Performance Comparison of Nonlinear Pre–Calibrate Low–Cost PM2.5 Sensors Using an SPS30 Reference

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Abstract

This research presents a performance comparison of low–cost particulate matter (PM2.5) sensors, widely used in Internet of Things (IoT) applications for air quality monitoring. Since sensor calibration is often costly, this study proposes a cost–reduction strategy by applying pre–calibration before full calibration. The SPS30 was selected as the primary reference device due to its combination of low cost and near–regulatory–grade performance. Unlike other low–cost sensors, the SPS30 benefits from factory calibration against reference instruments (e.g., TSI DustTrak DRX 8533, OPS 3330), and it has demonstrated very low intra–model variability (<1.5% for PM2.5) and strong correlations across all concentrations with Federal Equivalent Method (FEM) instruments. It is also MCERTS–certified (UK Environment Agency), confirming its compliance with PM2.5 monitoring standards. To validate the methodology, the SPS30's accuracy was additionally examined using an air purifier in the test setup. A nonlinear mathematical model was then applied to calibrate commonly used sensors, including the Plantower PMS series (PMS7003, PMS5003, PMS3003) and SDS011. Experiments were conducted in an indoor environment at 33 ± 1°C and 69 ± 4% relative humidity. The results showed coefficient of determination values of 0.98, 0.98, 0.96, and 0.88, with root mean square error values of 1.2, 1.47, 1.84, and 3.26 for the PMS7003, PMS5003, PMS3003, and SDS011, respectively. The findings indicate that low–cost sensors, particularly the PMS7003 and PMS5003, can achieve high measurement accuracy when combined with appropriate pre–calibration and a suitable reference device. The SDS011 also demonstrated consistent performance. In addition, applying a nonlinear model reduces costs and enhances sensor reliability. For initial deployment, pre–calibration lowers expenses by approximately one–third compared to full calibration, while pairwise pre–calibration for recalibration can substantially reduce or even eliminate recurring calibration costs during long–term operation and maintenance. These results highlight the practicality of deploying low–cost sensors in air quality monitoring applications.

Keywords: Low–cost, Nonlinear calibration, PM2.5 sensors, Internet of Things (IoTs), Air quality monitoring

1. Introduction

Particulate matter (PM), especially PM with a diameter of 2.5 micrometers (PM2.5), is a major contributor to air pollution globally, posing serious risks to human health. In 2019, the World Health Organization (WHO) estimated that a significant portion of premature deaths caused by outdoor air pollution was linked to health impacts from fine PM, especially PM2.5. These tiny particles can penetrate deep into the lungs and enter the bloodstream, leading to serious health conditions. According to WHO, about 68% of these deaths were due to ischemic heart disease and stroke, 14% were caused by chronic obstructive pulmonary disease (COPD), another 14% were from acute lower respiratory infections, and 4% were due to lung cancer. This highlights the hidden danger of air pollution, particularly PM2.5, as a silent threat to global human health [1]. To mitigate risks, online PM2.5 monitoring has become increasingly important, with most systems relying on low–cost sensors. However, ensuring the accuracy of these sensors remains a significant challenge.

Low–cost PM2.5 sensors (LCSs) typically use one of two principles for detecting PM: the photometer principle or the laser scattering principle. Laser scattering methods, based on Fraunhofer and Mie theories, provide detailed particle size distributions by analyzing light diffraction and scattering patterns. Unlike photometers, which measure only bulk light attenuation, laser scattering can resolve size–dependent scattering intensities and detect a wide range of particle sizes with high accuracy. This makes it more suitable for precise particle characterization, especially in research and industrial applications [2]. On the other hand, the laser scattering principle offers an effective and economical solution for low–cost applications, albeit with some trade–offs in measurement accuracy. To enhance the accuracy of their sensors, the low–cost sensors were calibrated before use. Two calibration methods were employed: linear (traditional) [3–7] and non–linear (polynomial) methods [8],[9]. Linear calibration is a common method for correcting measurement deviations in the LCSs like the PMS7003, PMS5003, and SDS011. However, this approach often fails to account for significant errors at higher particulate concentrations. These inaccuracies stem largely from the inherent nonlinear response of low–cost sensors, causing substantial deviations from reference devices. To address this limitation, nonlinear calibration techniques, particularly polynomial regression models of an appropriate degree (typically second or third order), have been explored. These models enable a more accurate mapping between raw sensor output and true concentration values from certified reference instruments. By fitting a polynomial curve to the observed sensor–reference data, it becomes possible to correct both offset and sensitivity errors, as well as more complex nonlinearities across a wider concentration range [9],[10].

The LCSs such as the PMS3003, PMS5005, PMS7003, and SDS011 have become increasingly popular with IoTs–based monitoring systems [11],[12],[13],[14]. However, these sensors are generally not pre–calibrated before being released to the market, resulting in significant measurement inaccuracies, especially at higher particle concentrations. In contrast, the higher–end LCSs like the SPS30 sensor are factory–calibrated [15] and exhibit greater accuracy and stability across a broad range of conditions. The lack of pre–calibration in the LCSs presents a major challenge. Post–deployment calibration typically involves multiple iterations of sensor validation and correction using reference devices. This process not only increases implementation costs but also limits scalability for widespread deployment. Additionally, many low–cost sensors exhibit nonlinear response characteristics, meaning that traditional (the linear mathematical model) calibration techniques often fail to provide adequate correction, particularly in variable environmental conditions. To mitigate these limitations, this study proposes the nonlinear pre–calibration framework for selected the LCSs using the SPS30 sensor as a reference device. By employing the nonlinear regression models, particularly third–degree polynomial fitting. This pre–calibration method significantly reduces the cost of multiple iterations of sensor validation.

2. Materials and Methods

2.1 Low–cost sensors

In this study, we investigated the use of the LCSs for monitoring PM2.5, in indoor environments. These LCSs, such as the PMS7003/5003/3003, SDS011, and SPS30, are widely used in Internet of Things (IoTs) applications due to their ability to measure PM2.5 concentrations in real time. The LCSs employ a light–scattering technique to measure PM concentrations. **Table 1** summarizes the basic specifications of these LCSs [15–19]. All the LCSs can detect PM2.5 concentrations up to approximately 1000 $\mu g/m^3$. Their maximum operating temperature is around 60°C, except for the SDS011 which has a maximum of 50°C. Similarly, all the LCSs can operate in a maximum humidity range exceeding 95%, except for the SDS011 which is limited to 70%. The SDS011 also has higher power consumption compared to the other LCSs, although all operate under a 5 V ± 0.5 V power supply. All the LCSs communicate with microcontrollers or microcomputers via the Universal Asynchronous Receiver Transmitter (UART) protocol. The SPS30 was selected as the primary reference device due to its combination of low cost, portability, accuracy, reliability, and practicality. Unlike other the LCSs, the SPS30 benefits from factory calibration using reference instruments such as the TSI DustTrak™ DRX 8533 Ambient Mode and TSI OPS 3330. It has also been extensively evaluated against FEM instruments (e.g., GRIMM, MetOne BAM, T640), demonstrating very low intra–model variability (<1.5% for PM2.5) and strong correlations (the coefficient of determination is approximately 0.83 for PM2.5) [20]. Furthermore, the SPS30 supports flexible communication via both UART and Inter–Integrated Circuit (I2C) protocols. The sensor is certified under the MCERTS Performance Standards by the UK Environment Agency and assessed by CSA Group, confirming its compliance with PM2.5 measurements [21]. These features collectively indicate that the SPS30 provides near–regulatory–grade performance and is suitable as a reference device for this study.

Table 1 List of the LCSs with models and basic details.

Details	PMS7003 /5003/3003	SDS011	SPS30
Detection range ($\mu g/m^3$)	0.3 – ~1000		
Temperature range (°C)	-10 ~ +60	-10 ~ +50	-10 ~ +60
Humidity range (%)	0 ~ 99	0~70	0~ 95
Power supply (V)	5±0.5	4.7~ 5.3	5±0.5
Power consumption (W)	0.5	>1	0.4
Maximum error (%)	±10	±15	±10
Communications	UART	UART	I2C/UART
Factory–calibrated	NA	NA	YES
Price (USD)	18.57 /18.84 /17.62	25.76	70.09

2.2 The cubic polynomial regression

The cubic polynomial regression model was selected for pre–calibration because it effectively captures the nonlinear response of low–cost PM sensors, which linear models cannot adequately represent. Linear calibration performs well for particle number concentration. Still, it is less accurate for mass concentration, especially at higher ranges, and adding parameters such as refractive index or humidity does not always improve performance [9]. Polynomial regression offers a flexible framework that minimizes errors, aligns sensor outputs with reference devices, and inherently incorporates the linear model when higher–order coefficients are zero, thereby ensuring adaptability and robustness [10]. This model was employed to express the relationship between the raw LCS output (PM_{LCS}) and the reference PM2.5 concentration (PM_{RD}) to evaluate calibration performance. The cubic polynomial regression can be expressed as

$$PM_{RD} = a_1 * PM_{LCS} + a_2 * PM_{LCS}^2 + a_3 * PM_{LCS}^3 + C \quad (1)$$

where the parameters a_1, a_2, and a_3 are denoted as the slope factors of low, medium, and high PM2.5 concentrations, respectively. The parameter C represents the intercept of the cubic polynomial regression. These parameters were modified and can be represented by

$$\begin{cases} a_1 = \dfrac{\sum_{i=0}^{n} PM_{RD(i)}}{\sum_{i=0}^{n} PM_{LCS(i)}} \\ a_2 = \dfrac{\sum_{i=0}^{n} PM_{RD(i)} - \{a_1 \sum_{i=0}^{n} PM_{LCS(i)} + C\}}{\sum_{i=0}^{n} PM_{LCS(i)}^2} \\ a_3 = \dfrac{\sum_{i=0}^{n} PM_{RD(i)} - \{a_1 \sum_{i=0}^{n} PM_{LCS(i)} + a_2 \sum_{i=0}^{n} PM_{LCS(i)}^2 + C\}}{\sum_{i=0}^{n} PM_{LCS(i)}^3} \\ C = \sum_{i=0}^{n} PM_{RD(i)} - a_1 \sum_{i=0}^{n} PM_{LCS(i)} \end{cases} \quad (2)$$

where n is the number of measurements.

2.3 The coefficient of determination and the root mean square error statistics

Eqs. (3)–(4) represent the coefficient of determination and the root mean square error, where the parameters PM_{xi}, PM_{yi}, $\overline{PM_y}$ and n are the PM2.5 values from the calibrated LCSs, the PM2.5 values from the reference device, the PM2.5 average concentration from the reference device, and the number of measurements, respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(PM_{xi} - PM_{yi})^2}{\sum_{i=1}^{n}(PM_{yi} - \overline{PM_y})^2} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(PM_{xi} - PM_{yi})^2}{n}} \quad (4)$$

3. Sensor Nodes and Uncalibrated LCSs

3.1 Sensor nodes

To demonstrate the capabilities of the LCSs, we designed a system for online PM2.5 recording using Google Sheets services. **Figure 1(a)** shows the sensor nodes sending PM2.5 data to the Google Sheet via an access point with Wi–Fi. **Figure 1(b)** shows the block diagram of a sensor node. It includes an ESP32–based NodeMCU microcontroller connected to a DHT22 sensor (reading temperature and humidity) and the LCS (PM2.5 sensor). The specific LCSs for sensor nodes 1 to 5 are the PMS7003, PMS5003, PMS3003, SDS011, and SPS30, respectively. **Figure 1(c)** illustrates the implementation of the sensor nodes.

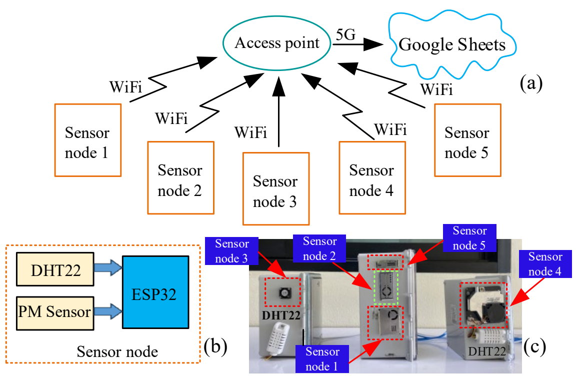


Figure 1 Sensor nodes for **(a)** recording PM2.5 data on Google Sheets **(b)** the block diagram **(c)** implementation.

3.2 Uncalibrated LCSs

Particulate matter generated from stick incense can reach PM2.5 concentrations of up to approximately 1000 µg/m³ [22]. This characteristic has been utilized to generate PM2.5 in a controlled laboratory chamber for testing and comparing the performance of various PM2.5 monitoring instruments. In this study, the experimental chamber had a volume of approximately 1 m³ and was equipped with LCSs and a reference device, positioned approximately 10 cm apart to ensure uniform particle distribution. To sweep the PM2.5 concentration for calibration purposes, particles were generated by burning stick incense until the desired maximum concentration was achieved, after which particle generation was ceased. The concentration subsequently decreased gradually through continuous air intake by an air purifier, allowing a controlled sweep from high to low levels. Measurements from both the LCS and the reference device were recorded every 10 seconds, providing time–resolved data for plotting calibration curves and evaluating sensor responses. The criteria for selecting the reference device included its ability to provide reliable PM2.5 measurements from incense–generated particles, incorporate PM2.5 filtration, be cost–effective, and be readily available. Based on these considerations, the Xiaomi Mi Air Purifier 2S (RD_{AP2S}) was selected as the reference device. This unit is equipped with the Plantower PMS9003M, a laser–based optical particle counter that detects particles of 0.3 µm or greater and reports PM2.5 mass concentrations in the range of 0–1000 µg/m³ with a resolution of 1 µg/m³. According to the manufacturer's datasheet, the reported consistency error is ±10% for concentrations between 100 and 500 µg/m³ [23]. While the manufacturer does not provide explicit evidence of calibration against FRM or FEM instruments, previous studies have shown that Plantower PMS sensors correlate well with FRM or FEM instruments, though potential systematic biases may arise under varying humidity or aerosol composition [24]. Furthermore, previous studies have reported that the Xiaomi PM2.5 monitor exhibits a strong linear correlation with the GRIMM when measuring PM2.5 from stick incense across the full concentration range [25]. Together, these findings provide additional confidence in using the RD_{AP2S} as a practical reference device in this study.

Figure 2 shows a comparison of uncalibrated PM2.5 concentration measurements by the LCSs with those of the RD_{AP2S}. The demonstration started with an initial PM2.5 concentration of 600 $\mu g/m^3$ and was recorded over 1000 seconds. It can be observed that the PM2.5 measurements from the SPS30 sensor were closer to those of the RD_{AP2S} compared to the other sensors. The PM2.5 measurements from the PMS7003, PMS5003, and PMS3003 were higher than those of the RD_{AP2S}, while the PM2.5 measurements from the SDS011 sensor were the lowest.

Figure 3 shows plotted graphs of the PM2.5 concentration of each uncalibrated LCSs versus the RD_{AP2S}. The uncalibrated PM2.5 measurements from the SPS30 sensor were closer to the RD_{AP2S} likely because it had already been factory–calibrated with the TSI DustTrak™ DRX 8533 Ambient Mode and the TSI OPS 3330 reference devices [15].

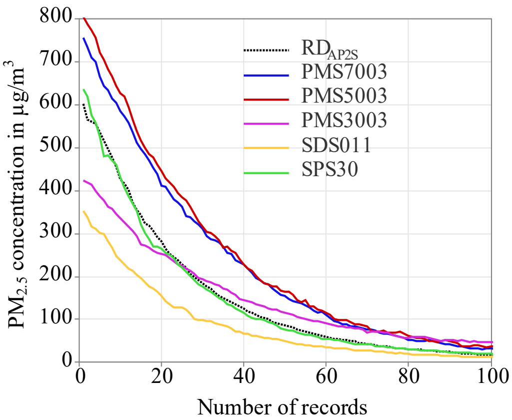
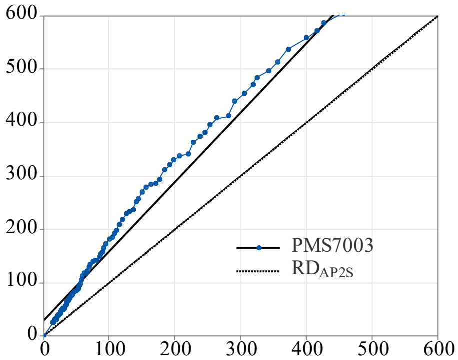


Figure 2 Comparison of uncalibrated PM2.5 measurements by the LCSs with the RD_{AP2S}.



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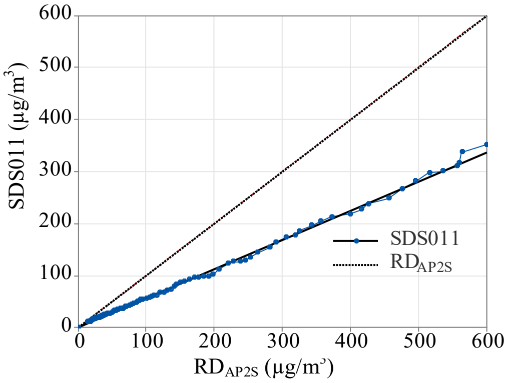

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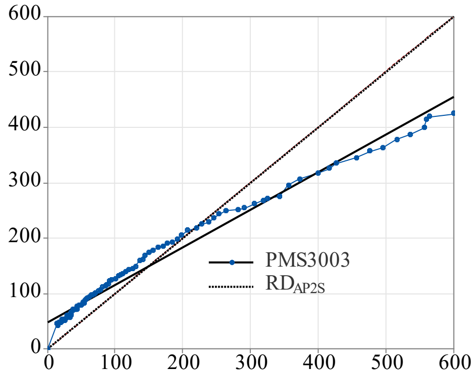

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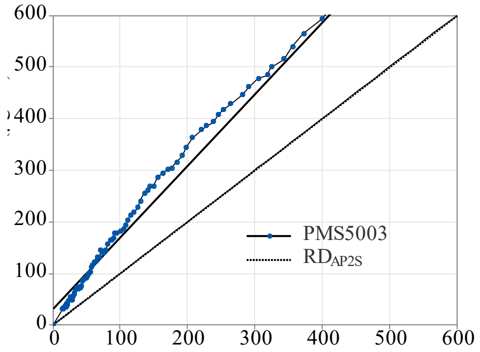

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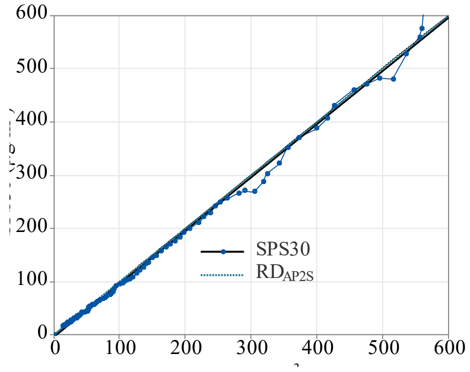


(**e**)

Figure 3 Plotted graphs of the PM2.5 of each uncalibrated LCSs vs. the RD_{AP2S} (**a**) PMS7003 vs. the RD_{AP2S} (**b**) SDS011 vs. the RD_{AP2S} (**c**) PMS3003 vs. the RD_{AP2S} (**d**) PMS5003 vs. the RD_{AP2S} (**e**) SPS30 vs. the RD_{AP2S}

4. Pre–calibrated LCSs

4.1 LCSs calibrated comparison with the RDAP2S

Therefore, we have been calibrated all LCSs except the SPS30 sensor. The LCSs were calibrated using the cubic polynomial regression calibration from Eqs. (1)–(2). **Table 2** summarizes the parameters a_1, a_2 and a_3. **Figure 4** shows a comparison of uncalibrated PM2.5 concentration measurements by the LCSs with those of the RD_{AP2S}. **Figure 5** displays graphs of the PM2.5 concentration for each calibrated LCSs versus the RD_{AP2S}. The PM2.5 concentrations of all the calibrated LCSs were closer to the PM2.5 concentrations from the RD_{AP2S}.

Table 2 The parameters a_1, a_2, a_3 and C.

LCS	Parameters			
	a_1	a_2	a_3	C
PMS7003	0.56	16.73×10^{-6}	452.43×10^{-9}	-1.53
PMS5003	0.51	100.91×10^{-6}	272.39×10^{-9}	-0.68
PMS3003	0.47	2.46×10^{-6}	-173.38×10^{-9}	-1.25
SDS011	1.76	119.66×10^{-6}	-487.59×10^{-9}	-0.93

Table 3 presents the comparison of uncalibrated versus calibrated performance. The PM2.5

concentration levels are classified into three categories: high (300–600 μg/m³), medium (100–300 μg/m³), and low (0–100 μg/m³). To obserbed uncalibrated LCSs, the SPS30 achieved an R^2 of approximately 1 across all PM2.5 concentration levels. Additionally, it had an RMSE of 3.77 at low PM2.5 concentrations. Other LCSs achieved low R^2 and high RMSE values. After calibration, all LCSs except the SPS30 showed improved performance, with increased R^2 values and decreased RMSE ranges compared to their uncalibrated state. The factory–calibrated SPS30 maintained a near–perfect R^2 of approximately 1 across all PM2.5 concentration levels.

The other calibrated LCSs achieved varying R^2 values (generally lower than the SPS30) and had the following RMSE ranges: PMS7003 (2.23–15.87 μg/m³), PMS5003 (2.50–14.14 μg/m³), PMS3003 (5.58–20.88 μg/m³) ,and SDS011 (4.07–11.25 μg/m³). In summary, among the uncalibrated LCSs, the SPS30 demonstrated higher accuracy due to its factory calibration. Therefore, we used the SPS30 as a reference device (RD_{SPS30}) for comparison with the Xiaomi Mi Air Purifier 2S reference device (RD_{AP2S})

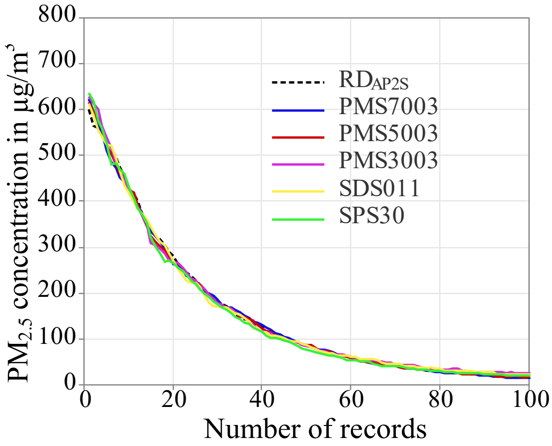
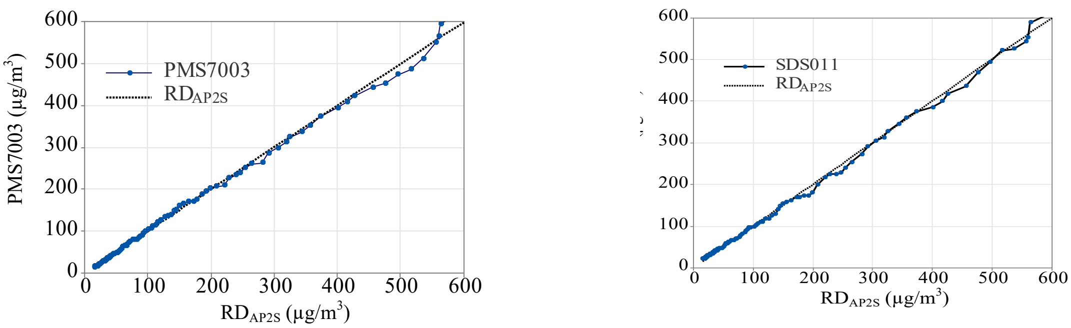


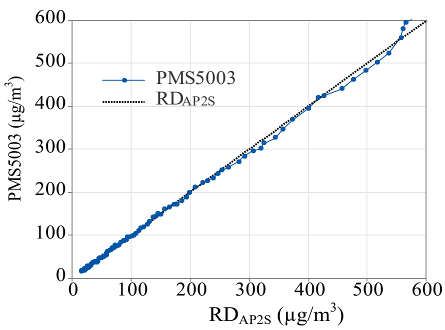
Figure 4 Comparison of uncalibrated PM2.5 measurements by the LCSs with the RD_{AP2S}

Table 3 Comparison of uncalibrated vs. calibrated performance: coefficient of determination and root mean square error statistics for different PM2.5 levels.

Sensor node	LCS model	PM2.5 level	Uncalibrated		Calibrated (calculated)	
			R^2	RMSE	R^2	RMSE
1	PMS7003	High	-1.57	150.27	0.97	15.87
		Medium	-3.32	117.66	0.99	6.30
		Low	-1.59	36.88	0.99	2.23
2	PMS5003	High	-3.15	190.75	0.98	14.14
		Medium	-4.41	131.66	0.99	4.43
		Low	0.28	42.94	0.99	2.50
3	PMS3003	High	-0.45	112.72	0.95	20.88
		Medium	0.88	19.82	0.99	5.21
		Low	-0.66	29.55	0.94	5.58
4	SDS011	High	-3.43	197.13	0.99	11.25
		Medium	-1.21	84.10	0.97	9.09
		Low	0.32	18.92	0.97	4.07
5	SPS30	High	0.94	22.96	–	–
		Medium	0.98	8.91	–	–
		Low	0.97	3.77	–	–



(a) **(b)**



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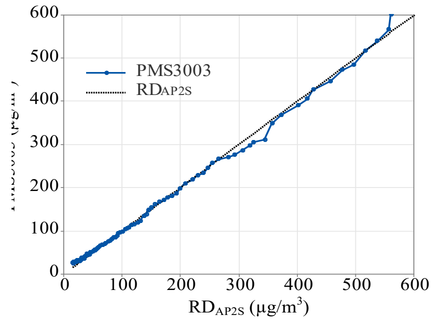


(**d**)

Figure 5 Plotted graphs of the PM2.5 of each calibrated LCSs vs. the RDAP2S. (**a**) PMS7003 vs. the RDAP2S (**b**) PMS5003 vs. the RDAP2S (**c**) PMS3003 vs. the RDAP2S (**d**) SDS011 vs. the RDAP2S

4.2 LCSs calibrated comparison with the RD_{SPS30}

Table 4 displays the comparison of the LCSs performance across all PM2.5 concentration levels. These low–cost sensors were uncalibrated and compared with the RD_{AP2S}. The SPS30 shows an R^2 value close to 1 and lower RMSE values than other low–cost sensors. When the calibrated LCSs were compared with the RD_{AP2S}, they achieved an R^2 of approximately 1 and RMSE values ranging from 6.34 to 9.88 $\mu g/m^3$. Compared with the RD_{SPS30} the calibrated LCSs also achieved an R^2 of approximately 1 and RMSE values ranging from 7.34 to 10.22 $\mu g/m^3$. This comparison indicates that the R^2 and RMSE of the calibrated LCSs compared with the RD_{SPS30} are nearly identical to those compared with the RD_{AP2S}. In summary, the PMS7003, PMS5003, PMS3003 and SDS011 LCSs were calibrated with the RD_{SPS30} achieved R^2 and RMSE values close to the RD_{AP2S} **Figure 6** displays graphs of the PM2.5 concentration for calibrated the PMS7003, PMS5003, PMS3003, and SDS011 LCSs versus the RD_{SPS30} The PM2.5 concentrations of all the calibrated LCSs were closer to the PM2.5 concentrations from the RD_{SPS30}. The spiky points around 280 and 500 $\mu g/m^3$ are likely caused by transient non–uniform particle distribution in the 1 m^3 chamber, leading to short–term mismatches between the LCSs and RD_{SPS30} readings. Nevertheless, the deviations are limited (e.g., less than 6% for PMS3003) and do not significantly affect the overall calibration performance. **Table 5** presents the comparison of the LCS performance by classifying into three categories of the PM2.5 ranges which are high, medium, and low ranges. These LCSs were calibrated with the RD_{SPS30}. All the LCSs achieved an R^2 of approximately 1 and lower RMSE than 20 $\mu g/m^3$.

Table 4 Coefficient of determination and root mean square error statistics: comparison of uncalibrated vs. performance calibrated with the RD_{AP2S} and RD_{SPS30}.

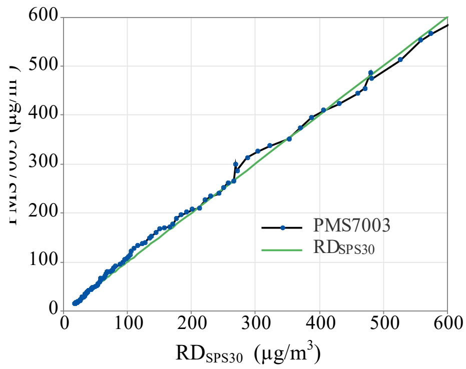
LCSs vs RD	**LCS models**	**Calculated**	
		R^2	**RMSE**
Uncalibrated vs RD_{AP2S}	PMS7003	0.663	90.19
	PMS5003	0.518	107.78
	PMS3003	0.925	52.16
	SDS011	0.647	92.28
	SPS30	0.997	10.80

Table 4 Coefficient of determination and root mean square error statistics: comparison of uncalibrated vs. performance calibrated with the RD_{AP2S} and RD_{SPS30}.(cont.)

LCSs vs RD	**LCS models**	**Calculated**	
		R^2	**RMSE**
Calibrated vs RD_{AP2S}	PMS7003	0.998	7.43
	PMS5003	0.998	6.34
	PMS3003	0.996	9.88
	SDS011	0.998	7.21
Calibrated vs RD_{SPS30}	PMS7003	0.997	8.85
	PMS5003	0.998	7.34
	PMS3003	0.997	7.8
	SDS011	0.996	10.22

Table 5 Coefficient of determination and root mean square error statistics for different PM2.5 levels: comparison of the LCSs vs. the RD_{SPS30}.

LCS models	**PM2.5 levels**	**Calculated**	
		R^2	**RMSE**
PMS7003	High	0.98	12.34
	Medium	0.95	13.03
	Low	0.96	4.71
PMS5003	High	0.99	11.95
	Medium	0.97	9.59
	Low	0.97	4.02
PMS3003	High	0.98	12.69
	Medium	0.98	7.45
	Low	0.93	6.20
SDS011	High	0.96	19.25
	Medium	0.96	11.39
	Low	0.95	5.34



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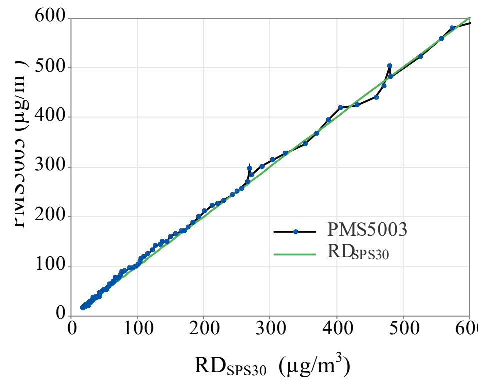

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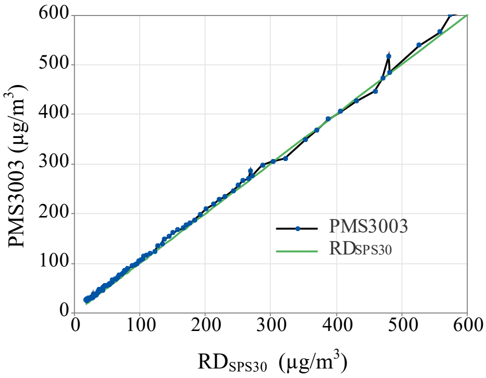

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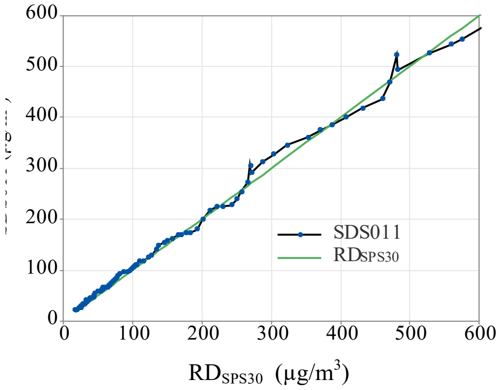

(**d**)

Figure 6 Plotted graphs of the PM2.5 concentration of the each calibrated LCSs vs. the RD_{SPS30} (**a**) PMS7003 vs. the RDSPS30 (**b**) PMS5003 vs. the RDSPS30 (**c**) PMS3003 vs. the RDSPS30 (**d**) SDS011 vs. the RDSPS30

4.3 Indoor environment

For this study, all sensing devices were set up in an indoor environment. The monitoring of fine PM2.5 concentrations was specifically conducted by installing these devices in areas with active air exchange, such as near entrances or corridors that are exposed to outdoor airflow, as illustrated in **Figure 7**. These locations were strategically chosen due to their high potential for air exchange between indoor and outdoor environments, thereby enhancing the effectiveness of detecting PM by infiltrating the building. Such positioning enables more accurate tracking of PM2.5 concentration trends and provides a realistic representation of indoor air quality conditions. Data acquisition was performed using wireless communication via Wi–Fi, with all measurements automatically recorded to a Google Sheet. The continuous monitoring period was extended over a duration of six days.

Figure 7 Photograph of the indoor environment for all the LCS experiments with the RD_{SPS30}.

Table 6 shows the comparison of R^2 and RMSE for the PM2.5 indoor environment with comparison of the LCSs versus the RD_{SPS30}. To observe that an R^2 of approximately 1 and less RMSE values when the temperatures are less than 35 Celsius degree and the humidities are more than 65 percent, respectively.

Table 7 summarizes the performance of the five low–cost PM2.5 sensors evaluated in this study. It reports: a) overall sensor ratings from indoor tests with optimal temperature (T) and relative humidity (RH) where applicable, and b) average R^2 and RMSE over six days of indoor monitoring (from **Table 6**). PMS7003 and PMS5003 perform best under specific indoor conditions (T ≈ 33 ± 1°C, RH ≈ 69 ± 4%), while SDS011 maintains consistent accuracy. SPS30, the reference sensor, is factory–calibrated and MCERT–certified, providing a reliable baseline.

Table 6 Coefficient of determination and root mean square error statistics for PM2.5 indoor environment: comparison of the LCSs vs. the RD_{SPS30}.

Day	LCS model	Calculated		T(°C)	RH(%)
		R^2	RMSE		
1	PMS7003	0.53	4.05	37 ± 2	51 ± 9
	PMS5003	0.49	4.23		
	PMS3003	0.28	5.03		
	SDS011	0.75	2.98		
2	PMS7003	0.67	4.46	35.5 ± 4.5	56.5 ± 16.5
	PMS5003	0.73	4.02		
	PMS3003	0.78	3.66		
	SDS011	0.92	2.21		
3	PMS7003	0.83	4.79	36.5 ± 4.5	52 ± 18
	PMS5003	0.83	4.77		
	PMS3003	0.81	5.01		
	SDS011	0.91	3.47		
4	PMS7003	0.54	6.75	35 ± 4	54 ± 13
	PMS5003	0.58	6.46		
	PMS3003	0.35	8.01		
	SDS011	0.85	3.85		
5	PMS7003	0.98	1.2	33 ± 1	69 ± 4
	PMS5003	0.98	1.47		
	PMS3003	0.96	1.84		
	SDS011	0.88	3.26		
6	PMS7003	0.98	2.11	31 ± 1	72 ± 6
	PMS5003	0.95	3.04		
	PMS3003	0.86	5.03		
	SDS011	0.95	2.96		

4.4 Quantifying Cost Reduction via Pre–Calibration of Low–Cost Sensors

Before deploying LCS in real environment, proper calibration is essential to ensure measurement accuracy. Typically, two to three calibration events per sensor are required, at an estimated cost of 500 USD per event, resulting in approximately 1,500 USD per sensor. By contrast, the proposed pre–calibration approach combined with a single full calibration requires only 500 USD, yielding a cost reduction of about 66.7%. (Note: these estimates exclude travel, labor, and ancillary expenses.) Previous studies Gäbel and Hertig [26] indicate that LCS generally require seasonal recalibration with reference instruments or standardized PM2.5 monitoring stations to maintain high quantitative accuracy. To address this challenge, pairwise calibration against a reference or reliable sensor on a monthly basis has been recommended as a practical and cost–saving alternative. For the SPS30, performance evaluations demonstrated stable accuracy across concentration ranges and time periods, likely due to the built–in calibration algorithm provided by Sensirion, consistent with prior findings [15],[20],[21]. Thus, unlike many other LCS, the SPS30 does not require monthly recalibration.

In scenarios where seasonal recalibration is applied (three times annually), the cost amounts to 1,500 USD per year. With pairwise pre–calibration used for ongoing maintenance, additional calibration costs can be minimized, resulting in up to 100% cost savings compared to conventional approaches. Therefore, for initial deployment, pre–calibration reduces costs by approximately 66.7%, while for long–term operation, pairwise pre–calibration can virtually eliminate recurring calibration expenses.

Table 7 Summary of sensor performance:

Sensor	Rank/Category	Indoor Use	Outdoor Use	Avg. R^2	Avg. RMSE (μg/m^3)	Notes
SPS30	Best/ Reference device	Excellent	N/A	N/A	N/A	Factory–calibrated, MCERT certified
PMS7003	Best/ (in optimal T/RH)	Very Good	N/A	0.755	3.89	R^2~0.98 and RMSE ~1.2 at T = 33 ± 1°C and RH = 69 ± 4%
PMS5003	Best/ (in optimal T/RH)	Very Good	N/A	0.76	4.00	R^2~0.98 and RMSE ~1.47 at T = 33 ± 1°C and RH = 69 ± 4%
SDS011	Consistently Good	Very Good	N/A	0.88	3.12	R^2~0.88 and RMSE ~3.26 at T = 33 ± 1°C and RH = 69 ± 4%
PMS3003	Suitable for general use	Moderate	N/A	0.67	4.76	R^2~0.96 and RMSE ~1.84 at T = 33 ± 1°C and RH = 69 ± 4%

Note: Average values are based on the full six–day indoor dataset (**Table 6**). Optimal conditions were identified from daily variability

In practical terms, the calculation of cost savings is straightforward. The percentage reduction in cost can be expressed as Eq. (5)

$$\text{Cost Reduction (\%)}=\frac{\text{Cost}_{\text{Full}}-\text{Cost}_{\text{Pre}}}{\text{Cost}_{\text{Full}}}\times 100 \quad (5)$$

where $\text{Cost}_{\text{Full}}$ and Cost_{Pre} are defined as the full calibration cost and pre–calibration cost, respectively.

In conclusion, pre–calibration and pairwise pre–calibration represent a cost–effective strategy for LCS deployment. This approach significantly reduces calibration expenditures, maintains data reliability, and enhances operational efficiency. By demonstrating concrete cost comparisons, this study substantiates the proposal that pre–calibration offers a resource–efficient and financially sustainable pathway for air quality monitoring programs.

5. Conclusions

This study aimed to compare the performance of commonly used the LCSs (the PMS7003, PMS5003, PMS3003, and SDS011) in IoTs air quality monitoring systems. We introduced the nonlinear (the cubic polynomial regression) pre–calibration approach to enhance their accuracy without requiring expensive reference–grade instruments for every calibration, utilizing the high–accuracy, factory–calibrated Sensirion SPS30 sensor as an internal reference. Our experiments, conducted in an indoor environment, demonstrated that applying the cubic polynomial regression models significantly improved sensor accuracy, with the PMS7003 and PMS5003 showing the best correlation to the SPS30 reference, and a clear increase in R^2 values after pre–calibration. This nonlinear pre–calibration method offers an efficient and cost–effective alternative to traditional calibration, which typically requires multiple repetitive tests. The low–cost PM2.5 sensors evaluated in this study demonstrated good accuracy at low to medium concentrations but showed larger errors at higher levels. The use of adaptive parameter sets (a_1, a_2, a_3) for different concentration ranges, while accounting for temperature and humidity variations, is highly valuable and could further improve sensor performance.

However, it is important to note that while the SPS30's high performance our internal accuracy assessment using an air purifier, though practical for a cost–effective setup, represents a simplified approach compared to rigorous validation with FRM or FEM. This highlights that when these LCSs are deployed in dynamic outdoor environments with numerous additional influencing factors, further calibration using standard reference instruments like FRM or FEM may still be required to ensure optimal accuracy and reliability. Although this study evaluated the sensor performance in an indoor environment with air ventilation, certain limitations remain in fully reflecting sensor behaviour under highly dynamic real–world conditions. Therefore, future work should extend evaluations to diverse outdoor conditions, considering environmental variables such as temperature, humidity, and wind, as well as investigate long–term sensor stability and the influence of different particulate matter characteristics. Such comprehensive assessments will provide stronger evidence of the sensor's performance in practical applications.

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