

Calibration of IoT-based System for Indoor Air Quality Monitoring

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Abstract— The calibration of low-cost sensors is crucial for ensuring their accuracy and reliability. Calibration models introduce corrections to sensor readings by comparing them with reference data obtained from reference measuring instrument. This study examines two primary calibration approaches for an Internet of Things (IoT) sensor node equipped with an MQ-9 carbon monoxide sensor and a Nova SDS011 particulate matter sensor: algorithmic calibration based on manufacturer specifications, and on-field calibration (comprising single-point and multivariate linear regression approaches). The calibration models are evaluated using the coefficient of determination (R^2), the sum of squared errors (SSE), and the mean absolute error (MAE). The results indicate that all three models are applicable for the MQ-9 sensor depending on the required precision, the obtained values are $R^2 = 0.7$ (algorithmic), $R^2 = 0.67$ (single-point), $R^2 = 0.93$ (multivariate linear regression). In Nova SDS011, mandatory calibration is required, the best results are obtained with multiple linear regression: $R^2 = 0.95$, $SSE = 1.13$, $MAE = 0.62$. In contrast, the Nova SDS011 sensor necessitates mandatory calibration, with the best performance achieved via multivariate linear regression ($R^2 = 0.95$, $SSE = 1.13$, $MAE = 0.62$).

Keywords— calibration model, MQ-9, NOVA SDS011, air pollution, IoT

I. INTRODUCTION

The past decade has witnessed a growing interest in atmospheric monitoring and air quality assessment. This interest is driven by accelerating globalization and the concentration of a large part of the population in major urban areas. Air pollution has become a primary threat to human health and the proper functioning of ecosystems, exhibiting a bidirectional relationship with climate change. Regular exceedances of maximum allowable concentrations for major air pollutants significantly increase the incidence of various chronic diseases, thereby burdening healthcare systems [1, 2]. Poor air quality directly affects the entire population, especially children, pregnant women, and the elderly.

Although air pollution has long been recognized as a persistent public health threat, this hazard has taken a central position on the global agenda of international institutions. The issue of atmospheric pollutants was classified as a top-tier global risk in the 2025 Global Risks Report by the World Economic Forum [3]. Furthermore, the United Nations

recognizes air pollution as a major risk factor contributing to the rise in cardiovascular diseases, strokes, and various types of cancer. also recognizes air pollution as a major risk factor for the increase in heart disease, strokes and various types of cancer.

The provision of timely, reliable, and real-time air quality information is critical for mitigating and preventing health risks [4]. Despite the implementation of various regulatory measures in recent years, data gaps still persist, and localized access to real-time air quality data remains limited. Consequently, there is an urgent need to expand monitoring networks and enhance access to real-time measurement data to improve public awareness regarding ambient air quality.

Official monitoring of air pollutant levels is conducted by state institutions utilizing specialized equipment with valid calibration certificates. These regulatory frameworks employ automatic monitoring stations (AMS) for continuous assessment of primary pollutants, adhering to national legislative requirements regarding the normative and metrological assurance of measurements. Additionally, mobile stations and certified indoor sensors are used. The National Air Quality Monitoring System (NAQMS) of the Ministry of Environment and Water (MOEW) of the Republic of Bulgaria comprises 48 stationary stations distributed across the country [5]. However, this infrastructure is insufficient to provide a comprehensive, high-resolution spatial overview of air pollution

Low-cost sensors (LCS) have gained significant popularity as alternative tools for measuring air pollutants and meteorological parameters at both the localized ambient level and in indoor environments. This adoption is attributed to their affordability, simplicity, and ease of integration [6, 7, 8]. These devices facilitate the expansion of air monitoring networks, enabling the identification of air quality issues at a micro-local scale [9, 10, 11].

The Internet of Things (IoT) can be defined as a network of interconnected physical objects capable of exchanging and storing data within cloud platforms. IoT-based air quality systems typically utilize low-cost environmental sensors to collect, share, and analyze data, managed by an appropriate microcontroller featuring integrated Wi-Fi and Bluetooth capabilities [12, 13, 14]. The measurement data are transmitted wirelessly, can be displayed locally, and can be

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exported in real-time as CSV files for subsequent statistical analysis.

Low-cost sensors implemented in IoT nodes for air quality assessment generally exhibit lower accuracy compared to reference instruments and require systematic calibration [15, 16, 17]. The calibration process is vital for ensuring accurate and reliable measurements. A critical aspect of both measurement and calibration processes is the evaluation of measurement uncertainty, which requires accounting for the contributions of all its components [18]. While the comprehensive assessment of measurement uncertainty for low-cost sensors remains an open research question, current efforts focus on investigating suitable calibration models for LCS and predicting primary air pollutants [19, 20].

The objective of sensor calibration within a node is to align sensor responses with true values to ensure measurement accuracy. Calibration is mandatory prior to initial deployment, following prolonged operation (especially under extreme environmental conditions), or upon detecting anomalous measurement readings. The aim of this paper is to compare different calibration models applied to an IoT-based indoor air quality monitoring system, focusing on methods most commonly used for low-cost sensors. The proposed IoT sensor node integrates a Nova SDS011 optical particulate matter sensor, a MQ-9 metal-oxide semiconductor gas sensor for carbon monoxide (CO), and a DHT11 temperature and humidity sensor. These sensors operate on distinct physical principles, which necessitates different calibration approaches. The adequacy of the calibration models is evaluated using Statgraphics Centurion 19

II. IOT BASED SYSTEM

The proposed IoT system for indoor air quality monitoring is designed to collect and store environmental data. The hardware configuration features an ESP32-S DevKit microcontroller utilized for data acquisition, processing, and logging onto an SD card module, while simultaneously displaying current measurements on a local web page. The sensing layer consists of a Nova SDS011 particulate matter sensor, a MQ-9 semiconductor gas sensor for carbon monoxide concentration measurements, and a DHT11 temperature and relative humidity module.

A. Espressif ESP32-S DevKit Microcontroller

The Espressif ESP32-S DevKit is a low-cost microcontroller suitable for IoT system development. The ESP32 features a dual-core processor operating at 240 MHz, making it highly efficient for concurrent multitasking and rapid processing of incoming sensor data. It includes 520 KB of usable SRAM, allowing for the management of large datasets. This System-on-Chip (SoC) integrates native Wi-Fi and Bluetooth connectivity, provides 32 general-purpose input/output (GPIO) ports for peripheral interfacing, and maintains low power consumption

B. Nova SDS011 Laser Dust Sensor

The Nova SDS011 is a digital sensor designed to measure the concentration of particulate matter within the range of 0.3 to 10 μm (specifically $\text{PM}_{2.5}$ and PM_{10}). The sensor is designed as a module containing a digital output and an integrated fan. Due to its specific design, the device provides two pulse-width modulation (PWM) outputs for particle measurement, alongside RX and TX pins that enable Universal Asynchronous Receiver-Transmitter (UART)

communication. The measurement range of the sensor spans from 0 to 999 $\mu\text{g}/\text{m}^3$.

The Nova SDS011 module operates on the principle of laser scattering. The measurement device communicates with the microcontroller via a UART interface. Due to this specific connection, software-controlled sleep and wake cycles must be implemented to extend the operational lifespan of the sensor. The sensor module is factory-calibrated by the manufacturer [21].

C. MQ-9 Carbon Monoxide Sensor

The MQ-9 is a metal-oxide-semiconductor (MOS) gas sensor used to measure carbon monoxide (CO) concentrations. The sensitive element of the MQ-9 is composed of tin dioxide (SnO_2), a material characterized by low electrical conductivity in clean air, which detects gases through cyclic temperature modulation. The module is designed to exhibit high sensitivity to CO at a heating voltage of 1.5 V. The sensor provides an analog output for signal transmission to the microcontroller and a digital output used for sensitivity adjustment. The CO measurement range of the sensor is 10 to 1000 ppm.

D. DHT11 Sensor Module

The DHT11 is a widely used, low-cost digital module for measuring ambient temperature and relative humidity. It features an integrated pull-up resistor and capacitor, which facilitates direct interfacing with the microcontroller without requiring external components

E. System connection diagram

Fig. 1 illustrates the schematic connection diagram of the system. To ensure voltage stability at the sensor inputs, a regulated power supply module with a 12 V input and selectable 3.3 V or 5 V outputs is utilized in conjunction with a compatible development board.

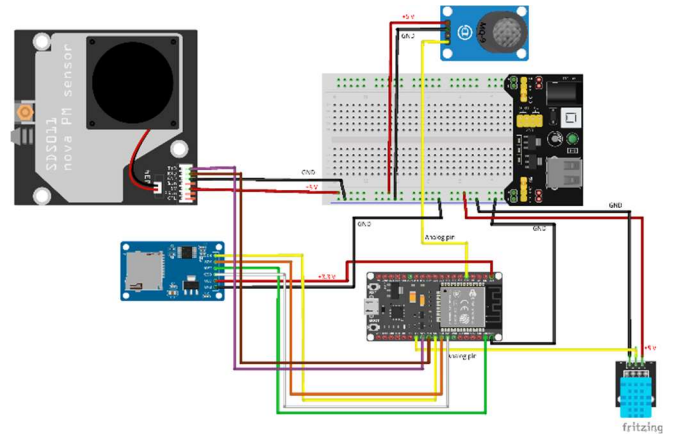


Fig. 1. Connection diagram of IoT sensor node.

The configuration of the individual sensor modules and the microcontroller firmware was developed using the Arduino IDE. Measurement data are transmitted to a local server and simultaneously logged onto a SD card module connected to the microcontroller. The generated output file utilizes the CSV format structured as a data table, which facilitates subsequent post-processing and analysis.

III. CALIBRATION OF THE IOT SYSTEM

Every measuring instrument must undergo calibration prior to its initial deployment, a requirement that extends to

low-cost sensors. Generally, manufacturers of low-cost sensors provide specific guidelines for calibration based on the underlying operating principle or specify the maximum permissible measurement errors. This section explores several calibration methodologies for the deployed sensors: algorithmic calibration using manufacturer datasheet specifications, and on-field calibration, which includes single-point calibration and calibration via statistical regression models. To evaluate the adequacy and accuracy of the IoT sensor node calibration, the results are compared against reference data. An automatic monitoring station (AMS) located in the Mladost district of Sofia, Bulgaria, serves as the reference standard in this study [5]. The AMS is operated by the Executive Environment Agency, runs continuously, and provides real-time data for main air pollutants, including PM₁₀, nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and carbon monoxide (CO). It also records meteorological parameters such as temperature, humidity, wind speed, wind direction, and solar radiation

A. Algorithmic Training of the System's Sensors Using Data from the Manufacturer

The Nova SDS011 particulate matter sensor operates on the principle of laser scattering and cannot be manually calibrated. According to the manufacturer specifications, the module is factory-calibrated in a laboratory environment, with a declared relative error of $\pm 15\%$ [21]. To verify the sensor's accuracy and validate the manufacturer's claims, it is necessary to perform alternative calibration methods.

The MQ-9 sensor, utilized for carbon monoxide detection, requires software or hardware calibration in a clean air environment. According to the manufacturer, calibration can only be performed after a mandatory sensor preheating procedure [22]. This procedure involves operating the module continuously for 48 hours to heat the surface membrane, thereby removing contaminants. Subsequently, a software script is executed to sample the analog values repeatedly (100–500 times) in clean air to compute an average value. This calculated value represents the sensor resistance in clean air (R_0) and serves as a fundamental baseline for successful calibration. The compiled source code incorporates the load resistance (R_L) of the module and evaluates the sensor resistance (R_s) using the following voltage divider relationship:

$$R_s = R_L * \frac{(V_{cc} - V_o)}{V_{out}} \quad (1)$$

where R_s is the operational sensor resistance during measurement.

Because the absolute sensor resistance varies between individual devices, the normalized resistance ratio (R_s/R_0) is utilized to obtain stable and comparable results. To establish a linear relationship, a logarithmic transformation is applied since the correlation between gas concentration and the sensor signal follows an exponential function:

$$CO_{ppm} = 10^{\frac{\log_{10}(R_s/R_0) - b}{m}} \quad (2)$$

where b represents the intercept determining the position of the characteristic curve, and m denotes the slope of the logarithmic sensitivity curve, both derived from the manufacturer's sensor sensitivity characteristics chart.

Since most reference monitoring stations report concentrations in mg/m³, the gas sensor readings must be

converted using the molar mass and molar volume of carbon monoxide:

$$CO_{mg/m^3} = CO_{ppm} * \frac{M}{24.45} \quad (3)$$

where the molar mass of CO $M = 28.01$ g/mol and the molar volume is 24.45 L/mol at 25°C and 1 atm.

Following the configuration of both sensor modules, a series of experimental measurements were conducted to evaluate measurement accuracy and data reliability.

B. On-Field Calibration of IoT System

To execute on-field calibration, the IoT sensor node was co-located adjacent to the reference standard at the Mladost AMS in Sofia. Utilizing the parallel data streams collected from the IoT system (PM₁₀ and CO) and the reference data from the AMS, two additional calibration models for low-cost sensors were evaluated: single-point calibration and a multivariate linear regression (MLR) calibration model

B.1. Single-Point Calibration

Single-point calibration represents the simplest calibration methodology, aimed at correcting the offset or drift of the sensor output signal relative to the reference instrument. This approach assumes a linear sensor response across its operational measurement range. It can also serve as a periodic drift check to identify operational degradation, aging, or anomalous sensor outputs.

Single-point calibration requires obtaining concurrent measurements from the target sensors (the particulate matter sensor and the carbon monoxide sensor) and comparing their outputs directly with the reference readings from the automated monitoring station.

The calibration function for the single-point model is expressed as:

$$y = a + x$$

where “ x ” represents the raw measurement from the sensor, “ y ” denotes the calibrated value, and “ a ” is the calculated offset ($a = y - x$). The offset is determined by subtracting the raw sensor reading from the reference value. This correction factor is then integrated into the firmware code to adjust all subsequent sensor measurements

B.2. Multivariate Linear Regression (MLR) Calibration Model

Multivariate linear regression (MLR) is the most widely adopted mathematical model for the calibration of low-cost sensors. This statistical method models the linear relationship between a single dependent variable and two or more independent variables. Utilizing this approach enables both the calibration of measurement data and the prediction of target variables based on multiple environmental factors.

MLR analyzes the dependencies between multiple environmental predictors and the target variables. The multivariate linear regression model is structured as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon \quad (4)$$

where:

- y is the dependent variable.
- $x_1, x_2, \dots, x_k$ are the independent variables.

- β_0 are the independent variables – the value of y , for each $x = 0$.
- $\beta_1, \beta_2, \dots, \beta_k$ represent the regression coefficients indicating the change in y per unit change in the respective predictor.
- ϵ is the residual error component

To quantify the performance of the calibration models regarding the PM and CO sensor data, the coefficient of determination (R^2), the standard error of the estimate (SEE), and the mean absolute error (MAE) were computed. These statistical metrics are defined as:

$$R^2 = 1 - \frac{SS_r}{SS_t} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \quad (5)$$

where SS_r is the residual sum of squares, SS_t is the total sum of squares, y_i represents the observed reference values, $\hat{y}_i$ denotes the predicted values from the model, and $\bar{y}_i$ is the mean of the dependent variable.

$$SEE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \quad (6)$$

where n represents the number of observations.

The mean absolute error is calculated using the following expression:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

Achieving a correlation coefficient greater than 0.80 demonstrates that the applied calibration model is adequate and can be successfully used for data correction. A SEE and MAE error value approaching zero would indicate an optimal fit between the reference values and the sensor-derived measurements.

IV. RESULTS AND DISCUSSION

Following the hardware configuration of the IoT sensor node, compliance with the manufacturer's preheating protocols for the carbon monoxide sensor, and assuming factory calibration for the particulate matter sensor, a series of validation measurements were conducted.

The measurement accuracy of the sensor node was validated through direct comparison with reference data obtained from the Mladost AMS. The sensor node was co-located at the station for five consecutive business days, recording data during daylight hours (from 09:00 to 16:00). Initial analysis shows difference between the sensor readings and reference data, which were more pronounced for the particulate matter sensor. The initial baseline coefficients of determination, used as a primary indicator for low-cost sensor accuracy, were $R^2 = 0.70$ for the MQ-9 sensor and $R^2 = 0.20$ for the Nova SDS011 sensor. While the initial performance of the MOS MQ-9 sensor may satisfy basic requirements for indoor air monitoring, the low correlation exhibited by the particulate matter sensor emphasizes the necessity of mandatory calibration using a suitable mathematical model. This conclusion is further supported by the error metrics (SEE and MAE), which deviated significantly from zero. For the CO sensor, the baseline errors were $SEE = 0.014$ and $MAE = 0.01$, whereas the Nova SDS011 sensor exhibited elevated errors: $SEE = 3.074$ and $MAE = 2.40$.

The implementation of the single-point calibration model yielded the following validation metrics:

- For the MQ-9 carbon monoxide sensor: $R^2 = 0.67$, $SEE = 0.034$, $MAE = 0.023$
- For the Nova SDS011 (PM_{10}) sensor: $R^2 = 0.59$, $SEE = 3.32$, $MAE = 2.18$.

Based on these results, it was determined that single-point calibration did not introduce significant improvements to the accuracy of the CO sensor. Conversely, the particulate matter sensor demonstrated a slight performance improvement, with the R^2 value increasing to 0.59; however, this remains well below the critical threshold of 0.80, and the residual errors remained high. Consequently, single-point calibration proves insufficient for generating correct and reliable data for carbon monoxide and PM_{10} evaluation.

Multivariate linear regression (MLR) relies on the existence of linear relationships between the dependent target variable and multiple independent predictors. This study investigated the cross-dependencies between the two target pollutants, PM_{10} and CO, and two meteorological variables: ambient temperature and relative humidity. Temperature and humidity were selected because they significantly influence human thermal comfort in indoor environments and are easily monitored. Independent evaluations were conducted to assess the pairwise relationships between CO and temperature, CO and relative humidity, and CO paired with both predictors simultaneously. An identical analytical procedure was performed for PM_{10} . The highest model performance was achieved when incorporating both temperature and relative humidity as co-predictors for the CO and PM_{10} sensor outputs.

Ultimately, accounting for environmental cross-sensitivities, the regression analysis generated the following MLR model for carbon monoxide:

$$CO_{ref} = 0.012 + 0.0014 * CO_{real} + 0.0007 * humidity + 0.005 * temperature \quad (8)$$

Following the software implementation of this model for real-time data correction, the evaluation metrics improved to $R^2 = 0.93$, $SEE = 0.010$, $MAE = 0.007$.

An identical MLR procedure was applied to the PM_{10} dataset, resulting in the following mathematical expression:

$$PM10_{ref} = 16.07 + 0.075 * PM10_{real} + 0.055 * humidity - 0.07 * temperature \quad (9)$$

Following the application of this calibration model, the resulting validation metrics were: $R^2 = 0.95$, $SEE = 1.13$, $MAE = 0.62$.

These outcomes indicate a strong linear correlation between the reference data and the calibrated sensor measurements for both CO and PM_{10} . In both scenarios, the R^2 values exceeded 0.90. The errors for the CO measurements approached zero, demonstrating excellent agreement between the reference standard and the sensor outputs. For the particulate matter sensor, the SEE was approximately 1.13 and the MAE was 0.62. When analyzed together, these three statistical indicators validate that the MLR method can be successfully utilized to calibrate low-cost particulate matter sensors.

V. CONCLUSION

The proposed IoT system is intended for monitoring PM_{10} and CO concentrations in indoor environments characterized by continuous human occupancy. Two primary calibration

methodologies were analyzed: algorithmic (software-based) calibration utilizing manufacturer specifications, and on-field calibration involving direct comparison with reference data using single-point and multivariate linear regression models. Due to the absence of standard reference instrumentation designed specifically for indoor environments, co-location with the outdoor ambient Mladost AMS was utilized to perform sensor node calibration

Initial algorithmic calibration revealed prominent data discrepancies between the raw sensor outputs and the reference measurements, which were substantially higher for the particulate matter sensor. The baseline coefficients of determination were $R^2 = 0.7$ for the MQ-9 sensor and $R^2 = 0.2$ for the Nova SDS011 sensor. After applying single-point calibration, the validation metrics for the MQ-9 gas sensor shifted $R^2 = 0.67$, $SEE = 0.034$, $MAE = 0.023$, while the particulate matter sensor achieved $R^2 = 0.59$, $SEE = 3.32$, $MAE = 2.18$.

Algorithmic and single-point calibration models can be successfully implemented for the MQ-9 sensor, provided that the resulting precision aligns with the specific indoor measurement requirements. For both models, the R^2 values remained consistent, and the residual errors were close to zero. However, the Nova SDS011 sensor exhibited inadequate performance despite a near two-fold increase in R^2 under single-point calibration. This indicates that the particulate matter sensor requires alternative calibration models, a requirement further necessitated by its distinct physical operating principle compared to the metal-oxide MQ-9 sensor.

The multivariate linear regression model achieved the highest performance by incorporating ambient temperature and relative humidity to compensate for environmental cross-sensitivities. As anticipated, the MQ-9 sensor exhibited enhanced metrics: $R^2 = 0.93$, $SEE = 0.010$ and $MAE = 0.007$. Notably, the Nova SDS011 sensor demonstrated a substantial performance increase, reaching R^2 value of 0.95, which indicates a robust correlation with the reference standard. Furthermore, its residual errors were significantly minimized, $SEE = 1.13$ and $MAE = 0.62$, approaching optimal values.

The experimental results demonstrate that single-point calibration requires a stable environment with controlled temperature and relative humidity, alongside a predictable range of PM_{10} and CO fluctuations within the targeted indoor space. While it can be applied to correct the readings of the MQ-9 sensor (which independently requires preliminary manufacturer-aligned baseline tuning), it is unsuitable for the Nova SDS011 sensor. Conversely, the implementation of multivariate linear regression delivers superior efficacy and significantly enhances measurement accuracy for both carbon monoxide and particulate matter by successfully compensating for the cross-sensitivity effects of ambient temperature and relative humidity.

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