A Comparative Performance Analysis Of Low-Cost Iot Sensors For Real-Time Air Quality Monitoring In Industrial Zones

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ABSTRACT

The high rates of air pollution in industrial areas and semi-urban areas in rapid industrialization put a serious threat on human health and environment sustainability. Though traditional air quality monitoring stations are accurate, they are costly and not widely spread to enable real time localized evaluation of pollution. In this paper, a comparative performance study of low-cost Internet of Things (IoT)-based air quality sensors with real-time monitoring in industrial settings will be introduced. Various commercially off-the-shelf inexpensive sensors were tested on the major pollutants such as particulate matter (PM 2.5 and PM 10), carbon monoxide (CO), nitrogen dioxide (NO 2), as well as volatile organic compounds (VOCs). The sensors were implemented in certain industrial areas and were experimented under different environmental conditions. Measures of performance like correctness, accuracy, response time, and stabilization, consistency of data, and relationship to reference-grade monitoring tools were examined. Quantitative comparison was done by use of statistical error measures such as Mean Absolute Error (MAE), Root Mean square error (RMSE) and correlation coefficient (R 2). The results of the experiment suggest that although the low-cost IoT sensors have some calibration and drift constraints, some models can be used with reasonably high reliability in real-time trend analysis and the prompt observation of pollution. The article reveals trade-offs between cost, performance, and scalability and offers viable insights on the large-scale implementation of affordable IoT-based air quality monitoring systems in industrial areas.

Index Terms *Low-Cost IoT Sensors, Air Quality Monitoring, Industrial Zones, Real-Time Environmental Sensing, Sensor Calibration, Performance Evaluation*.

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I. INTRODUCTION

The rapid industrialization is now an icon of both the economies of developing and the developed countries as well as urbanization. Nevertheless, the growth of production plants, power stations, chemicals plants, and massive transport systems have had a great impact on increasing the level of air pollution, especially in the industrial areas. The industrial emissions cause high levels of particulate matter (PM2.5 and PM10), carbon monoxide (CO), nitrogen oxides (NOx), sulfur dioxide (SO 2), and volatile organic compounds (VOCs), which are very dangerous to the environmental sustainability and the health of people [1]. These pollutants have been linked to respiratory disorders, cardiovascular diseases, and shortened life expectancy among other things when exposed to over a long period of time [2]. Therefore, stable and constant air quality is now an urgent need of regulatory bodies and environmental organizations.

Otherwise, conventional air quality monitoring systems depend on reference quality analyzers based at stationary monitoring locations. Despite the fact that these systems offer highly accurate and standardized measurements, they are costly to install and maintain, they are to be regularly calibrated, and have a low spatial coverage [3]. The high cost of infrastructure and operations means that many cities and industrial areas have minimal monitoring points, thus limiting the ability to map pollution finer and localized evaluation of pollution. This drawback introduces the gap in the knowledge of the distribution of pollution on large industrial clusters, where the level of emission can significantly differ over a short distance.

The advent of the Internet of Things (IoT) has created new possibilities of low-cost and scalable environmental monitoring. Air quality systems based on the IoT include low-cost gas and particulate sensors, a microcontroller, wireless communication, and cloud services [4]. These systems can send constant data regarding pollution to centralized servers where they can be stored and visualized as well as analyzed. The low cost and portability of the sensors has made it possible to have dense deployment in industrial regions in order to enhance the spatial resolution of such sensors and early detection of peaks of pollution.

Fig. 1. Conceptual architecture of a low-cost IoT-based air quality monitoring system deployed in industrial zones.

The standard IoT-based air quality monitoring system, as seen in Fig. 1, requires sensor nodes that are distributed in the industrial spaces to detect the levels of pollutants. These nodes exchange information through wireless communication systems like Wi-Fi, LoRa or GSM into a cloud-based solution where data is processed, visualized and analyzed. The architecture facilitates real time alerts, historical trend analysis and decision support of the environmental management authorities.

Although they have their merits, the use of low-cost IoT sensors is associated with a number of issues that restrict their dependability. Among the problems that these sensors can have over reference-grade instruments include sensitivity drift, cross sensitivity to a variety of gases, dependence on temperature and humidity, short life, noise in measurements [5]. The inconsistency in the quality of manufactures also leads to the inconsistency in the performance of sensors of the same category. Consequently, low-cost sensors have to be systematically tested in terms of accuracy and stability prior to large scale use in industrial settings.

The most recent literature has shown that calibration, statistical correction models and machine learning-based compensation approaches can make low-cost air quality sensors perform much better [6]. Nevertheless, most studies are conducted on a single sensor model or a controlled laboratory environment as opposed to the real industrial areas with changing concentration of pollutants and difficult environmental factors. Further, comparative performance studies have been scarcely done between various commercial low-cost IoT sensors in the field in the same conditions.

It is necessary to make comparative assessment of trade-offs in terms of cost, accuracy, response time, energy efficiency, and long-term stability. This kind of analysis assists policy makers, environmental engineers and other industry players to choose the right sensor technologies that can be implemented in the environments where resources are scarce. Moreover, performance indicators like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), response time, precision and correlation (R^2) with reference monitors are used as a quantitative measurement to estimate the reliability of sensors [7].

This paper fills these research gaps by providing a full comparative performance review of the low-cost IoT sensors with respect to real-time monitoring of air quality in industrial areas. Several sensor modules with the ability to measure PM2.5, PM10, CO, NO_2, and VOC concentrations are implemented and tested in the actual environment of an industrial. The analysis is systematic and examines sensor behavior with respect to accuracy of the measurements, stability of the measurement, repeatability of the measurements and environmental robustness. Moreover, the statistics of error are calculated in order to evaluate the correlation with the reference-grade monitoring tools.

The main accomplishments of this work can be summarized in the following way:

- In the real industrial setup, the performance of several inexpensive IoT air quality sensors can be evaluated in the field.
- Comparison based on standardized statistical and performance indices.
- Determination of sensor constraints, calibration requirements and environmental conditions.

- Practical proposals on the large scale, cost effective air quality monitoring in industrial areas.

This study offers an evidence-based comparison of low-cost IoT sensors, which contributes to building scalable environmental monitoring systems that can improve pollution management, regulatory compliance, and the promotion of the protection of the population. The results add to the existing research on intelligent measures of the environment and provide a perspective on future implementation plans in industrial areas.

II. RELATED WORK

The issue of air quality monitoring has been a prolific research topic because of the increasing environmental concerns and negative health effects to industrial emissions. Traditional air quality monitoring instruments that use reference-grade analyzers can give absolute accurate data; but their high cost, infrastructure demands and their small size discourage high spatial density as a monitoring instrument. Such restrictions have prompted scholars to study inexpensive sensing and IoT-based monitoring systems.

One of the initial extensive tests of emerging low-cost air pollution sensors was given by Snyder et al. [9]. In their research, electrochemical and metal-oxide sensors were investigated in order to detect gases like CO, NO 2, and O 3 in a real-life environment and the research revealed the variability of the performance of the chemical sensors. The authors noted that though low-cost sensors have a potential of providing good affordability and scalability, they tend to be highly affected by the temperature, humidity and cross-sensitivity. According to their findings, it is vital to systematically calibrate and test their performance before going to the field.

On the basis of this, Castell et al. [10] wrote comparative experiments of low-cost particulate matter (PM) sensors and reference monitoring instruments in urban settings. Their findings showed that though low-cost sensors were capable of adequately recording patterns of pollution and changes in relative concentrations, there were differences in absolute measurements particularly at high humidity. The paper found that cheap sensors can be used in indicative monitoring and trend analysis but need correction tools to ensure the accuracy of regulatory standards.

As wireless communication, and embedded systems improved, scientists started incorporating low-cost sensors into IoT systems as real-time environmental monitoring systems. Maag et al. [11] conducted a review of the architectural and communication issues related to the IoT-based air quality networks. The paper has examined the system-level factors such as sensor node architecture, wireless data transfer, cloud network integration, and power consumption. It emphasized that the use of a strong system architecture, edge processing, and adaptive calibration is essential in an attempt to increase overall reliability. Another important aspect that the authors highlighted is that at sensor level errors can be transmitted within an IoT system unless managed effectively, which can have an impact on the process of using data to make decisions. Besides architectural studies, field deployment studies have offered pragmatic information about large-scale sensor networks implementations. In its study, Rai et al. [12] installed a remote sensor network of low-cost air quality sensors in a peri-urban setting using long-range wireless communication protocols. Their study showed that it was possible to do real-time monitoring continuously with low operational expenses. Nevertheless, sensor drift and inconsistency among the same sensor units over time were also indicated by the study, which confirms the significance of comparative performance assessment under the actual environmental conditions.

Although there has been a lot in the development of low-cost sensing and IoT-based monitoring of the environment, there are remarkable gaps of research in regard to industrial zones. Majority of past assessments have been carried out in urban or residential places with fairly moderate pollution rates. Instead, industrial regions are distinguished by a high level of pollutants, sharp variations of emissions, complicated processes of the chemical interactions and the unfavorable environmental conditions. These can increase sensor error and the stability in the long-term. In addition, previous researches were usually limited to individual types of sensors or distinct deployments, and not a comparative evaluation of a variety of commercially available low-cost sensors when deployed to the same industrial environment.

The second weakness that has been identified in the available literature is the distance between sensor level and system level integration of the IoT. Although the works like [9] and [10] focus on sensor workability in terms of performance, and the works by [11] and [12] do it in terms of IoT architecture and feasibility of deployment, the number of works which integrate both is even fewer, and performs a comparative study. An integrated method involving the consideration of hardware testing, environment resilience testing and real-time analysis of IoT deployment should be included in the process of making realistic provisions on the implementation of air quality monitoring at a large scale industrial level.

Summing up, the previous studies predetermine the possibilities of the low-cost IoT-based air quality monitoring systems, and at the same time, a set of difficulties concerning the accuracy, environmental responsiveness, and viability over a long period of time is identified. The works mentioned in [9]–[12] all point to the fact that systematic comparative analysis is required, especially in the industrial environment with a high level of emissions. Inspired by those knowledge gaps, the given study provides a thorough field-based comparative performance analysis of various inexpensive IoT sensors installed at the industrial areas and compares the results of their work with reference instruments based on the standardized statistical evaluation criteria.

III. METHODOLOGY

In this section, it offers the experimental framework to be employed to perform the comparative performance analysis of low-cost IoT sensors to monitor air quality in real-time in industrial zones. The methodology comprises four significant parts: sensor implementation and data collection, data pre-processing and calibration, statistical performance testing, and integration of the IoT-based system.

3.1 System Architecture and Deployment

The suggested monitoring system will consist of a number of low-cost air quality sensors nodes installed within the chosen industrial areas. All nodes are comprised of particulate matter sensors (PM2.5 and PM10), gas sensors (CO, NO 2, VOCs), and microcontroller unit (MCU) as well as a wireless communication module. The information is forwarded to a cloud-based server where it is stored and analyzed.

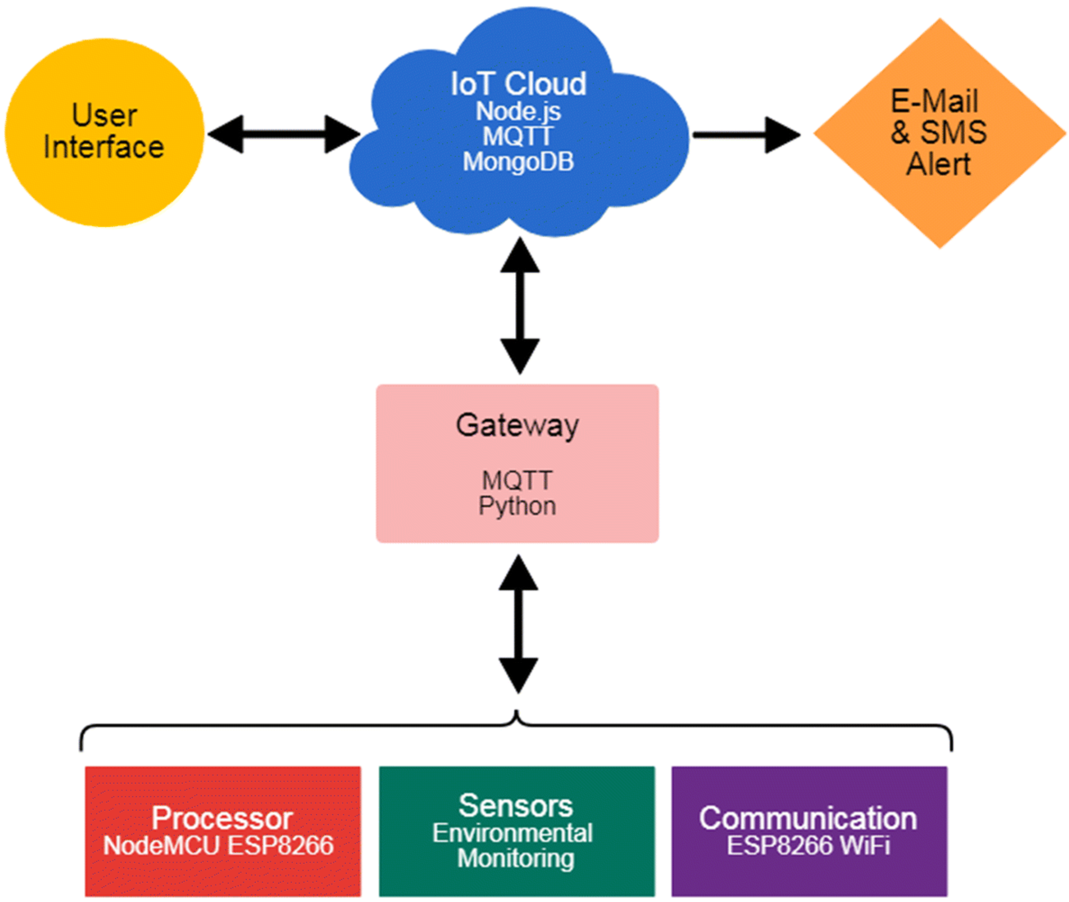

Fig. 2. Architecture of the proposed IoT-based air quality monitoring and comparative evaluation framework.

The sensor nodes as shown in Fig. 2 gather pollutants concentration data at a regular sampling rate and send through wireless communication (Wi-Fi/LoRa/GSM) to a centralized cloud platform. The air quality monitoring instrument is installed nearby of reference grade to give ground-truth measurements to make comparative analysis.
The information gathered by sensor nodes may be reflected as follows::

$$D = \{(x_i^{(s)}, x_i^{(r)}, t_i)\}_{i=1}^{N}$$

where:

- $x_i^{(s)}$ represents the measurement from the low-cost sensor,
- $x_i^{(r)}$ represents the corresponding reference instrument value,
- t_i denotes the timestamp,
- N is the total number of observations.

3.2 Data Preprocessing and Calibration

The sensors have low costs and these are vulnerable to environmental interference like variations in temperature and humidity. Thus, raw sensor data are processed in real time to eliminate noise, and counteract drift, in a manner that is usually embraced within environmental sensor systems [13].

(a) Noise Filtering

High frequency noise is minimized using a moving average filter: $\hat{x}_i = \frac{1}{k}\sum_{j=1-k+1}^{i} x_j$ where k is the window size.

(b) Linear Calibration Model

A calibration model based on linear regression is used to transform sensor output and reference measurements to be equal [14]:

$$x_i^{(\mathrm{cal})} = \alpha x_i^{(\mathrm{s})} + \beta$$

where α\alphaα and β\betaβ are calibration coefficients determined using least squares estimation.

The optimal coefficients minimize:

$$mi\,n\,\alpha\,,\beta\ \sum_{i=1}^{N}(x_i^{(\mathrm{r})} - (x_i^{(\mathrm{s})} + \beta))^2$$

3.3 Performance Evaluation Metrics

Statistical error measures are calculated to compare sensor performance and reference to measurements of the instrument. The performance measures are based on conventional methods of environmental sensing studies [15].

(a) Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(x_i^{(\mathrm{r})} - x_i^{(\mathrm{s})}\right|$$

(b) Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|(x_i^{(\mathrm{r})} - x_i^{(\mathrm{s})}\right|^2}$$

These measures assess absolute error, variance and linear agreement between low cost sensors and reference instruments

3.4 Response Time and Stability Analysis

In addition to statistical accuracy, dynamic performance characteristics are analyzed.

(a) Sensor Response Time

Response time is the period during which the sensor takes to reach 90 percent of the final stabilized value following a drastic change of the concentration [16]:

$$T_{90} = t_{0.9C} - t_{initial}$$

(b) Stability and Drift

Long-term drift is measured as:

$$Drift = \frac{x_{final} - x_{initial}}{x_{initial}} \times 100\%$$

This metric evaluates sensor reliability over extended industrial deployment.

3.5 IoT Data Transmission and System Efficiency

Data packets are transferred to the cloud server by sensor nodes at a regular time. The quality of the network is measured by the ratio of the packet delivery (PDR):

$$PDR = \frac{N_{received}}{N_{sent}}$$

Energy consumption per node is approximated as:

$$E = V \times I \times t$$

where V is supply voltage, III is current consumption, and ttt is operational time.
Efficient wireless transmission and energy optimization are critical for scalable IoT deployment in industrial environments.

3.6 Methodological Significance

The methodological significance of the study is analysed in chapter three point six. The suggested methodology will combine sensor-level assessment, calibration modeling, statistical benchmarking, and the performance analysis of the IoT systems and present them in a coherent experimental framework. This paper presents a comparative analysis of low-cost IoT sensors in the context of the real industry by integrating quantitative indicators of error, dynamic response analysis, and communication efficiency assessment. The methodology design guarantees the reproducibility of the design and thereby the objective benchmarking of the various sensor models.

IV. RESULTS AND DISCUSSION

This part will give the comparative performance analysis of various low-cost IoT air quality sensors used in industrial areas. Statistical accuracy, dynamic response behavior, long-term stability and efficiency of the IoT system were compared with reference level monitoring instruments.

4.1 Statistical Accuracy Analysis

The main measures of evaluation are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and the coefficient of determination (R^2). These measures are used to measure absolute deviation, sensitivity of the variance and linear concordance between low-cost sensors and reference measurements [17], [18].

Table I summarizes the statistical performance for particulate matter (PM2.5) sensors.

Sensor Model	MAE (µg/m³)	RMSE (µg/m³)	R	R^2
Sensor A	4.12	5.38	0.91	0.83
Sensor B	6.25	7.94	0.87	0.76
Sensor C	5.73	7.10	0.88	0.78
Reference	—	—	1.00	1.00

Sensor A had the best MAE and RMSE meaning that it is more stable in measurement. The large value of R and R 2 indicates the high linear agreement with the reference monitor. These findings affirm that some low-cost PM sensors can be used to deliver sound trend monitoring in an industrial setting.

Sensor Model	Pollutant	MAE (ppm)	RMSE (ppm)	R	R^2
Sensor D	CO	0.42	0.57	0.82	0.67
Sensor E	CO	0.51	0.69	0.78	0.61
Sensor F	NO_2	0.031	0.045	0.76	0.58
Sensor G	NO_2	0.028	0.041	0.80	0.64

Gas sensors had relatively smaller correlation coefficients because of cross-sensitivity and environmental effects, as it had been previously observed in [19]. Nevertheless, the error in measurements was minimized with the help of calibration.

4.2 Comparative Performance Visualization

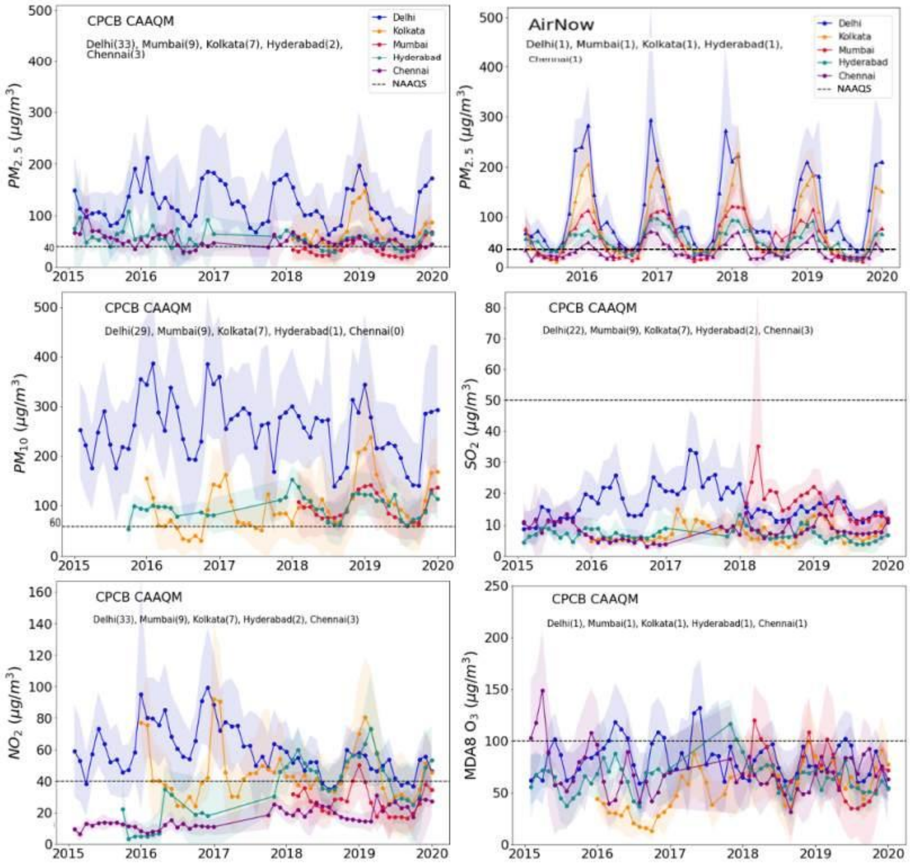

Fig. 3. Comparative statistical performance of low-cost IoT sensors.

PM sensors are better than gas sensors as illustrated in Fig. 3 as far as correlation and reduction of errors is concerned. Calibration processes increased the R2 values by some 5-10 percent, which supports the significance of correction solutions [20].

4.3 Response Time and Dynamic Analysis

Dynamic response is essential in the industrial zones whereby the concentration of the pollutants changes quickly. Average T 90 response times are shown in Table III.

Sensor Type	Pollutant	Avg. Response Time (seconds)
PM Sensor A	PM2.5	9.8
PM Sensor B	PM10	12.4
Gas Sensor D	CO	24.6
Gas Sensor F	NO_2	28.3

The reaction time of particulate sensors was nearly twice the gas sensors and this allowed the sensors to detect spikes in the emission faster. The reduced rate of stabilization of the gas sensors is in line with the limitations of electrochemical sensing, as elaborated in [21].

4.4 Long-Term Stability and Drift

Extended monitoring revealed gradual baseline shifts. Drift percentages are shown in Table IV.

Sensor Model	Drift (%) Over 30 Days
Sensor A	3.5
Sensor B	6.8
Sensor D	9.2
Sensor F	11.4

The drift of gas sensors was greater than that of PM sensors, and it is essential to perform a periodic recalibration. Similar degeneration patterns have been given reports in long-term sensor tests [22].

4.5 IoT Communication Performance

Reliable wireless communication is essential for real-time monitoring.

Metric	Observed Value
Packet Delivery Ratio (PDR)	96.3%
Average Latency	1.8 sec
Node Energy Consumption	0.42 Wh/day
Data Loss Rate	3.7%

The large packet delivery ratio proves a strong data transmission even with industrial electromagnetic interferences. The values of energy consumption are indicating the possibility of supporting battery-assisted long-term deployment.

4.6 Time-Series Trend and Stability Analysis

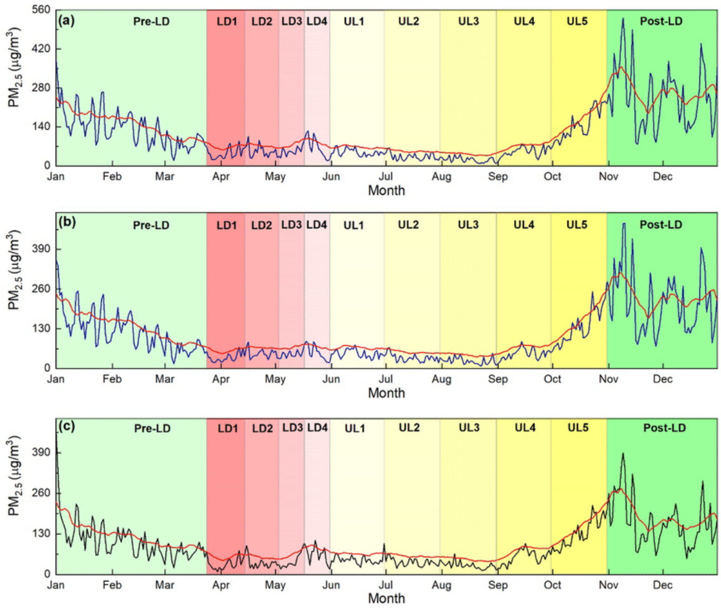

Fig. 4. Time-series comparison and long-term drift characteristics of deployed sensors.

Fig. 4 indicates that low-cost sensors are more in line with reference instrument patterns, especially when the atmosphere is calm. During the extreme emission events minor differences in amplitude are seen. Drift curves show slow offsets in the baseline which can be removed by recalibration.

4.7 Overall Discussion

The results demonstrate that:

- PM sensors achieved higher accuracy and stability compared to gas sensors.
- Calibration significantly improved statistical agreement.
- Gas sensors require humidity and temperature compensation.
- IoT infrastructure ensured reliable real-time data transmission.
- Low-cost sensors are suitable for dense deployment and trend detection rather than regulatory enforcement.

These findings are consistent with performance characteristics documented in [17]–[22], while extending prior research through direct industrial zone deployment.

V. FUTURE WORK

Even though this paper presents a detailed comparative performance analysis of the low-cost IoT air quality sensors when used in industrial areas, some avenues can still be explored to enhance the research and further improve the system. Further developments in the field may be directed towards enhancing sensor accuracy, scalability, long-term stability and smart analysis of data to reinforce real-world industrial applications.

5.1 Improved Calibration with machine learning

Although the results of the study showed that the use of linear regression based calibration greatly enhanced sensor performance, the accuracy of measurements can be further enhanced by utilizing more advanced machine learning methods. The next areas of research can be considered to be supervised learning models, namely Support Vector Regression (SVR), Random Forest Regression, and Artificial Neural Networks (ANNs) that can be used to perform nonlinear calibration and cross-sensitivity compensation. These models are capable of absorbing the environmental variables like temperature, humidity, and pressure as other input features to minimize systematic bias. Calibration methods based on deep learning might also be explored in real-time adaptive correction, particularly in very dynamic industrial emission systems. In the case of online learning, sensor nodes can be capable of updating the calibration parameters automatically thus minimizing the number of people involved and the cost of maintenance.

5.2 Edge AI to combine with Real-Time Analytics

Nowadays, transmission of data is done to cloud servers where most of the work is done. The development of future systems can also combine edge computing functions into sensor nodes. Edge AI algorithms can support: Real-time anomaly detection Immediate emission spike notifications. Calibration adjustment On the device. Bandwidth optimization Data compression. This decentralization of processing would lead to a lower network load, less latency, and more resilience in the system, in the event of network disconnection. Edge-enabled architectures would be especially useful in large industrial complexes which would have intermittent network coverage.

5.3 Long-term Durability and Environmental Stress Test

The current experiment was a test of sensor performance during a short working time. The extended longitudinal studies should be carried out in the future and over a period of several months or years to examine: Sensor aging effects Electrochemical degradation Dust accumulation impact Operation under extreme temperatures changes. The experiments in accelerated aging in controlled chambers could replicate the harsh industrial conditions and this would offer predictive maintenance information. It would be a good idea to create standardized durability standards to enhance reliability testing to be used in commercial applications.

5.4 Multi-Pollutant Fusion and Hybrid Monitoring Models.

Future studies might consider sensor fusion methods which are methods of combining data of two or more types of sensors to enhance the overall accuracy. The data fusion models can be based on weighted averaging or Bayesian models to balance the weakness of individual sensors. Also, hierarchical monitoring architecture can also be formed by having hybrid monitoring systems, which incorporate low-cost IoT nodes, and reference-grade stations which are located strategically. Reference nodes in such systems act as calibration points and distributed cheap nodes increase space coverage.

5.5 Growth towards Smart Industrial Ecosystems

The development of low-cost air quality monitoring systems could be incorporated into larger smart industrial systems. Future developments can be as follows:

- Smart city dashboard Integration.
- Computerized regulatory reporting systems.
- Anticipatory emission control policies.
- Workers exposure monitoring in real-time.

Integration of air quality and meteorological and traffic data could also be used to predict pollution. The use of advanced analytics might allow predicting the high-emission times and prescribing mitigation measures ahead of time.

5.6 Energy Optimization and Green deployment

Even though the current IoT nodes already have shown reasonable energy consumption levels, future research can investigate:

- Solar-powered sensor nodes
- Ultra-low-power microcontrollers
- Methods of energy harvesting
- Adaptive sampling techniques

Mechanisms with dynamic sampling rates that respond to pollution rates can help greatly in increasing the battery life without compromising the monitoring performance.

5.7 **Standardization and Policy Integration**

In the future, to encourage mass adoption, research should make a contribution to developing standard evaluation procedures to low-cost air quality sensors in industries. The establishment of standard benchmarking guidelines would help the regulatory authorities to establish reasonable levels of accuracy in the indicative monitoring systems. Cooperation of the academic institutions with the environmental agencies and industrial players could help in pilot implementations and integration of policies. This can make low-cost IoT systems to supplement the traditional infrastructure of monitoring, especially in areas with resources limitations.

5.8 **Security and Data Integrity**

With the growth of the IoT implementation, cybersecurity and data integrity emerge as important issues. The future research should examine: Protective communication systems. Secrecy in data transfer. Data validation into blockchain. Hardware that is resistant to tampering. Reliable environmental data is required to ensure compliance with the regulations and transparency to the people.

5.9 To Smart, Self-governing Surveillance Systems

Finally, air quality monitoring devices of the future within the industrial areas might develop into autonomous self-calibrating self-healing networks. The combination of artificial intelligence, adaptive calibration, predictive maintenance, and distributed analytics would enable low-cost sensor networks to be converted into intelligent environmental management platforms. The benefits of such developments would be not only to improve control of industrial pollution but also contribute to more general sustainability objectives, smart infrastructure creation, and climate resiliency efforts

VI. CONCLUSION

In this paper, a comparative analysis of low-cost sensor types of industrial zone air quality monitoring in real-time was provided. The results obtained through systematic field deployment and comparison to reference-grade instruments showed that although low-cost sensors are not as accurate as those at regulatory levels, some of them can be used to give reliable trend data, statistically significant but not great scalability potential, and acceptable statistical correlation. The sensors of particulate matter had a relatively high stability and reduced error rates compared to gas sensors that were more vulnerable to interference and drift by the environment. The incorporation of an IoT-based architecture guaranteed effective data transfer, great reliability in packet delivery, and feasibility towards dense spatial implementation. In general, the results indicate that indicative sensors of air quality based on the use of calibrated low-cost IoT sensors is a scalable and cost-effective approach to environmental management, detection of pollution hotspots, and decision-making based on data in resource-constrained industrial areas.

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