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Evaluations of Low-cost Air Quality Sensors for Particulate Matter ($PM_{2.5}$) under Indoor and Outdoor Conditions

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Air quality (AQ) monitoring is crucial for maintaining human health and well-being, whether outdoors or indoors. Particulate matter (PM) is among the most critical parameters that must be routinely monitored. Traditional reference particulate analyzers are expensive and difficult to deploy on a large scale, leading to poor spatial and temporal AQ information. However, the reliability and accuracy of these sensors are yet to be established. This study is aimed at assessing the performance of five low-cost sensors by comparing them with a particulate reference analyzer for AQ monitoring in accordance with the United States Environmental Protection Agency (US EPA)-recommended guidelines. The sensors were tested for indoor and outdoor environments using simple linear regression (SLR) models. The results indicate that low-cost sensors are unreliable for accurately measuring AQ in indoor environments. The correlation between the sensors and the reference analyzer was poor, with coefficient of determination (R^2) values ranging from 0.2 to 0.58 during the three-week analysis period for a 1-h average. However, after increasing the average time interval, the sensor (HPMA115) satisfied the US EPA-recommended guideline with an R^2 value of 0.72. Root-mean-square error ($RMSE$) values for some sensors exceeded the US EPA guideline of less than 7 μgm^{-3} for PM sensors. The concentration of $PM_{2.5}$, indoor relative humidity (RH), and temperature were identified as potential factors contributing to sensor behavior. The air conditioning system also affected the sensor performance, with variations in RH and temperature observed between tests with and without occupants. The results showed that low-cost sensors could be utilized for outdoor

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environments, with Honeywell's HPMA115 performing well. However, the calibration process must be performed for each specific environment. Our findings highlighted the limitations of low-cost sensors for AQ monitoring and the need for further research to develop reliable sensors.

1. Introduction

The occurrence of haze phenomena is consistently associated with elevated concentrations of particulate matter (PM) $PM_{2.5}$ and PM_{10}.(1) These PM pollutants pose significant risks to human respiratory health, including the development of lung cancer, heart disease, and eye irritation.(1) As a result, numerous countries have implemented continuous AQ monitoring stations (CAQMS) to assess $PM_{2.5}$ and PM_{10} levels in ambient air. The most common techniques for monitoring $PM_{2.5}$ and PM_{10} are to use the tapered element oscillating microbalance (TEOM) and the beta attenuation monitor (BAM), both of which are recommended by the United States Environmental Protection Agency (US EPA). However, the limitations of relying solely on TEOM and BAM techniques for PM monitoring include high instrument and maintenance costs, dependence on skilled personnel for calibration, and the need for secure locations.(2) Consequently, only a limited number of CAQMS are installed, often located away from emission sources, resulting in inadequate spatial AQ data coverage and the neglect of the influence of local emission sources.(3) Because of the limitations of these traditional methods, a paradigm shift towards using small, portable, low-cost, and real-time sensor packages for AQ measurement is necessary.

The current alternative for monitoring AQ, which is gaining much attention among researchers worldwide, involves using a low-cost AQ sensor (LAQS).(4,5) The effectiveness of LAQS has been evaluated in various AQ network settings, including urban areas, rural areas, roadside, and laboratory environments.(6,7) These models include the renowned Alphasense OPC-N2,(8) Shinyei PPD,(7,9) and Plantower PMS3003 and PMS5003.(10) Some LAQS demonstrated impressive values of the coefficient of determination (R^2) when collocating by the Federal Reference Method (FRM) or Federal Equivalent Method (FEM), with some R^2 values being up to 0.92.(7–10) Because of the cost-effectiveness of LAQS, deploying these sensors in multiple locations can significantly enhance the resolution of temporal and spatial AQ data.

Despite the satisfactory R^2 values, it is crucial to consider certain limitations associated with the data obtained from LAQSs, including uncontrolled relative humidity (RH) and temperature, validation and calibration reliability, and the presence of other pollutants.(3,4,11) In tropical regions like Malaysia, high humidity levels may influence LAQS measurements. Therefore, conducting further investigations using LAQS is necessary to evaluate their performance.

Moreover, the absence of a well-established method to ensure data quality during field deployment of LAQS raises concerns. In previous studies, different assessment techniques, such as simple linear regression (SLR), multiple linear regression (MLR), and the adaptive neuro-fuzzy inference system (ANFIS), have been proposed, resulting in varying outcomes.(12–14) To address this issue, the US EPA has introduced Micro Analysis Tools (MAT), a dedicated assessment tool for LAQS, that generates R^2 and Bias.(15) In addition, the US EPA has introduced its performance metric guideline specifically designed for assessing the performance of LAQS.(16) These advancements are aimed at the standardization of the assessment process and enhancement of the reliability of LAQS measurements. The primary objective of this study is to build upon the findings of Alhasa *et al.*(12), who primarily focused on developing a calibration method for O_3, NO_2, and CO. In contrast, we aim to assess various types of PM sensors through laboratory and field-testing experiments. Furthermore, we employ MAT to generate R^2 and Bias. Additionally, we evaluate all the sensors using the performance metrics for LAQS provided by the US EPA.

2. Methodology

Five state-of-the-art commercial sensors were selected for this experiment from various credible manufacturers, namely, SEN55 (Sensirion AG.), SPS30 (Sensirion AG.), PMS5003 (Beijing Plantower Co. Ltd.), HPMA115S0 (Honeywell International Inc.), and ZH03B (Zhengzhou Winsen Electronics Technology). The critical specifications for all the LAQS are shown in Table 1. The main factors for choosing all the sensors used in this experiment are cost and size. The usual price for LAQS ranges from 50–1000 US dollars (USD). LAQS costing less than USD 100 were chosen for testing in this experiment. LAQSs such as PMS7003 (Plantower, China), PMS5003 (Plantower, China), ZH03B (Winsen, China), and OPC-N2 (Alphasense, UK) have been evaluated in various studies and were shown to be promising tools for monitoring PM.(17) Some models even show that the LAQS R^2 with a reference instrument is higher than 0.70. R^2, which is higher than the benchmark established in the Performance Testing Protocols, Metrics, and Target Values for Fine Particulate Matter Air Sensors Guidebook provided by the US EPA.(16) Nevertheless, a high R^2 does not guarantee a good performance in a realistic situation since most of the LAQSs still suffer from fluctuating RH and temperature.(11) Recommended performance metrics and target values for $PM_{2.5}$ for testing have been proposed and can be referred to in Table 2.

Measurement of $PM_{2.5}$ for the reference is conducted using a Turnkey Instruments Optical Particle Analysis System (TOPAS). TOPAS is a fixed monitoring device capable of continuously recording environmental total solid particles (TSP), PM_{10}, $PM_{2.5}$, PM_1, ambient temperature, and RH. TOPAS uses Turnkey's specially designed nephelometer, whereby air samples are continuously drawn through it, and individual particles are analyzed as they pass through a laser

Table 1
Technical specifications for LAQSs used in the experiment.

Sensor model	PMS5003	SPS30	SEN55	HPMA115	ZH03B
Manufacturer	Plantower	Sensirion	Sensirion	Honeywell	Winsen
Approximate price (US$)	~12	~45	~48	~60	~10
Dimensions (mm)	50 × 38 × 21	41 × 41 × 12	53 × 44 × 22	43 × 36 × 23.7	50 × 32.4 × 21
Approximate weight (g)	~42	~26	~45	~40	30
Power supply (V)	4.5–5.5	4.5–5.5	4.5–5.5	5	4.5–5.5
Working current (mA)	<100	55	100	80	70–100
Detectable size range (μm)	0.3–10	0.3–10	0.3	N/A	0.3–10
Size bins	6 size bins	4 size bins	N/A	N/A	N/A
Estimated PMx concentration	PM_1, $PM_{2.5}$, and PM_{10}	PM_1, $PM_{2.5}$, and PM_{10}	PM_1, $PM_{2.5}$, PM_4, and PM_{10}	$PM_{2.5}$ and PM_{10}	PM_1, $PM_{2.5}$ and PM_{10}
Concentration range (μg/m³)	0–1000	0–1000	0–1000	0–1000	0–1000

Table 2
Recommended performance metrics of LAQSs provided by US EPA.[16]

Performance Metric		Target Value	
		Base Testing	Enhanced Testing
Precision	Standard Deviation (SD)	≤5 μg/m³	No target values recommended; results to be reported
	-OR- Coefficient of Variation (CV)	≤30%	
Bias	Slope	1.0 ± 0.35	
	Intercept (b)	$-5 \leq b \leq 5$ μg/m³	
Linearity	Coefficient of Determination (R^2)	≥0.70	
Error	Root Mean Square Error (*RMSE*) or Normalized Root Mean Square Error (*NRMSE*)	*RMSE* ≤ 7 μg/m³ or *NRMSE* ≤ 30%	

beam. The particles are then accumulated on the reference filter while the nephelometer's microprocessor analyzes individual particles. TOPAS has also received the Environment Agency MCERTS accreditation for recording PM_{10} and $PM_{2.5}$ data. Detailed information on MCERTS and technical specifications can be found on the official Turnkey website.[18]

Extracting the measurement from the sensors requires the integration of sensors with a microcontroller. All the sensors use UART or I2C for the communication protocol; hence, custom code scripts were developed for each sensor. The framework used to create the code script uses Arduino IDE. The hardware circuit includes a low-power microcontroller with a Wi-Fi module for data transmission and a real-time clock module for accurate interval transmission. The data are then posted to the Thingspeak cloud using a JSON message. Each sensor is allocated a channel inside the Thingspeak to prevent data collision during transmission. The time interval between each transmission is set at one minute.

Measurements were carried out at two locations with indoor and outdoor conditions. The initial site selected for indoor AQ measurements was a privately owned laboratory at Bangi Gateway in the central district of Bandar Baru Bangi, Malaysia; the LAQS arrangement is depicted in Fig. 1. The laboratory is a hybrid between a laboratory and an administrative office. It is a closed space with an air conditioning system. The emitted PM originated from the laboratory's activity, which consists of drilling, machining, soldering, and 3D printing. The ambient temperature inside the laboratory is measured to be 23 to 31 °C, while the RH ranged from 40 to 80%. Figures 2(a) and 2(b) show the second monitoring location, which represents the outdoor environment, situated on the balcony of the Administration building at Universiti Kebangsaan Malaysia (UKM) Kuala Lumpur Branch. The position of the balcony is situated near a car park and is located on level 3. The PM emissions originated mainly from vehicle emissions and human activities. Since UKM Kuala Lumpur Branch is in the middle of the Kuala Lumpur Central Business District (CBD), the location has a high PM concentration since Kuala Lumpur is a bustling city.

Although most LAQSs are claimed to be factory calibrated, a calibration method must be established before data acquisition. Most LAQSs are recommended to be calibrated under the actual conditions of deployment.[19] The calibration method for all the LAQSs uses simple linear regression (SLR). Previous findings on PM calibration methods have demonstrated a wide range

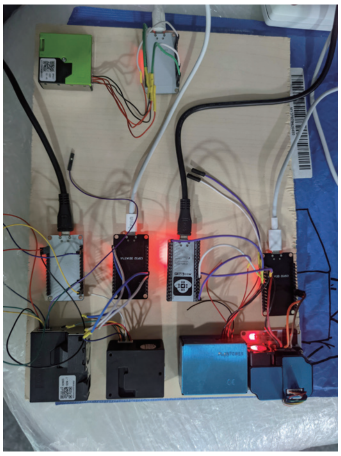

Fig. 1. (Color online) Arrangement of LAQSs inside the laboratory.

(a) (b)

Fig. 2. (Color online) (a) LAQS encased in ABS enclosure to block raindrops during the outdoor experiment and (b) TOPAS with MCERT certification.

of R^2 values, indicating a scattered distribution of results. In studies in which SLR was employed, high R^2 values exceeding 0.95 were reported, whereas the performance of multiple linear regression (MLR) was lower with R^2 values below 0.5.(20) The SLR is employed in our study to establish a functional relationship between two variable sets. Specifically, the *y*-axis represents the dataset obtained from the LAQS, while the *x*-axis represents the dataset acquired from the reference analyzer. The initial step in determining the calibration factor involves plotting a concentration graph, as depicted in Fig. 3. We use hypothetical PM concentration data for visualization. Subsequently, the calibration factor is derived using the best-fit line. The general formula for the calibration factor is

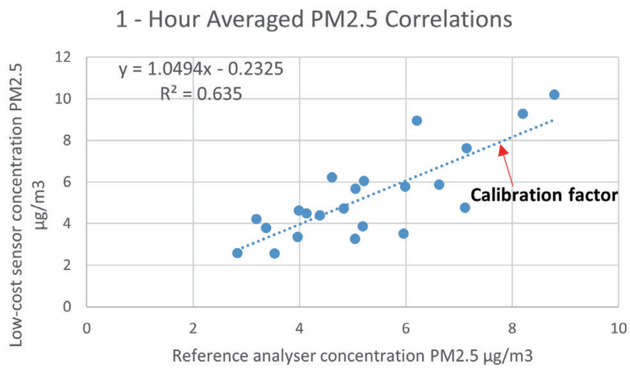

Fig. 3. (Color online) Scatter plot of LAQS concentration vs reference analyzer concentration with best-fit-line calibration factor.

$$y = \beta_0 + \beta_1 x. \tag{1}$$

To utilize Eq. (1) to generate the calibration factor, it is necessary to determine the parameters where y is the measured LAQS concentration and x is the calibrated LAQS concentration. β_0 represents the predicted y-intercept, and β_1 represents the predicted slope. Equation (1) is then rearranged into Eq. (2) before the calibration factor is applied to the output of an uncalibrated LAQS, improving the LAQS Bias and reducing the root-mean-square error (*RMSE*). Past scientific work has shown that the SLR can reduce the Bias of LAQS if the relationship between the dataset acquired from the LAQS and the dataset acquired from the reference analyzer is linear.[21]

$$x = (y - \beta_0) / \beta_1 \tag{2}$$

Indoor data collection spanned three weeks (October 15–November 3, 2022), while outdoor data collection took place over five days (December 1–5, 2022). The discrepancy in sampling dates was due to budget limitations and security considerations. The TOPAS instrument, rented for a limited time, was deployed outdoors only for five days for security reasons. As a tropical country, Malaysia exhibits seasonal variations in average monthly temperature and RH. The experiment was conducted during the period of the inter-monsoon transition towards the northeast monsoon season, which is characterized by increased rainfall. This season experiences the highest precipitation, resulting in higher average monthly RH levels that reach 90%. Consequently, the sensor was tested under elevated RH conditions, which can potentially affect the performance of the LAQS. The LAQSs are placed close to TOPAS at a distance of approximately 1 m. All the LAQSs and TOPAS are placed about 1.5 m above the floor to ensure the data collection is completed at the average height of human breathing. This prevents LAQSs from picking up different PM concentrations.

SLR was used to generate the calibration factor for all LAQSs. The PM concentration data from all LAQSs is downloaded from the Thingspeak cloud. In contrast, the data from

TOPAS is downloaded directly from the device storage. The performance of each LAQS in indoor and outdoor environments is assessed by evaluating R^2, Bias, and *RMSE*. R^2 is useful to quantify the correlation between LAQS and TOPAS. At the same time, Bias consistently shows an error between LAQS and TOPAS. This outcome means that the higher the R^2, the stronger the correlation between LAQS and TOPAS. The LAQS *RMSE* determines the LAQS accuracy; the lower the *RMSE*, the higher the LAQS accuracy. The tool and method used to generate R^2 and Bias, called Macro Analysis Tool (MAT), are provided by the US EPA, and the information is available at the official US EPA website.(15) R^2 is derived for 1-h, 4-h, 12-h, and 24-h averages.

3. Results and Discussion

3.1 Indoor setting inside an operational office

3.1.1 Sensor calibration using SLR model under indoor conditions.

Before any analysis was conducted, each LAQS was calibrated using the SLR. All LAQS measurements were taken with collocated TOPAS on October 17, 2022 (1 day). The environmental conditions were set to a moderate temperature in the range of 28 to 30 °C and RH in the range of 30% to 65%. The calibration factor was generated from the collocation for the 1-h average, and later, we used it to calibrate the sensor. Table 3 lists all the calibration factors for each sensor.

3.1.2 Three-week (October 15, 2022–November 3, 2022) analysis of LAQS performance in indoor setting

Results obtained from a three-week analysis of LAQSs in an indoor setting are presented in this section. The RH and temperature are not set to a particular state because we aim is to assess the performance of the LAQSs under actual indoor conditions. Nonetheless, the recorded RH and temperature range from 29.5 to 75% and 24 to 31 °C. Table 4 shows R^2, Bias, and *RMSE* for the 1-h average. On average, the LAQS correlation was poor (R^2 = 0.22–0.57). The values show that the LAQS readings correlate with those of TOPAS, but the outcome falls short of the US EPA recommended level ($R^2 \geq 0.7$). The highest R^2 is shown by HPMA115 (R^2 = 0.57), while SEN55 shows the lowest R^2 (R^2 = 0.22).

Table 3
Calibration factors generated with collocated LAQSs and TOPAS in an indoor setup.

Sensor model	Calibration factor
HPMA115	$y = 2.55x - 1.35$
PMS5003	$y = 4.66x + 1.43$
SEN55	$y = 2.56x - 0.21$
SPS30	$y = 2.07x + 0.75$
ZH03B	$y = 2.28x + 1.26$

Table 4
Performance of LAQSs during three-week analysis before and after calibration.

Sensor model	Before calibration			After calibration		
	R^2	Bias	*RMSE*	R^2	Bias	*RMSE*
HPMA115	0.57	$y = 1.23x + 1.50$	3.59	0.58	$y = 0.49x + 1.12$	2.20
PMS5003	0.41	$y = 2.53x + 4.21$	11.84	0.41	$y = 0.54x + 0.60$	2.23
SEN55	0.22	$y = 0.82x + 4.25$	4.78	0.22	$y = 0.32x + 1.74$	3.07
SPS30	0.41	$y = 1.23x + 1.70$	4.19	0.42	$y = 0.60x + 0.48$	2.40
ZH03B	0.41	$y = 1.40x + 2.35$	5.31	0.41	$y = 0.61x + 0.48$	2.22

Although there is another report of an increase in R^2 determined by analyzing a 24-h average, our findings indicate that this approach did not result in any drastic increment except for HPMA115.[(6)] On the basis of the results presented in Table 5, it is apparent that R^2 increases as the average time interval is increased. However, only HPMA115 achieved the recommended R^2 value of 0.70 when the average time interval was 12 h. While other LAQSs show an incremental increase in R^2 with increasing average time interval, the US EPA guideline is still not met.

It is worth noting that the US EPA recommends increasing the average time interval to 24 h to smooth out any noise present in the collected data. Our results demonstrate an improvement in R^2 each time the average time interval is increased, except when we analyze the data for 24 h. In this case, the R^2 value decreases because of our limited data collection.

On the basis of Fig. 4, throughout the experiment, the highest 1-h average concentration measured by TOPAS was 19.4 μgm^{-3}, which falls within the low concentration range. This result aligns with those of prior scientific research, demonstrating that LAQSs may have difficulty detecting $PM_{2.5}$ levels below 20 μgm^{-3}.[(6)] This issue is a widely recognized limitation of LAQSs utilizing a light-scattering-based approach, with which it is often a struggle to detect fine PM.[(22)]

Figure 5 indicates improvement in *RMSE* following the calibration of LAQSs. Prior to calibration, the PMS5003 sensor exhibited the highest *RMSE* of 11.81 μgm^{-3}, while the HPMA115 sensor had the lowest *RMSE* of 3.59 μgm^{-3}. According to US EPA guidelines, *RMSE* should be less than 7 μgm^{-3}. After calibration, *RMSE* for PMS5003 decreased to a favorable level of 2.23 μgm^{-3}. On average, the *RMSE* reduction achieved through calibration was nearly 2.5-fold. Despite the SLR model's effectiveness in reducing *RMSE*, the R^2 value did not improve. Generally, evaluating LAQSs in indoor environments is challenging and requires extended sampling periods to cover a wide concentration range. Despite this, R^2 and *RMSE* results suggest that HPMA115 could be suitable for detecting PM concentrations. Nevertheless, LAQSs can be a valuable tool for informing the public about increases in indoor air pollution.

3.1.3 Analysis of LAQS performance for indoor settings with and without occupants

Given the unsatisfactory results obtained from the three-week analysis, it is imperative to investigate the underlying cause of such outcomes. We hypothesize that the air conditioning system being turned off when there are no occupants results in a consistent RH and temperature. In contrast, its operation in the presence of occupants produces variations in these variables. To investigate this hypothesis, we segmented the data into two sets: three days with occupants

Table 5
R^2 analysis in indoor setup for different average time intervals.

LAQS	R^2 (1-h Avg)	R^2 (4-h Avg)	R^2 (12-h Avg)	R^2 (24-h Avg)
HPMA115	0.58	0.58	0.72	0.62
PMS5003	0.41	0.41	0.54	0.45
SEN55	0.22	0.24	0.44	0.42
SPS30	0.42	0.43	0.60	0.49
ZH03B	0.41	0.42	0.57	0.48

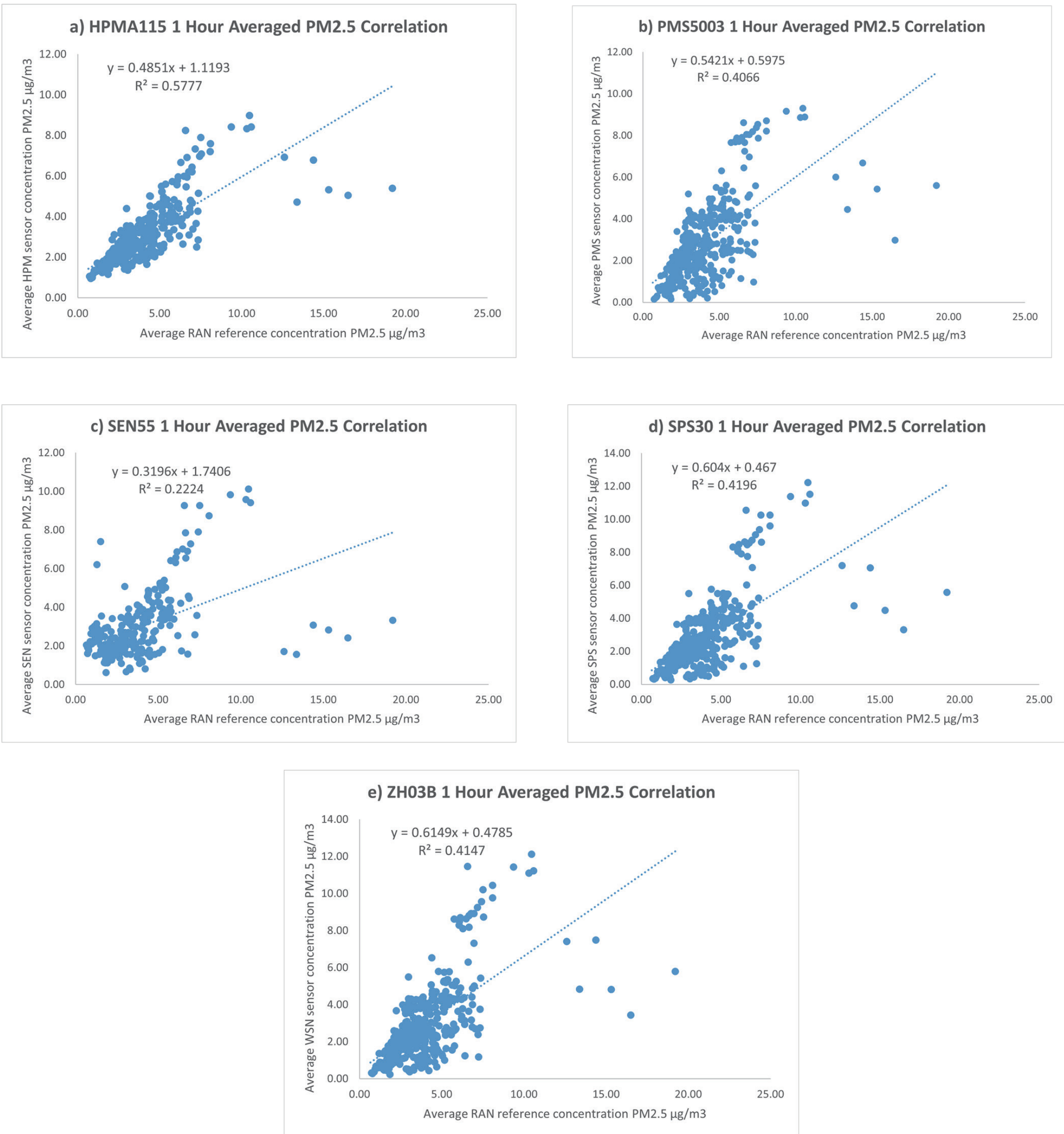

Fig. 4. (Color online) SLR model generated from the collocation of LAQSs with TOPAS.

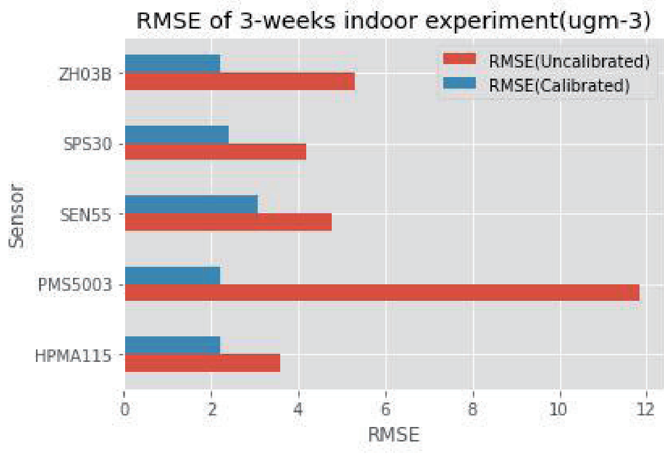

Fig. 5. (Color online) *RMSE* reduction after the calibration process.

(November 1–3, 2022) and three days without occupants (October 17–19, 2022). The statistical measures, including R^2, Bias, and *RMSE*, are reported in Tables 6 and 7.

On the basis of the results, it can be inferred that the behavior of LAQSs varies between the no-occupant and with-occupant campaigns. The R^2 values indicate that the readings of all LAQSs are strongly correlated with those of TOPAS during the no-occupant campaign, with R^2 values being greater than 0.7. The highest R^2 value is observed for HPMA115 (R^2 = 0.92), whereas the lowest is for PMS5003 (R^2 = 0.84). However, such conclusions cannot be drawn from the campaign results with occupants, as the R^2 values for all LAQSs fall below the recommended level of 0.70, indicating a low correlation. Among the sensors, HPMA115 displays the highest R^2 value of 0.42, whereas PMS5003 shows the lowest R^2 value of 0.08. Thus, it can be concluded that the correlation between LAQSs and TOPAS is weak and unreliable, as indicated by the observed R^2 values.

Upon further investigation, it was discovered that the factors that explain the discrepancy between the two campaigns are the ambient temperature and RH. During the no-occupant campaign, the air conditioning system is not switched on, resulting in the temperature and RH being maintained at optimum conditions. It is seen in Figs. 6 and 7 that the temperature recorded is between 27.1 and 30.1 °C, while the RH is between 30.1 and 68.6%. In contrast, in the campaign with occupants, the air conditioning system is often switched on and off; hence, temperature and RH vary. Figures 6 and 7 show that the recorded temperature ranges between 25.9 and 29.3 °C, and the RH ranges from 30 to 81.1%. This finding is consistent with the results reported in existing scientific literature, which suggests that LAQSs often tend to show low R^2 when RH reaches 100%.[11] When RH is high, particle growth is detected, which gives an incorrect signal to the LAQS because it lacks a drying system at the inlet. Given the lack of temperature and RH compensation in all LAQSs, it is imperative to consider this limitation when employing these sensors in industrial applications.

Table 6
Performance of LAQSs during the no-occupant campaign.

Sensor Model	Before calibration			After calibration		
	R^2	Bias	*RMSE*	R^2	Bias	*RMSE*
HPMA115	0.92	$y = 2.06x + 0.14$	5.55	0.92	$y = 0.81x + 0.58$	1.37
PMS5003	0.84	$y = 4.27x + 4.29$	20.15	0.84	$y = 0.92x + 0.62$	1.47
SEN55	0.90	$y = 2.48x + 0.10$	7.56	0.90	$y = 0.97x + 0.12$	1.35
SPS30	0.88	$y = 2.49x - 0.14$	7.44	0.88	$y = 1.20x - 0.43$	1.60
ZH03B	0.88	$y = 2.75x + 0.39$	9.17	0.88	$y = 1.21x - 0.38$	1.65

Table 7
Performance of LAQSs during the campaign with occupants.

Sensor Model	Before calibration			After calibration		
	R^2	Bias	*RMSE*	R^2	Bias	*RMSE*
HPMA115	0.42	$y = 0.74x + 2.40$	2.50	0.42	$y = 0.29x + 1.47$	1.87
PMS5003	0.08	$y = 0.80x + 6.82$	7.83	0.08	$y = 0.17x + 1.16$	2.43
SEN55	0.14	$y = 0.46x + 3.12$	2.56	0.14	$y = 0.18x + 1.30$	2.20
SPS30	0.10	$y = 0.38x + 3.23$	2.52	0.10	$y = 0.18x + 1.20$	2.34
ZH03B	0.09	$y = 0.42x + 4.25$	3.50	0.09	$y = 0.19x + 1.31$	2.29

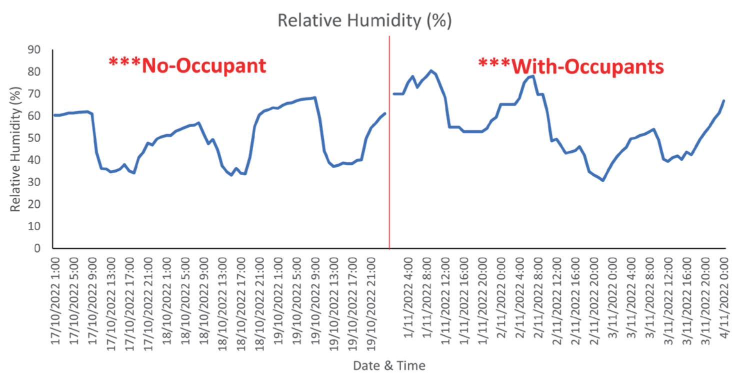

Fig. 6. (Color online) RH during the campaign with and without occupants.

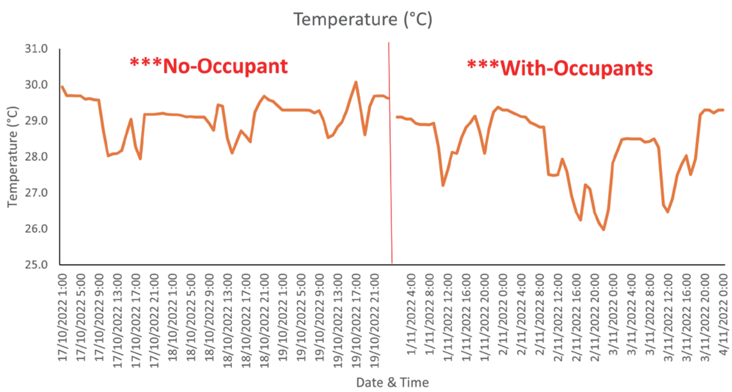

Fig. 7. (Color online) Temperature during the campaign with and without occupants.

3.2 Outdoor setting on the rooftop of UKM

3.2.1 Sensor calibration and complete analysis

The outdoor analysis was conducted over a 5-day period from November 1–5, 2022, during which a one-day dataset obtained on November 2022 was used to calculate the calibration factor for a 1-h average. Collocation was performed by collocating each LAQS with a TOPAS at the deployment site. The calibration factors presented in Table 8 were applied to correct the LAQS output.

This experiment was aimed at evaluating the performance of LAQS in a real outdoor setting. Table 9 shows the correlation of LAQSs with TOPAS. Only Honeywell's HPMA115 exhibits an outstanding R^2, with the correlation exceeding the US EPA R^2 guideline (R^2 = 0.72). The other LAQSs still correlate with TOPAS, although the correlation is somewhat lower than the US EPA recommendation. The experimentally determined R^2 is inconsistent with the results of similar reported experiments involving outdoor settings. As a result of numerous pollution sources existing on-site, in most of the past experiments, fairly high 1-h-average levels of $PM_{2.5}$ were detected, with the maximum concentration detected being more than 20 μgm^{-3}.(17,23) During our experiment, the maximum 1-h-average level of $PM_{2.5}$ recorded by TOPAS was approximately 10.59 μgm^{-3}. The investigation was conducted under high precipitation conditions, which accounted for approximately 80% of the total campaign duration. The environmental conditions during the outdoor experiment were monitored using TOPAS, and the recorded temperature and RH values were found to fall within the range of 24.4 to 34.3 ℃ and 34.3 to 96.3%, respectively. As a result of the prevailing weather conditions, the concentration of $PM_{2.5}$ was found to be low. During rainfall, the raindrops washout the PM, which helps reduce the concentration of $PM_{2.5}$.(24) Even though the LAQSs were tested during peak hours in the center of the busy Kuala

Table 8
Calibration factor generated using SLR model in outdoor setup.

Sensor model	Calibration factor
HPMA115	$y = 1.52x - 1.81$
PMS5003	$y = 4.06x + 5.82$
SEN55	$y = 2.01x - 3.01$
SPS30	$y = 1.90x + 2.72$
ZH03B	$y = 2.09x + 2.56$

Table 9
Performance of LAQSs during outdoor experiment.

LAQS	Before calibration			After calibration		
	R^2	Bias	*RMSE*	R^2	Bias	*RMSE*
HPMA115	0.71	$y = 1.52x - 1.81$	1.98	0.72	$y = 1x - 0.0002$	1.14
PMS5003	0.63	$y = 4.06x - 5.82$	11.19	0.63	$y = 1x - 0.0004$	1.33
SEN55	0.60	$y = 2.01x - 3.01$	3.64	0.60	$y = 1x + 0.0002$	1.38
SPS30	0.60	$y = 2.01x - 3.01$	3.63	0.60	$y = 1x + 2 \times 10^{-6}$	1.40
ZH03B	0.60	$y = 2.09x - 2.56$	3.64	0.60	$y = 1x - 4 \times 10^{-6}$	1.39

Lumpur CBD, we discovered that the $PM_{2.5}$ concentration was low owing to the washout effect caused by the raindrops.

The results in Table 10 demonstrate the impact of increasing the average time interval in the R^2 analysis. Unfortunately, it was not feasible to determine 12-h and 24-h averages because of insufficient outdoor data collection. Nevertheless, the results of the 4-h average indicate a positive increase in R^2. However, the observed increment is inadequate to satisfy the US EPA guideline, except for HPMA115, which showed an R^2 of 0.77 with a 4-h average.

According to the results presented in Fig. 8, prior to the application of any calibration factor, the *RMSE* values are relatively high, with PMS5003 exhibiting the highest value (*RMSE* = 11.19 μgm^{-3}) and HPMA115 displaying the lowest (*RMSE* = 1.98 μgm^{-3}). Concerning compliance with the US EPA guideline, only PMS5003 does not meet the standard of having an *RMSE* below 7 μgm^{-3} prior to calibration. However, following the application of the calibration factor, each LAQS exhibits an *RMSE* below 1.5 μgm^{-3}, with PMS5003 demonstrating the greatest reduction of 8.4 times. Notably, in the outdoor experiment, *RMSE* after calibration is lower than that in the indoor experiment, the decrease being approximately twofold. These findings suggest that the SLR calibration factor is adequate, even for outdoor conditions, despite the lack of monitoring of temperature and RH.

Collocating all LAQSs in outdoor environments poses challenges owing to high RH. However, the R^2 and *RMSE* results indicate that HPMA115 is excellent for outdoor PM

Table 10
R^2 analysis in outdoor setup for different average time intervals.

LAQS	R^2 (1-h Avg)	R^2 (4-h Avg)	R^2 (12-h Avg)	R^2 (24- Avg)
HPMA115	0.72	0.77	n/a	n/a
PMS5003	0.63	0.65	n/a	n/a
SEN55	0.60	0.65	n/a	n/a
SPS30	0.60	0.63	n/a	n/a
ZH03B	0.60	0.64	n/a	n/a

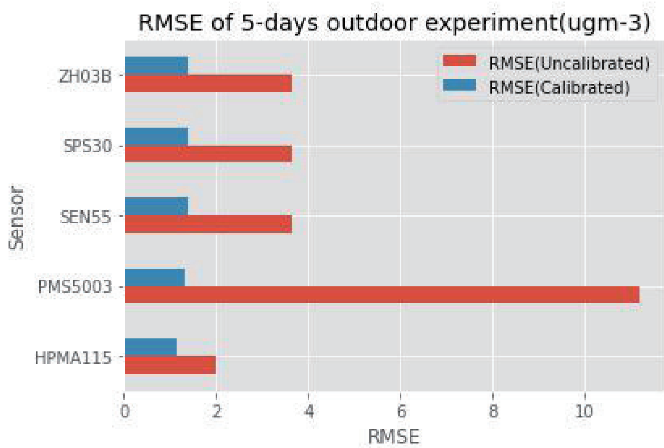

Fig. 8. (Color online) Reduction of *RMSE* after calibration.

monitoring, with R^2 surpassing 0.70 and *RMSE* below 7 μgm^{-3}. This trend aligns closely with that of TOPAS, a reliable reference instrument, affirming HPMA115's precision and reliability. Nevertheless, other LAQSs show promise as valuable tools for detecting PM concentrations based on R^2 and *RMSE*.

4. Conclusions

In this study, we evaluated five LAQSs available on the market and found that all five LAQSs tested exhibited linearity with TOPAS. Among them, HPMA115 demonstrated superior suitability for indoor and outdoor applications, having R^2 consistently above 0.7 and *RMSE* below 7 μgm^{-3} during collocation experiments with TOPAS. HPMA115 exhibited the highest R^2 values for short-time averaging, indicating a strong linear relationship with TOPAS. However, the other LAQSs demonstrated only moderate correlations with TOPAS, rendering them suitable only as indicators.

Our data analysis emphasized the importance of a wide range of $PM_{2.5}$ concentrations to comprehensively describe sensor characteristics. Notably, the impact of air conditioning on indoor LAQS performance was significant, as air conditioner operation led to fluctuations in RH and temperature, affecting the linearity with TOPAS.

Most LAQS displayed improved results in outdoor experiments, with higher R^2 and lower *RMSE*. Nonetheless, HPMA115 emerged as the best performer, demonstrating high linearity with TOPAS and superior accuracy based on R^2 and *RMSE*.

Overall, the result of this study underscores the potential effectiveness of LAQSs for ambient AQ monitoring. Our findings contribute to the systematic evaluation of the most suitable PM LAQS and provide insights into their behavior under tropical conditions, which are under-represented in existing research publications.

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