable for some of the dataset, specifically the one obtained from the second classroom (EC-2). The presence of the error may be due to the following reasons:

Table 10 Experimental set-up of our experiment EC-k: kth Empty Classroom NEC-k: kth non-empty classroom; all with different conditions

	EC-1	EC-2	EC-3	NEC-1	NEC-2	NEC-3
Position	Ground floor	Second floor	Ground floor	Second floor	Ground floor	Second floor
No. of fans (ON)	2	0	4	3	4	6
No. of open doors	1	0	0	0	0	2
No. of AC (ON)	0	0	2	2	2	0
No. of occupants	4 – 6	0	0	40 – 45	20 – 25	70 – 80
Nature of room	Computer LAB	Seminar hall	Classroom	Computer LAB	LAB	Classroom

1. **The spatial differences** The locations and structures of the classrooms are different which may lead to change in pollutant concentration. Affecting parameters may vary due to variation in the direction and number of doors/windows etc. Apart from these variations, the classroom has different number of occupants present in there for different duration.
2. **The temporal variations** These variations are very crucial and depends mainly on (i) the outside weather conditions which vary in different time periods and (ii) the variation in the nearby road traffic which is almost unpredictable.
3. **Manufacturing defect of the Sensors** One of the most common reason for variation, in the same type of sensors, is the manufacturing variations.

In our case, measuring temporal variations in all the different classrooms is a very tough task, as it is mainly related to meteorological and traffic information.

So, we model the system separately for all the different rooms and we get better results. The accuracy of the result obtained is high but, it is not feasible as, for each location, the system cannot be modelled separately. Now, it is clear that the sensors are affected by the temporal as well as spatial factors. It means that by only correcting the error once at a certain environmental condition or space, the erroneous result at different locations may not be avoided. This is due to the spatial variance of the classrooms such as, different floor, different direction of doors and windows, etc. Moreover, as we have seen the behaviour of different classrooms are not similar through Table 6–9, the selection of contributing features are challenging. Hence, we proposed a calibration technique considering the spatio-temporal behaviour of the classrooms by introducing the features which holds the spatial properties irrespective of its correlation score. Temperature and humidity are two major factors correlated with the spatial nature of the classrooms as these are dependent on the spatial factors such as, height, floor, AC status of the room, etc. Moreover, temperature and humidity are such two factors which are measured by the developed EMD for each samples of pollutants so, we have selected these parameters.

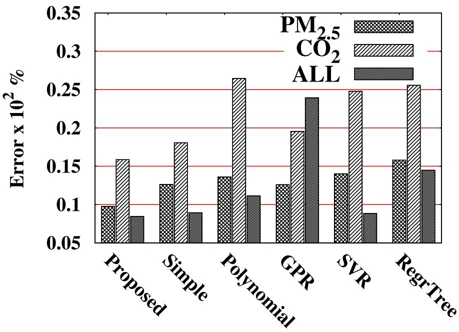


Fig. 11 Average error in the calibration of CO_2, $PM_{2.5}$, and overall error, by using the proposed calibration technique and other baseline calibration techniques; the proposed technique shows the least error as compared to the other baselines

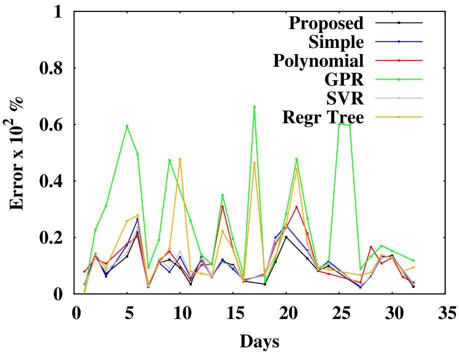


Fig. 12 Day wise variation of error by using the proposed spatio-temporal soft calibration technique with different state of the art calibration techniques techniques; shows that the proposed technique outperforms for most of the days

Now, Let us consider some features as, f_1, f_2, f_3,..., f_{n-4} which are the pollutants, directly affecting the measuring parameter say, D. Then a model can be formulated as,

$$D_{correct} = \sum_{i=1}^{n-4} (\beta_i * f_i) + \beta_{n-3} * T + \beta_{n-2} * H + \beta_{n-1} * D_{Err} + \beta_n \tag{3}$$

where, β_is, [such that, i = 1 ... n] are the constants and T is temperature, H is humidity, and D_{Err} is taken as the erroneous data.

We trained the model by the data of $n - 1$ days and tested it on the nth day's data and obtained a better performance for all the classrooms. We have used some baseline regression techniques to compare our model which shows that the proposed spatio-temporal calibration technique performs better than the existing models.

The baseline methods consists of, Simple Regression technique [46], Polynomial Regression [34], Gaussian Process Regression (GPR) [42], Support Vector Regression (SVR) [17], and Regression Tree [16] to perform the leaning mechanism for calibrating the sensors. The proposed spatio-temporal calibration model is validated and compared withe baselines using the collected data-set from different classrooms as mentioned in Table 10.

After a rigorous analysis of the system, a common result is shown in Fig. 11. The day-wise analysis of the result is also shown in Fig. 12.

In Fig. 11 the average error for pollutants like CO_2, $PM_{2.5}$ and the combinations of all other pollutants are measured. From Fig. 11 it can be observed that, among all the baseline algorithms, our proposed technique provides the least error ($\approx 6\%$) which holds in Fig. 12 also, where a day wise analysis has been shown. The day wise analysis shows that for $3-4$ days out of the 30 days, the simple regression performs slightly better, this may be due to the high variance in the temperature and humidity throughout the aforementioned days. Hence, the individual as well as day wise analysis show that, in most of the scenarios the proposed method performs better than other baseline techniques.

Key Observations: The proposed calibration technique considers the spatio−temporal features for the soft−calibration process, which improves the performance by reducing the error by approx 6% as compared to the other baseline calibration techniques.

6 Scheduling of Re-Calibration

On applying the soft calibration technique, the sensors are calibrated but, due to the issue of sensor drift, the sensors need to be re-calibrated after particular time intervals. Duration of re-calibration can be reduced by continuously monitoring the sensed data and validating it with actual data to get the exact time for re-calibrating the sensor. Validating the sensor data each time a new sample arrives is not feasible and computationally expensive. We can provide a certain time gap to validate the data for calibration, but the calibration requirement somewhere between the time gap may reduce the efficiency. This problem can be resolved using continuous validation of the sensors, which is practically infeasible. Moreover, setting a short period for periodic calibration is also not feasible as it leads to unnecessary calibration when there is no need for calibration. Hence, a method is required to analyze the EMD and results in an Optimal Calibration Period (OCP), after which an EMD is needed to be calibrated. We proposed a window-based technique for estimating the re-calibration duration to obtain the optimal period. The proposed algorithm uses a timer to make the system energy aware. Generally, we compare the generated data with a reference device, and if the error exists, the sensor is calibrated or gets replaced, or any other action is taken. Whenever data is generated, reference comparison increases the computation overhead; hence, energy consumption increases.

In this work, OCP is calculated using machine learning technique by learning pattern of erroneous data generated from the device.

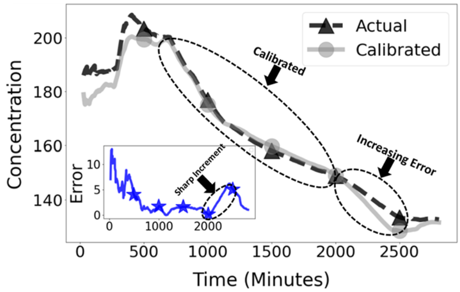


Fig. 13 Calibration using window base technique under the dashed oval-shaped marked as calibrated; After a certain duration, the sensor starts deviation shown is smaller dashed oval with increasing error

Algorithm 1 Window based technique for scheduling the re-calibration time

```
Data : ActualData, SensedData
Results : Optimal Calibration Period (OCP): The optimal period after which next calibration is to be carried out
Threshold //The maximum accepted level of deviation (Error)
winSize = N //The value up to which the error is tolerable
CalibratedData = calibration(SensedData[0:Bootstrap])
while SensedData do
    Error ← ActualData − CalibratedData
    win ← 0
    if Error > Threshold & win < winSize then
        win++
    end if
    if win == winSize then
        Calibration is Required
        CalibratedData ← calibration(CalibratedData)
        T_K ← Current time stamp
        K++
        Formulation of OCP using ML model
        OCP_K ← func(T_{K−1}, K)
        Re-calibration will be scheduled accordingly
    end if
end while
```

Here, actual data refers to the data collected through the reference station. The soft calibration has been used to get the calibrated data which are compared with the actual reference data to get the error. When the error generated for a number of continuous samples is greater than the threshold winSize.

6.1 Requirement of Re-calibration

We have collected data through the EMD placed at a location with a sampling rate of 1 sample per minute. After monitoring the data for a few days, we have obtained the drift point where the calibrated data is drifting as shown in Fig. 13. The mark of increasing error shows the drifting nature of the sensor, and the

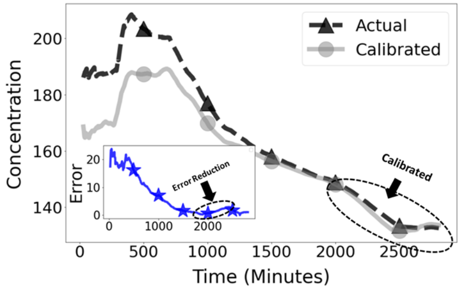


Fig. 14 Re-calibration of the system for minimizing the error; the calibrated dashed oval shows the minimization of the error; Error reduction shows the actual error between the actual and calibrated sensor readings which is close to zero

error is linearly increasing, hence satisfying the condition of re-calibration. After re-calibrating the sensor, the error is reduced to 0–2 as depicted in Fig. 14.

Hence, It shows the requirement of re-calibration of the sensor. Now, both the options can be opted for training firstly, by the device itself and secondly, using a separate server. The option of using a separate server would be the best, but it is not suitable in our scenario as for re-calibration, the data of the co-located device is required, which can not be stored at a server as it will increase the overhead. Moreover, this option is costly, and extra costs will be incurred for connectivity through the internet. Furthermore, the connectivity failure may hamper the system performance, which requires continuous monitoring and further increases the cost of deployment. Our main goal is to monitor the air quality with a minimal cost, whether in the form of deployment or energy consumption, but without compromising accuracy. It results in an optimal system and can be easily acquired by any school, college, institution, or organization. The device on which we have implemented the re-calibration is equipped with UDDO-NEO, which is a combination of a microprocessor and microcontroller. This device has the capability of training the model to reduce the error in the measurement. We have used a very lightweight regression model that can be run on UDDO-NEO with the following processing capabilities.

- Android Lollipop & Linux UDOObuntu2 (14.04 LTS)
- 1 GB RAM
- One ARM® Cortex-A9 core running up to 1 GHz and one Cortex-M4 core running up to 227 MHz for high CPU performance and real-time response.

6.2 Estimation of Optimal Calibration Period (OCP)

We have performed a behavioural analysis of the data for the requirement of the calibration. This usually requires the data for a long time duration. The required data has been emulated with a set of assumptions. The emulated data is then validated using the experimental data collected through the EMD. On applying the proposed algorithm, we finally obtain the OCP by formulating it in the form of timestamp. The details follow.

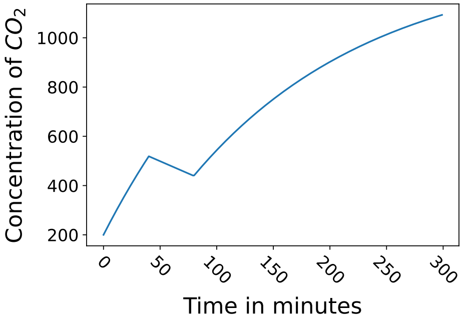


Fig. 15 Variations of CO_2 inside a classroom with time in ideal condition

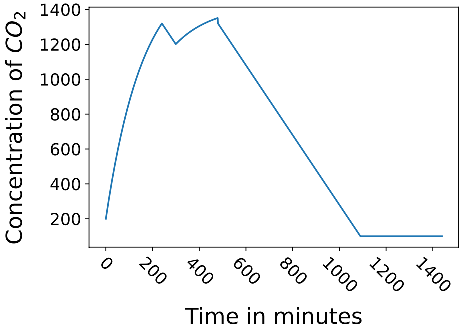


Fig. 16 Emulating the behavior CO_2 inside a classroom during and after the class duration

6.2.1 Data Emulation

Our target monitoring location is the educational buildings, and we primarily focus on the CO_2 concentration. We require the sensed data samples of CO_2 for an extended period with its corresponding actual data. In reality, we do not set up two devices simultaneously. We emulate the data through standard CO_2 generation formulation given, the volume of the room, no. of occupants, and other factors. Moreover, the noise has been imputed in the form of continuous drift of the sensor assuming that the sensor is a low-cost sensor. We have emulated the data in an ideal condition with the following assumption.

- The room environment is ideal with constant air flow rate, same rate of CO_2 generation by the occupants, with the same number of occupants through out the number of days of the experiment.
- The sensor is low-cost and have tendency to drift continuously with time, i.e., the noise follows the hyperbola like structure with negative slope.

We have computed the CO_2 concentration of a classroom using some equations follows the emulation of data as mentioned in [33, 38, 47]. The equation considers the volume of the room, number of occupants, etc. Initially, we have emulated the CO_2 in ideal condition as depicted in Fig. 15, then we have emulated the data for one day considering that the class duration is from 9:00 am to 4:30 pm with 100 min recess at 12:20 pm which is presented in Fig. 16. We have assumed that the classrooms

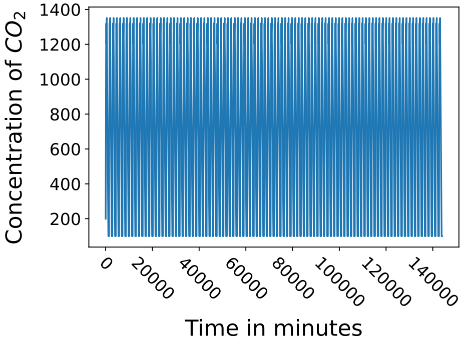


Fig. 17 Concentration of CO_2 for 100 days inside a classroom

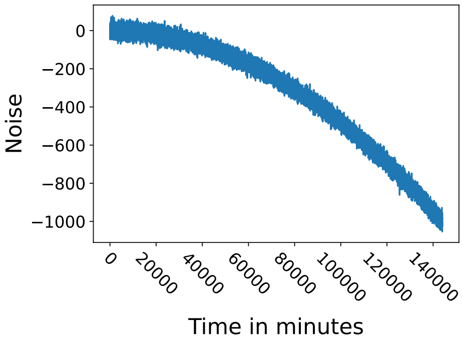


Fig. 18 Error in the sensor following the ideal drift condition

become vacant during the recess. We have observed that if classrooms becomes vacant the pollutants concentration starts decreasing though the decrements are slow [44]. This phenomenon has also been encoded in the data emulation process. We have emulated the data for a total of 100 days as shown in Fig. 17. As we are dealing with low and moderate cost sensors which suffer from the sensor drift, so we have also imputed the noise in the obtained data. We have computed the noise by considering the hyperbolic nature of the sensor drift as depicted in Fig. 18. On injecting the error/drift in the ideal data set we obtained the data with errors as in real time which is depicted in Fig. 19.

6.2.2 Validation of Emulated Data

Validation of the emulated data is crucial before using it for further processing. We validated the CO_2 data using the reference as our developed EMD. We have collected the data by placing the EMDs in the classroom for a certain duration. We then performed hypothesis testing between the collected actual data and the emulated data; we then obtained the *p* value as 0.52, which rejected the null hypothesis. Here, the null hypothesis signifies that the two sets of observations are not similar, and the rejection of the null hypothesis supports our assumption. Hence, the emulated data is validated, and it follows a similar variation as the actual data.

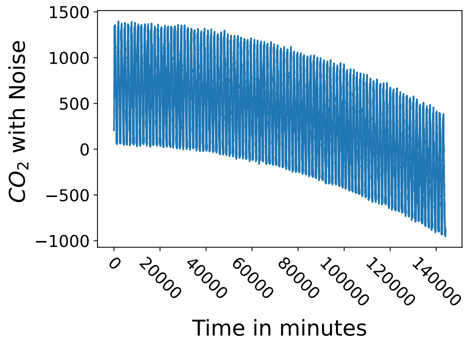


Fig. 19 On injecting the error to the normal behavior of the CO_2 in a classroom

6.2.3 OCP Modelling

Now, the optimal calibration period can be calculated using the model, which can identify the requirement of calibration, i.e., each time the calibration is triggered, that timestamp is marked. These timestamps are then used to train the model for identifying the next calibration point. The model provides the optimal calibration period (OCP) for re-calibrating the device. Ideally, the sensors will follow some pattern in drifting their sensitivity. Now, we obtain the pattern through the learning algorithm and determine the next time the calibration is required.

6.3 Real-Time Deployment

We have deployed two devices in the classrooms. One is normal EMD which might be erroneous, and the other is the calibrated EMD. Initially, we need two EMDs, but after developing the calibration model, only one EMD will be sufficient with periodic re-calibration. Following is the step-wise procedure of overall calibration.

Step 1: One EMD (say EMD1) is calibrated with a standard government-deployed air quality monitoring station.

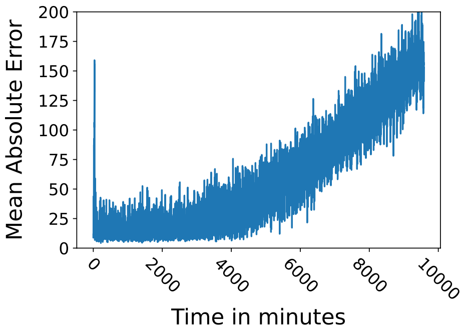
Step 2: Another EMD (say EMD2) is deployed in the classroom. Initially, the EMD1 is also co-deployed with EMD2 for a certain duration.

Step 3: Now, the EMD2 is calibrated with respect to th e standard EMD1 by training a regression model to reduce the error.

Step 4: EMD2 continues monitoring the air quality and calibrates the data according to the trained model.

Step 5: After the OCP, the recalibration process starts, for which the EMD1 will be co-deployed again for a few days, and the EMD2 will be retrained.

Fig. 20 Error in the sensor using the calibration in regular interval



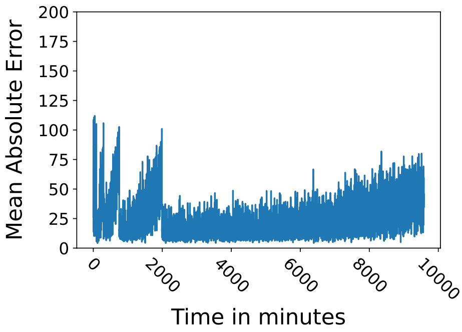
Note: We cannot use the data from air quality monitoring stations to calibrate the EMD2 as they are not co-deployed, so variation is evident, and any server for data storage also cannot help.

Here, the re-calibration signifies the retraining of the calibration model with the updated data-set. Calibration using a soft-calibration technique becomes energy hungry. Hence, re-calibration needs extra energy. We have measured the energy consumption for the execution of a simple linear regression in UDDO-NEO, which is 2.8 Watt, whereas in idle conditions it takes 1.5 Watt. So, re-calibration consumes almost double the energy as compared to the normal condition.

6.4 Results and Discussion

We have tested the proposed technique on our emulated data set. Due to the regularity in the data set, we have obtained the result with regular variations. The system's behavior shows that initially, the calibration is required very frequently, but later, the OCP interval increases with time. This behavior is due to the nature of sensors that try to shift from their original measurement. This drift needs close attention during the initial measurement phase, as the sensor needs some time to adapt to the actual behavior of the measurement by controlling the error. We obtained the calibration point at timestamps 1, 11, 22, 44, 69, 91, 297, 751, 1990, which is lesser than that of periodic calibration points at regular intervals. We select the regular intervals based on the initial few drift points that can be very recent; hence, the interval can be very high. Suppose we select the interval as 100, then for 5000 timestamps, 50 times calibration will be required very high than the proposed technique, i.e., only 9. Moreover, the initial value may have high variance; as we can see in the result of OCP, most of the timestamp lies up to 100. The Fig. 20 also depicts the mean absolute error when the calibration is done in regular intervals, and it shows that with time the error is increasing. The Fig. 21 depicts the error obtained when the proposed OCP is used, showing the reduction in error even by using the less number of calibration points in time. Hence, our proposed technique outperforms the traditional way of selecting the calibration point.

Fig. 21 Error in observations when OCP is used as the calibration points



Key Observations: The OCP is determined using the proposed method which improves the performance of the system by reducing the calibration period hence, reducing the energy of calibration compared to standard calibration in regular interval.

7 Literature Survey

In past studies, it has been evident that fair amount of work have been carried out in the field of environment monitoring in real-time. Moreover, the air quality monitoring in a cost-effective manner is desirable to effectively measure the air quality at different indoor scenario even in developing countries. There are two aspects of reducing the cost of an air quality monitoring device, (1) by using the sensors of low cost and (2) by reducing the cost constraints of energy consumption by the device. Use of low-cost sensors may hamper the reliability of the system so calibration is required. This section describes the state of the art in the different components of air quality monitoring such as (a) development of a cost-effective air quality monitoring units, (b) energy aware EMD development (c) calibration of the developed device to ensure the reliability.

Development of Environment monitoring device Recently, developing a cost effective environment monitoring device with high precision has become one of the most attractive as well as a challenging field of research.

Several solutions have been proposed for designing a cost effective device equipped with some gas sensors. Spachos and Hatzinakos [45] presented a real-time cognitive wireless sensor network system that monitors the concentration of carbon dioxide at a complex indoor environment and provides timely alerts. However, the system only measures CO_2 which is not appropriate in the scenario where other sources of pollutants exist. Parkinson et al. [35] described SAMBA (a state-of-the-art monitoring station) and introduced a strategy for data acquisition of indoor environment quality parameters. Shaban et al. [43] developed an intelligent sensing platform using low-cost air quality monitoring mote consisting of NO_2 and SO_2 as measuring parameters. Tu et al. [50] designed the environment monitoring device which measures CO_2, temperature, and humidity. They developed a software which interacts with the users for receiving and analyzing the parameters observed by the hardware. Here, in most of the cases only NO_2, CO_2, and SO_2 are measured, but in indoors, particulate matters is also an intensely affecting contaminant.

Usense by [3] relied on portable, low-cost sensor nodes equipped with gas sensors for O_3, CO, and NO_2. But, the system has measured these three pollutants with less data sampling rate (i.e. 30 min per data sample). Chen et al. [7] introduced a sensing technique to measure the concentration of particulate matters using Dylos-DC1700 sensor and evaluated the performance of heating, ventilation, and air conditioning (HVAC) which was used for filtering particulate matters from outside. Besides, there are different devices commercially available in the market viz. Airveda [29], Airbeam [2], Flow [39], Aeroqual [1] etc, which can measure some pollutants concentration. Flow [39] can measure the concentration of $PM_{2.5}$, PM_{10}, CO_2, and VOC, Airveda [29] measures the concentration of $PM_{2.5}$, PM_{10}, CO_2, with humidity and temperature, Airbeam [2] is equipped with $PM_{2.5}$, humidity and temperature whereas Aeroqual [1] consists of two variants one is for indoors and other for outdoors. From the observations of all the aforementioned works and devices, we can broadly summarize that there exist two types of devices: firstly, the costly device with more number of measuring parameters and others are cost effective devices which can measure relatively fewer parameters. In our case, the classrooms are the point of interest hence, the deployment of some cost effective devices is desirable. That means, the deployment of costly devices will not be feasible. The other type of devices (portable and cost effective) can not measure all the required pollutants concentration especially the meteorological data such as temperature and humidity which are highly correlated with indoor pollutants like CO_2 and $PM_{2.5}$. As a result, these devices will also not be feasible for indoor environment monitoring. Moreover, the aforementioned devices are not suitable for indoors as well as outdoors because of the measuring parameters being very restrictive in measurement and the data regarding these parameters are not easily accessible.

Energy Aware EMD In a work by Jelicic et al. [25], an energy aware air quality monitoring system has been proposed by using a separate module which counts the number of occupants. The Pyro-infrared (PIR) Sensor has been used to count the number of people and modify the behaviour of the node to reduce the energy consumption. They have used module of PIR sensor is used to capture the occupancy information and a single PIR sensor cannot detect the number of people present in a room so, multiple PIR sensor is required for exact count of inflow or outflow. Moreover, in our case we don't require the exact count of people as, it would be an extra add-on which consume extra energy apart from the EMD. Khedo and Chikhooreeah [26] have used a Hierarchical Based Genetic Algorithm (HBGA) to construct an energy efficient monitoring of indoor air quality. Authors have used the algorithm to provide an energy efficient communication of the nodes of the WSN. Vakiloroaya et al. [51] have proposed an energy aware HVAC system. Huynh [20] proposed a technique to find a dilemma between the techniques of energy saving of a building and indoor air quality. In this work the authors tried to achieve the low particles without modifying the existing mechanical ventilation by industrial hygiene sampling techniques and selecting the priority pollutants as tracers. Revel et al. [40] monitored the indoor air quality using ad-hoc sensors for different pollutants which provides the optimal rules to control the actuators such as switching on the ventilation, opening of windows, shutters operations and so on. Grace et al. [15] proposed a fuzzy controller which controls the ventilation and air-conditioning of a room by detecting the occupancy using the concentration of CO_2 in the room. Wei and Li [53] developed a system to monitor the energy consumption of an intelligent building with IoT. The system monitors the energy consumption during different monitoring and communication interfaces. Yan et al. [54] proposed the adaptive sampling of accelerometer in real-time depending upon the activity. They have presented the classification accuracy and energy overhead trade-off for different activity separately. Most of the works present in literature focused towards the energy efficiency of the building. Some of them have used different nodes or module to get the occupancy information etc., but in our scenario, the energy efficient air quality monitoring device without any extra overhead or module is desirable.

Calibration of the device Sensor calibration has been a crucial step since the last decade in the context of IoT and its applications. Alonso et al. [24] used an infrastructural approach to filter out the noise from the stored sensor data. They used Extensible Sensor Stream Processing (ESP) which consists of multiple pipeline stages(point, smooth, merge, arbitrate and virtualize) for filtering the data. But the timlely processing of these stages is costly and time consuming. Kularatna and Sudantha [27] used hardware calibration like zero air calibration and span calibration. In these methods, the devices should be calibrated before deployment. They did not use any real-time calibration technique. The researchers [10] discussed the results obtained for CO, NO_2 and estimation of total NO_x concentration with the multi-sensor device using multivariate correlation. Here, conventional air pollution monitoring station is used to provide reference data.

Laurent et al. [46] proposed field calibration using linear regression, multi linear regression and artificial neural network whereas Tsujita et al. [49] provides an auto calibration method using baseline shifting. In all the aforementioned works, the calibration was done using either some hardware or software techniques. Moreover, energy aware calibration has not been performed in the literature for air quality based sensors to the best of our knowledge. Although, the combination of these techniques can improve the reliability of the system. Hence, both types of calibration (hardware and software) is required to develop a desired system. On the other hand, the aforementioned works did not consider spatial variations for calibrating the devices in real time, irrespective of their locations.

8 Conclusion and Future Scope

Nowadays, indoor environment pollution is a major concern and to solve this problem, cost effective monitoring of air quality is very crucial. In this paper, (a) we have developed a portable, cost effective device equipped with gas, particle, and meteorological sensors, (b) we have used hard calibration as well as soft calibration techniques to the zero shifting protection and real-time calibration of the developed device respectively with an accuracy of 89%. The developed EMD is made energy-aware through incorporating the adaptive sampling rate feature. The EMD is made intelligent enough to capture the behaviour of the classroom by monitoring the rise and fall in the concentration of CO_2. The EMD is then samples according to the presence of the occupants in the classroom. It reduces the energy consumption of the EMD by 45% with respect to the normal condition. The proposed method increases the lifetime of the sensors by reducing the number of sensor triggering. An spatio-temporal calibration technique is developed by considering the spatial parameters of a classroom, and the proposed technique outperforms the baseline calibration techniques. The system provides an energy aware sensing but, the optimal sensing needs further investigation on the optimal deployment of the EMDs which further reduces the energy consumption. The proposed work also tries to determine the optimal time period for re-calibrating the EMD so that the calibration process need not be repeated multiple times blindly which ultimately make the whole system an energy aware.

Acknowledgements The authors are grateful to the anonymous reviewers for constructive suggestions and insightful comments which greatly helped to improve the quality of the manuscript. This publication is an outcome of the R &D work undertaken in the (a) Council of Scientific & Industrial Research (CSIR), India (Grant No. 09/973(0014)/2016-EMR-1), a premier national R &D organisation (b) Project IntAirSense funded by Department of Science & Technology (DST), West Bengal, India for funding our research work in parts (Grant No. 228(Sanc.)/ST/P/S&T/6G-9/2018).

References

1. Aeroqual: Air quality monitoring equipment. https://www.aeroqual.com/
2. Airbeam: Share & improve your air. https://www.kickstarter.com/projects/741031201/airbeam-share-and-improve-your-air
3. Anastasi, G., Bruschi, P., & Marcelloni, F. (2014) U-sense, a cooperative sensing system for monitoring air quality in urban areas. In *Smart Cities* (p. 34).
4. Annesi-Maesano, I., Hulin, M., Lavaud, F., Raherison, C., Kopferschmitt, C., de Blay, F., et al. (2012). Poor air quality in classrooms related to asthma and rhinitis in primary school children of the french 6 cities study. *Thorax, 67*(8), 682–688.
5. Bigi, A., Mueller, M., Grange, S. K., Ghermandi, G., & Hueglin, C. (2018). Performance of no, no 2 low cost sensors and three calibration approaches within a real world application. *Atmospheric Measurement Techniques, 11*(6), 3717–3735.
6. Chatzidiakou, L., Mumovic, D., & Summerfield, A. J. (2012). What do we know about indoor air quality in school classrooms? A critical review of the literature. *Intelligent Buildings International, 4*(4), 228–259.
7. Chen, X., Zheng, Y., Chen, Y., Jin, Q., Sun, W., Chang, E., & Ma, W. Y. (2014). Indoor air quality monitoring system for smart buildings. In *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*. (pp. 471–475). ACM.
8. Chithra, V., & Shiva, N. S. (2018). A review of scientific evidence on indoor air of school building: Pollutants, sources, health effects and management. *Asian Journal of Atmospheric Environment, 12*(2), 87–108.
9. Cordero, J. M., Borge, R., & Narros, A. (2018). Using statistical methods to carry out in field calibrations of low cost air quality sensors. *Sensors and Actuators B: Chemical, 267,* 245–254.
10. De Vito, S., Piga, M., Martinotto, L., & Di Francia, G. (2009). Co, no2 and nox urban pollution monitoring with on-field calibrated electronic nose by automatic Bayesian regularization. *Sensors and Actuators B: Chemical, 143*(1), 182–191.

11. Eranna, G., Joshi, B., Runthala, D., & Gupta, R. (2004). Oxide materials for development of integrated gas sensors—A comprehensive review. *Critical Reviews in Solid State and Materials Sciences, 29*(3–4), 111–188.
12. Fonollosa, J., Fernandez, L., Gutiérrez-Gálvez, A., Huerta, R., & Marco, S. (2016). Calibration transfer and drift counteraction in chemical sensor arrays using direct standardization. *Sensors and Actuators B: Chemical, 236,* 1044–1053.
13. Ghaffarianhoseini, A., AlWaer, H., Omrany, H., Ghaffarianhoseini, A., Alalouch, C., Clements-Croome, D., & Tookey, J. (2018). Sick building syndrome: Are we doing enough? *Architectural Science Review, 61*(3), 99–121.
14. Gottlicher, S., Gager, M., Mandl, N., & Mareckova, K. (2010) European union emission inventory report 1990–2008 under the unece convention on long-range transboundary air pollution (lrtap). Tech. rep.
15. Grace, S., Mohan Lal, D., & Sharmeela, C. (2004). Demand controlled systems with fuzzy controllers to maintain indoor air quality-an energy saving approach. *International Journal of Ventilation, 3*(1), 79–86.
16. Gunn, S. R., et al. (1998). Support vector machines for classification and regression. *ISIS Technical Report, 14*(1), 5–16.
17. Hernández, N., Talavera, I., Biscay, R. J., Porro, D., & Ferreira, M. M. (2009). Support vector regression for functional data in multivariate calibration problems. *Analytica Chimica Acta, 642*(1–2), 110–116.
18. Hess-Kosa, K. (2018). *Indoor air quality: The latest sampling and analytical methods*. London: CRC Press.
19. Houtman, I., Douwes, M., Jong, T. D., Meeuwsen, J., Jongen, M., Brekelmans, F., Nieboer-Op de Weegh, M., Brouwer, D., Bossche, S., Zwetsloot, G., et al. (2008). New forms of physical and psychosocial health risks at work. *European Parliament.*
20. Huynh, C. (2010). Building energy saving techniques and indoor air quality—A dilemma. *International Journal of Ventilation, 9*(1), 93–98.
21. Ionascu, M. E., Castell, N., Boncalo, O., Schneider, P., Darie, M., & Marcu, M. (2021). Calibration of co, no2, and o3 using airify: A low-cost sensor cluster for air quality monitoring. *Sensors, 21*(23), 7977.
22. Indoor air quality (2017). https://www.eea.europa.eu/signals/signals-2013/articles/indoor-air-quality
23. India 2020—energy policy review (2020)
24. Jeffery, S. R., Alonso, G., Franklin, M. J., Hong, W., & Widom, J. (2006). Declarative support for sensor data cleaning. In *International conference on pervasive computing* (pp. 83–100). Springer.
25. Jelicic, V., Magno, M., Brunelli, D., Paci, G., & Benini, L. (2012). Context-adaptive multimodal wireless sensor network for energy-efficient gas monitoring. *IEEE Sensors Journal, 13*(1), 328–338.
26. Khedo, K. K., & Chikhooreeah, V. (2017). Low-cost energy-efficient air quality monitoring system using wireless sensor network. In *Wireless sensor networks-insights and innovations*. IntechOpen.
27. Kularatna, N., & Sudantha, B. (2008). An environmental air pollution monitoring system based on the ieee 1451 standard for low cost requirements. *IEEE Sensors Journal, 8*(4), 415–422.
28. Martani, C., Lee, D., Robinson, P., Britter, R., & Ratti, C. (2012). Enernet: Studying the dynamic relationship between building occupancy and energy consumption. *Energy and Buildings, 47,* 584–591.
29. Measure pm and co2, temp, humidity with airveda monitors: Breathe well. http://www.airveda.com/
30. Martins, N. R., & da Graça, G. C. (2018). Impact of pm2.5 in indoor urban environments: A review. *Sustainable Cities and Society, 42,* 259–275.
31. McConnell, R., Islam, T., Shankardass, K., Jerrett, M., Lurmann, F., Gilliland, F., et al. (2010). Childhood incident asthma and traffic-related air pollution at home and school. *Environmental Health Perspectives, 118*(7), 1021–1026.
32. Meng, Q. Y., Turpin, B. J., Korn, L., Weisel, C. P., Morandi, M., Colome, S., et al. (2005). Influence of ambient (outdoor) sources on residential indoor and personal pm 2.5 concentrations: Analyses of riopa data. *Journal of Exposure Science and Environmental Epidemiology, 15*(1), 17.
33. Nielsen, P. V., Lin, C. H., Phillips, D., Al-Alusi, T., Chen, Y., Srebric, J., Dols, S., Walton, G., Lorenzetti, D., Musser, A., et al. (2005). Indoor environmental modelling: Chapter 34 in ashrae handbook, fundamentals.
34. Ostertagová, E. (2012). Modelling using polynomial regression. *Procedia Engineering, 48,* 500–506.

35. Parkinson, T., Parkinson, A., & de Dear, R. (2019). Continuous ieq monitoring system: Context and development. *Building and Environment, 149,* 15–25.
36. Patel, M. M., & Miller, R. L. (2009). Air pollution and childhood asthma: Recent advances and future directions. *Current Opinion in Pediatrics, 21*(2), 235.
37. Pérez-Lombard, L., Ortiz, J., & Pout, C. (2008). A review on buildings energy consumption information. *Energy and Buildings, 40*(3), 394–398.
38. Persily, A., & de Jonge, L. (2017). Carbon dioxide generation rates for building occupants. *Indoor Air, 27*(5), 868–879.
39. Plume labs: Be empowered against air pollution. https://flow.plumelabs.com/
40. Revel, G. M., Arnesano, M., Pietroni, F., Frick, J., Reichert, M., Schmitt, K., et al. (2015). Cost-effective technologies to control indoor air quality and comfort in energy efficient building retrofitting. *Environmental Engineering and Management Journal, 14*(7), 1487–1494.
41. Sarigiannis, D. A., Gotti, A., & Karakitsios, S. P. (2019). Indoor air and public health. In *Management of emerging public health issues and risks* (pp. 3–29). Elsevier.
42. Schulz, E., Speekenbrink, M., & Krause, A. (2018). A tutorial on gaussian process regression: Modelling, exploring, and exploiting functions. *Journal of Mathematical Psychology, 85,* 1–16.
43. Shaban, K. B., Kadri, A., & Rezk, E. (2016). Urban air pollution monitoring system with forecasting models. *IEEE Sensors Journal, 16*(8), 2598–2606.
44. Sharma, P. K., Poddar, B., Dey, S., Nandi, S., De, T., Saha, M., Mondal, S., & Saha, S. (2017). On detecting acceptable air contamination in classrooms using low cost sensors. In *2017 9th international conference on communication systems and networks (COMSNETS)* (pp. 484–487). IEEE.
45. Spachos, P., & Hatzinakos, D. (2015). Real-time indoor carbon dioxide monitoring through cognitive wireless sensor networks. *IEEE Sensors Journal, 16*(2), 506–514.
46. Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2017). Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. part b: No, co and co2. *Sensors and Actuators B: Chemical, 238,* 706–715.
47. Standard, A. A. (2012). *Standard guide for using indoor carbon dioxide concentrations to evaluate indoor air quality and ventilation*. West Conshohocken: American Society for Testing and Materials.
48. Suriano, D., Cassano, G., & Penza, M. (2020). Design and development of a flexible, plug-and-play, cost-effective tool for on-field evaluation of gas sensors. *Journal of Sensors* 2020
49. Tsujita, W., Yoshino, A., Ishida, H., & Moriizumi, T. (2005). Gas sensor network for air-pollution monitoring. *Sensors and Actuators B: Chemical, 110*(2), 304–311.
50. Tu, Z. X., Hong, C. C., & Feng, H. (2017). Emacs: Design and implementation of indoor environment monitoring and control system. In *2017 IEEE/ACIS 16th international conference on computer and information science (ICIS)* (pp. 305–309). IEEE.
51. Vakiloroaya, V., Samali, B., Fakhar, A., & Pishghadam, K. (2014). A review of different strategies for hvac energy saving. *Energy Conversion and Management, 77,* 738–754.
52. Vesitara, R., & Surahman, U. (2019). Sick building syndrome: Assessment of school building air quality. *Journal of Physics: Conference Series, 1375,* 012087.
53. Wei, C., & Li, Y. (2011) Design of energy consumption monitoring and energy-saving management system of intelligent building based on the internet of things. In *2011 international conference on electronics, communications and control (ICECC)* (pp. 3650–3652). IEEE.
54. Yan, Z., Subbaraju, V., Chakraborty, D., Misra, A., & Aberer, K. (2012) Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach. In *2012 16th international symposium on wearable computers* (pp. 17–24). IEEE.
55. Zimmerman, N., Presto, A. A., Kumar, S. P., Gu, J., Hauryliuk, A., Robinson, E. S., et al. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. *Atmospheric Measurement Techniques, 11*(1), 291–313.