Calibration of Low-cost Sensors for Measurement of Indoor Particulate Matter Concentrations via Laboratory/Field Evaluation

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ABSTRACT

Recently, low-cost sensors (LCSs) have been widely used in monitoring particulate matter (PM) mass concentrations. Maintaining the accuracy of the sensors is important and requires rigorous calibration and performance evaluation. In this study, two commercial LCSs, Plantower PMS3003 and Plantower PMS7003, were evaluated in the laboratory and in the field using a reference-grade PM monitor (GRIMM 11-D). Laboratory evaluation was conducted with polystyrene latex (PSL) particles in a 1 m³ chamber at 20°C with a relative humidity of 20%. Each LCS indicated higher mass concentrations than GRIMM 11-D for small-sized PSL particles (0.56 μm); however, the LCSs indicated lower mass concentrations than GRIMM 11-D for PSL particles larger than 0.56 μm. In addition, the difference in mass concentrations between the LCS and GRIMM 11-D became higher with particle sizes greater than 0.56 μm. Nonetheless, a high correlation (R² > 0.9) between each LCS and GRIMM 11-D was obtained.

Field evaluation was conducted at Yonsei University (Seoul, South Korea) from February 12 to March 31, 2022. The LCSs showed generally higher PM mass concentrations than GRIMM 11-D; however, some data points of the LCSs revealed different trends. We observed that outdoor PM10/PM2.5 and relative humidity had notable impacts on the LCS data; in addition, LCS sensitivity depended on whether the PM concentration was low or high. Based on these observations, regression-based calibration models were constructed using the selected independent variables (outdoor PM10/PM2.5 and relative humidity) after dividing the PM concentration into low and high sections. Consequently, the accuracy of the LCSs was significantly enhanced. Therefore, using LCSs with the calibration models can replace the use of expensive reference PM monitors, resulting in cost savings.

Keywords: Indoor air quality, Particulate matter, Regression analysis, PM2.5, PM10

1 INTRODUCTION

Recently, the use of low-cost particulate matter (PM) sensors that measure total light scattering intensity by particles has enabled wide-ranging and high-density spatiotemporal measurements to be conducted (Giordano et al., 2021; Zheng et al., 2018). As light scattering-based low-cost PM sensors (LCSs) can provide almost instantaneous feedback on changes in air quality, users can immediately check and respond to high air pollution levels (Bhattacharya et al., 2012; Kim et al., 2010; Zheng et al., 2018). The light scattering-based LCS generally comprises a laser (650 nm), a phototransistor, and a focusing lens (Fig. 1).

A major limitation of LCS is that they are not as accurate as expensive reference PM monitors (Gao et al., 2015; Kelly et al., 2017; Zheng et al., 2018). An LCS can be affected by operating conditions (relative humidity, temperature, PM mass concentration) and aerosol characteristics (aerodynamic size distribution). These disturbance factors can cause an LCS to produce output data showing different trends (Gao et al., 2015; Kelly et al., 2017). To minimize the different trends triggered by the disturbance factors, LCS output should be compared with output from a reference
PM monitor. In this study, GRIMM 11-D, one of the portable research-grade PM monitors widely used for indoor PM measurement was selected as a reference PM monitor. The GRIMM 11-D is an advanced optical particle counter (OPC) with the ability to divide particles from 0.253 to 35.15 µm by optical size into 31 channels and to count individual particles with a diode laser (30 mW, 655 nm).

In general, air quality regulations stipulate ‘dry’ PM when the relative humidity is less than 40%. In higher relative humidity environments, a hygroscopic effect may overestimate the LCS output value. Magi et al. (2020) reported that the hygroscopic effect started to affect Plantower PMS5003 when the relative humidity exceeded 65–70%. Jayaratne et al. (2018) showed that relative humidity has a significant effect on LCSs Sharp GP2Y and Shinyei PPD42NS, even when the relative humidity is over 50%. In Badura et al. (2019), linear regression models for relative humidity showed equal or better performance than nonlinear regression models. Zheng et al. (2018) suggested that applying a nonlinear empirical calibration model for relative humidity could improve the PM mass concentrations of Plantower PMS3003 to close to the dry state, even in a high humidity environment. Gao et al. (2015) and Malings et al. (2020) reported that nonlinear empirical calibration models can obtain lower mean absolute errors (MAE) and higher correlation coefficients than theoretical approaches can. Ultimately, the choice between linear/nonlinear and theoretical/empirical models to calibrate for relative humidity will depend on end-user preferences and requirements.

In contrast, temperature has less effect on LCSs than relative humidity. The literature generally reported that low error values (–5 to 5 µg m⁻³) were shown even at low temperatures (–5 to 5°C). In the linear/quadratic calibration model for temperature, the error term appears larger than the coefficient; thus, the effect of temperature can be neglected in normal environments but not in extreme environments, such as deserts (Magi et al., 2020).

In this study, laboratory and field (indoor) evaluations were conducted to construct an effective calibration model for LCSs. The GRIMM 11-D and LCSs were placed at the same location to measure PM₁₀, PM₂.₅, and PM₁₀. The room temperature and relative humidity were also measured using a temperature/humidity sensor module. The LCSs and the sensor module were controlled by Arduino and integrated into a wireless network type sensor box using Wi-Fi module. Simultaneously, real-time open API (Application Programming Interface) data (outdoor PM₂.₅ and PM₁₀) were collected by Air Korea (www.airkorea.or.kr). Among the collected data, the outdoor PM₁₀/PM₂.₅ ratio (written as (PM₁₀/PM₂.₅)₆) and relative humidity were selected as independent variables. The purpose of our study was to suggest an effective calibration model for LCSs to be used in indoor spaces using various regression analyses.
2 METHODS

2.1 Specifications of Sensor Modules

In this study, we evaluated Plantower PMS3003 and Plantower PMS7003 (PMS3003 and PMS7003, respectively). The shape and structure of each LCS are shown in Fig. 2, and the specifications of the LCSs are shown in Table 1. Each LCS simultaneously displays particle mass concentrations (µg m⁻³) for PM₁₀, PM₂.₅, and PM₁₀.

A guiding principle for LCSs is that particle mass concentrations are calculated by measuring scattered light intensity, which are obtained from a phototransistor, as shown in Fig. 1 (Sayahi et al., 2019; Kelly et al., 2017; Zheng et al., 2018; Badura et al., 2018, 2019). However, the results may differ depending on the unique expertise of each manufacturer. A DHT 22 sensor module was used to obtain temperature and humidity information.

2.2 Structure of Wireless Network Type PM Evaluation Sensor Box

First, the measured values of PM and temperature/humidity were determined by Arduino (Fig. 3). Second, Arduino converted the data into byte format and transmitted the converted data to a NodeMCU module by I2C (Inter-Integrated Circuit) communication method with 4 bytes for each measured value. Finally, the data transmitted to the NodeMCU module were converted back to string format, with the converted data being transmitted every 4.5 seconds and stored in a Google datasheet (data cloud) using wireless communication.

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**Table 1. Specifications of low-cost PM sensors.**

<table>
<thead>
<tr>
<th>Model</th>
<th>Light wavelength</th>
<th>Scattering angle</th>
<th>Aspiration</th>
<th>Stated lower particle size sensitivity</th>
<th>Output</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>PMS3003</td>
<td>650 nm</td>
<td>90°</td>
<td>0.1 lpm</td>
<td>0.3 µm</td>
<td>Particle mass concentrations</td>
<td>~26000 won</td>
</tr>
<tr>
<td>PMS7003</td>
<td>650 nm</td>
<td>90°</td>
<td>0.1 lpm</td>
<td>0.3 µm</td>
<td>Particle mass concentrations</td>
<td>~25000 won</td>
</tr>
</tbody>
</table>

---
The NodeMCU module has an operating voltage of 3.3 V, a power consumption of less than 1.0 mW, and an indoor transmission range of approximately 40 m and an approximately 100 m range outdoors, with an operating radio frequency of 2.4 GHz.

2.3 Light Scattering-based PM Measurement and Correction Factor

The GRIMM 11-D PM monitor and LCSs calculate particle number concentration by measuring scattered light intensity from particles entering each device. Assuming that the total light intensity and the particle number concentration have a proportional relationship, the total scattered light intensity \( I_{\text{total}} \) is a summation of each light intensity scattered by a single particle \( I(d_p) \) (Friedlander, 2000), as follows:

\[
I_{\text{total}} = \int I(d_p) \cdot n(d_p) \, dd_p
\]

where \( d_p \) is the particle diameter, and \( n(d_p) \) is the number concentration of particles of size \( d_p \).

The total mass concentration \( m_{\text{total}} \) can then be calculated from \( n(d_p) \) as follows:

\[
m_{\text{total}} = \int \rho_p \frac{\pi d_p^3}{6} n(d_p) \, dd_p
\]

where \( \rho_p \) is the particle density that is set in each device (usually 1 g cm\(^{-3}\)). Therefore, based on Eq. (1) and Eq. (2), \( m_{\text{total}} \) is calculated through \( I_{\text{total}} \) measurement.

The GRIMM 11-D, a research-grade reference PM monitor, displays the total mass concentration \( m_{\text{total,Ref}} \) by measuring the total light scattering intensity \( I_{\text{total,Ref}} \) with a diode laser (30 mW, 655 nm). The GRIMM 11-D measures particles in the range of 0.253–35.15 µm (optical diameter) with 31 channels. The GRIMM 11-D measures the particles every 6 seconds with a sampling flow rate of 1.2 lpm.

PMS3003 and PMS7003, the LCSs, display the total mass concentration \( m_{\text{total,LCS}} \) by measuring the total light scattering intensity \( I_{\text{total,LCS}} \) obtained from a phototransistor. Each LCS displays mass concentrations of PM\(_{1.0}\), PM\(_{2.5}\), and PM\(_{10}\) with three channels.
As \( m_{\text{total}} \) is calculated through \( I_{\text{total}} \) measurement, the following equations are obtained:

\[
\begin{align*}
\text{(3a)} & \quad m_{\text{total,Ref}} &= \eta_{\text{Ref}} I_{\text{total,Ref}} \\
\text{(3b)} & \quad m_{\text{total,LCS}} &= \eta_{\text{LCS}} I_{\text{total,LCS}}
\end{align*}
\]

where \( \eta_{\text{Ref}} \) and \( \eta_{\text{LCS}} \) represent the response coefficients of GRIMM 11-D and LCS, respectively.

From Eq. (3a) and Eq. (3b), the following equation is obtained:

\[
\text{(4)} \quad m_{\text{total,Ref}} = \alpha \cdot m_{\text{total,LCS}}
\]

where \( \alpha \) is a target correction factor between GRIMM 11-D and LCS and is expressed in Eq. (5):

\[
\text{(5)} \quad \alpha = \frac{\eta_{\text{Ref}}}{\eta_{\text{LCS}}} \cdot \frac{I_{\text{total,Ref}}}{I_{\text{total,LCS}}}
\]

Other factors may affect the light scattering intensity: temperature (T), relative humidity (RH), and particle shape (S). However, the effect of temperature was neglected in this study because the temperature barely changed in an indoor space. In addition, the effect of particle shape was ignored, as reported in previous studies (Badura et al., 2019; Barkjohn et al., 2020; Crilley et al., 2020; Magi et al., 2020).

The light scattering intensity of GRIMM 11-D, according to time resolution \( (\Delta t_n) \), is written in Eq. (6a):

\[
\text{(6a)} \quad I_{\text{total,Ref}}(\Delta t_n) = \int \left[ i(d_p, RH) \cdot n(d_p, \Delta t_n) \right] dd_p
\]

For LCS, the concentration section \((\Delta [PM])\) and the outdoor \( \text{PM}_{10}/\text{PM}_{2.5} \) ratio \((\text{PM}_{10}/\text{PM}_{2.5})_{\text{An}}\) are considered as factors that additionally affect the light scattering intensity. Therefore, the light scattering intensity of LCS according to time resolution can be expressed by Eq. (6b):

\[
\text{(6b)} \quad I_{\text{total,LCS}}(\Delta t_n) = \int \left[ i(d_p, RH, \Delta [PM], (\text{PM}_{10}/\text{PM}_{2.5})_{\text{An}}) \right] n(d_p, \Delta t_n) dd_p
\]

### 2.4 Laboratory Evaluation

The laboratory evaluation was performed in a \( 83 \times 83 \times 158 \) cm chamber (Fig. 4). To prevent particle leakage from the chamber, the edges were siliconized. In addition, four fans were mounted at the corners (mid-height of the chamber, 80 cm) to create a uniform particle distribution. To minimize the effects of temperature and humidity on the measurements, they were maintained at 20°C and 20%, respectively. Generated particles flowed into the chamber through a stainless-steel tube located at the top center of the chamber. While the GRIMM 11-D was located outside the chamber, two LCSs were located on the inside. The distance between the inlets of the LCSs was approximately 5 cm (narrow gap ratio, 0.06, to total chamber width, 83 cm). The distance between each LCS inlet and the sampling port inlet of the GRIMM 11-D was also approximately 5 cm. Therefore, GRIMM 11-D and LCS measure particles are assumed to exist in the same space (Li and Biswas, 2017).

Laboratory evaluation was conducted with two size distributions of polystyrene latex (PSL) particles: mono-disperse PSL (0.56 \( \mu \)m, corresponding to the peak of a typical atmospheric aerosol size distribution) and poly-disperse PSL (1.3, 1.5, 1.8, and 2.0 \( \mu \)m, realizing a \( \text{PM}_{2.5} \) size distribution) (Table 2). The PSL particles were generated by an atomizer (TSI, Jet Atomizer 9302) and passed through a diffusion dryer (TSI, Diffusion Dryer 3076) to remove moisture. The aerosolized PSL
particles flowed into the chamber to increase the particle concentration. The particle generation was stopped when the particle concentration did not increase further. Consequently, after stopping, the particle concentration started decreasing. The measurement was complete when the particle concentration could no longer be detected by the LCSs. Fig. 5 shows the size distributions of PSL aerosols immediately before the particle generation was stopped.

![Diagram of laboratory evaluation chamber test](image)

**Fig. 4.** Schematic diagram of laboratory evaluation (chamber test).

**Table 2.** Experimental conditions of laboratory evaluation test.

<table>
<thead>
<tr>
<th>Test number</th>
<th>Particles</th>
<th>Particle generator</th>
<th>LCS</th>
<th>Mass conc. range (µg m⁻³)</th>
<th>Average Temp/Humid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Singled PSL test</td>
<td>PSL 0.56 µm</td>
<td>TSI, Jet Atomizer  9302</td>
<td>PMS3003, PMS7003</td>
<td>1.14–363.37</td>
<td>23.72°C/20.81%</td>
</tr>
<tr>
<td>Mixed PSL test</td>
<td>PSL 1.3, 1.5, 1.8, and 2.0 µm</td>
<td></td>
<td></td>
<td>0.17–60.26</td>
<td>20.19°C/21.67%</td>
</tr>
</tbody>
</table>
2.5 Field Evaluation

Fig. 6(a) shows the field experimental setting, which was conducted in the Engineering Building at Yonsei University (37.5618°N, 126.9366°E) located in Sinchon, Seoul, South Korea. In this study, for accurate evaluation and calibration, all inlets of LCSs and GRIMM 11-D were proximately positioned at a height of approximately 0.8 m to reduce noise caused by re-dispersion of fine dust (Giordano et al., 2021). Fig. 6(b) shows the PM evaluation sensor box comprising PMS3003, PMS7003, and DHT22. Each sensor was operated by Arduino, and the measured data were transmitted wirelessly through the Wi-Fi module (NodeMCU).

Using GRIMM 11-D, operating conditions for temperature and relative humidity (RH) were 0–40°C and 0–40%, respectively. Therefore, dehumidification was required when the relative humidity exceeded 40%. For dehumidification, we fabricated a heat-based dehumidifier capable of increasing the temperature up to 60°C, with a total length of 30 cm (heating part: 10 cm from the front end, Fig. 6(c)). The heat-based dehumidifier was connected to the inlet of GRIMM 11-D and was used when the indoor RH exceeded 40%. Therefore, the RH term in Eq. (6a) can be neglected and can be expressed as Eq. (7):

$$I_{\text{total,Ref}}(\Delta t_n) = \frac{\int_{d_p} j(d_p) n(d_p, \Delta t_n) dd_p}{\Delta t_n}$$

(7)

In the field evaluation, we collected open API PM data (atmospheric PM$_{2.5}$ and PM$_{10}$) as well as output values from the PM evaluation sensor box (T, RH and PM$_{1.0}$, PM$_{2.5}$, PM$_{10}$ mass concentrations) together with the GRIMM 11-D (PM$_{1.0}$, PM$_{2.5}$, PM$_{10}$ mass concentrations). The open API PM data were collected hourly from a measurement station available near the field test site. In this study, two stations were selected: 0.75 km distance from the site and 3.8 km away from the site. After collecting data from the two stations, average values were used for (PM$_{10}$/PM$_{2.5}$) API. The PM mass concentrations measured from GRIMM 11-D and LCS were averaged per 1-hour and are represented as PM$_{\text{Ref}}$(PM mass concentration measured with GRIMM 11-D) and PM$_{\text{LCS}}$(PM mass concentration measured with LCS), respectively. The field test was conducted from 12 February to 31 March 2022.

2.6 Calibration Model

In this study, to create a calibration model based on regression analysis, the following three steps were used: 1) select useful independent variables through the regression analysis of collected data; 2) derive the correction factor (CF) corresponding to $\alpha$ of Eq. (5); and 3) construct a calibration model by applying the derived CF.

We constructed four calibration models, and the detailed description of each model is as follows (a description of each calibration model is also summarized in Table 3):
Fig. 6. (a) Field evaluation; (b) PM evaluation sensor box; (c) Cross-section schematic diagram of lab-made heat-based dehumidifier.
Table 3. Description of CF1–CF4.

<table>
<thead>
<tr>
<th>Calibration model</th>
<th>Regression</th>
<th>Separate Conc. sections</th>
<th>Independent variables</th>
<th>Dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>CF1</td>
<td>Simple Linear</td>
<td>X</td>
<td>PM\textsubscript{LCS}</td>
<td>PM\textsubscript{Ref}</td>
</tr>
<tr>
<td>CF2</td>
<td>Univariate</td>
<td>X</td>
<td>(PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API}</td>
<td>CF\textsubscript{Ref}</td>
</tr>
<tr>
<td>CF3</td>
<td>Univariate</td>
<td>O</td>
<td>(PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API}</td>
<td>CF\textsubscript{Ref}</td>
</tr>
<tr>
<td>CF4</td>
<td>Multivariate</td>
<td>O</td>
<td>(PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API}, RH</td>
<td>CF\textsubscript{Ref}</td>
</tr>
</tbody>
</table>

2.6.1 Simple calibration model

After plotting the data of PM\textsubscript{LCS} and PM\textsubscript{Ref} in an X-Y graph, the slope and intercept were obtained by assuming a linear relationship between PM\textsubscript{LCS} and PM\textsubscript{Ref}. Subsequently, the newly obtained PM\textsubscript{LCS} (PM\textsubscript{Cal.LCS}) was calculated using the following equation:

$$\text{PM}^{\text{Cal.LCS}} = \text{CF1} \cdot \text{PM}_{\text{LCS}} + \text{CF1}_\text{Intercept} \Rightarrow \text{PM}^{\text{Ref}}$$

(8)

where CF1 represents the correction factor 1, and \text{CF1}_\text{Slope} and \text{CF1}_\text{Intercept} are the slope and intercept, respectively. Therefore, PM\textsubscript{Cal.LCS} implies a CF applied to PM\textsubscript{LCS}. To evaluate the calibration performance of PM\textsubscript{Cal.LCS}, a comparison is made with PM\textsubscript{Ref}.

2.6.2 Calibration model with (PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API}

CF2 is a correction factor that applies (PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API} as an independent variable. Therefore, CF2 applied to PM\textsubscript{LCS} results in PM\textsubscript{Cal.LCS}. The PM\textsubscript{Cal.LCS} is calculated using the following equations:

$$\text{PM}^{\text{Cal.LCS}} = \text{CF2} \cdot \text{PM}_{\text{LCS}}$$

(9)

$$\text{CF2} = a \cdot (\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}^2 + b \cdot (\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}} + c$$

(10)

In the above equations, the constants a, b, and c represent regression coefficients. The target correction value of CF2 is the reference correction factor (CF\textsubscript{Ref}) defined by Eq. (11):

$$\text{CF}^{\text{Ref}} = \frac{\text{PM}^{\text{Ref}}}{\text{PM}^{\text{LCS}}}$$

(11)

where, the CF\textsubscript{Ref} is same as \alpha of Eq. (5). To evaluate the calibration performance of PM\textsubscript{Cal.LCS} (Eq. (9)), a comparison is made with PM\textsubscript{Ref}.

2.6.3 Calibration model with (PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API} by dividing concentration sections

As the sensitivity of LCS decreases at low concentrations owing to the limit of detection (LOD), low and high PM concentrations should be considered prior to applying the regression analysis. The criterion for dividing the PM concentration section was PM\textsubscript{1.0} of LCS (PM\textsubscript{1.0.LCS}). CF3 is a correction factor that applies (PM\textsubscript{10}/PM\textsubscript{2.5})\textsubscript{API} as an independent variable after dividing PM concentration sections. Therefore, CF3 applied to PM\textsubscript{LCS} results in PM\textsubscript{Cal.LCS}. The PM\textsubscript{Cal.LCS} is calculated using the following equation:

$$\text{PM}^{\text{Cal.LCS}} = \begin{cases} \text{CF3}_{\text{low}} \cdot \text{PM}_{\text{LCS}}^{\text{low}}, & \text{PM}_{1.0} < \text{Threshold} \\ \text{CF3}_{\text{high}} \cdot \text{PM}_{\text{LCS}}^{\text{high}}, & \text{PM}_{1.0} \geq \text{Threshold} \end{cases}$$

(12)

where,

$$\text{CF3}_{\text{low}} = a \cdot (\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}^2 + b \cdot (\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}} + c$$

(12a)
\[ \text{CF3}_{\text{High}} = a \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}}^2 + b \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}} + c \]  

(12a)

where the constants \( a, b, \) and \( c \) represent regression coefficients. \( \text{CF3}_{\text{low}} \) and \( \text{CF3}_{\text{high}} \) are CF3 in the low and high concentration sections, respectively. The target correction value of CF3 is the reference correction factor (\( \text{CF3}_{\text{ref}} \)) of Eq. (11). To evaluate the calibration performance of \( \text{PM}^{\text{Cal.LCS}} \) (Eq. (12)), a comparison is made with \( \text{PM}^{\text{Ref}} \).

### 2.6.4 Calibration model with \((\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}\) and RH by dividing concentration sections

\( \text{CF4} \) is a correction factor that applies \((\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}\) and RH as independent variables after dividing PM concentration sections. Therefore, \( \text{CF4} \) applied to \( \text{PM}^{\text{LCS}} \) results in \( \text{PM}^{\text{Cal.LCS}} \). The \( \text{PM}^{\text{Cal.LCS}} \) is calculated using the following equation:

\[
\text{PM}^{\text{Cal.LCS}} = \begin{cases} 
\text{CF4}_{\text{low}} \cdot \text{PM}^{\text{LCS}}, & \text{PM}^{\text{LCS}} < \text{Threshold} \\
\text{CF4}_{\text{high}} \cdot \text{PM}^{\text{LCS}}, & \text{PM}^{\text{LCS}} \geq \text{Threshold}
\end{cases}
\]  

(13)

Here,

\[
\text{CF4}_{\text{low}} = a \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}}^2 + b \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}} + c \cdot \text{RH} + d
\]  

(13a)

\[
\text{CF4}_{\text{high}} = a \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}}^2 + b \cdot \left( \frac{\text{PM}_{10}}{\text{PM}_{2.5}} \right)_{\text{API}} + c \cdot \text{RH} + d
\]  

(13a)

In the above equation, the constants \( a, b, c, \) and \( d \) represent regression coefficients. \( \text{CF4}_{\text{low}} \) and \( \text{CF4}_{\text{high}} \) represent CF4 in the low and high concentration sections, respectively. The target correction value of CF4 is the reference correction factor (\( \text{CF4}_{\text{ref}} \)) of Eq. (11). To evaluate the calibration performance of \( \text{PM}^{\text{Cal.LCS}} \) (Eq. (13)), a comparison is made with \( \text{PM}^{\text{Ref}} \).

### 2.7 Evaluation of Calibration Models Performance

In this study, we used three indicators to evaluate the performance of calibration models: correlation coefficient (\( R^2 \)), root mean square error (\( \text{RMSE} \)), and match rate (\( \text{MR} \)). The \( R^2 \), \( \text{RMSE} \), and \( \text{MR} \) are represented by Eqs. (14), (15), and (16), respectively:

\[
R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]  

(14)

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{n}} \text{ (\( \mu g \text{ m}^{-3} \))}
\]  

(15)

\[
\text{MR} = \left(1 - \frac{\sum_{i=1}^{n} |a - b|}{n}\right) \times 100 \text{ (%)}
\]  

(16)

Here, \( n \) is the amount of data; \( y_i \) denotes a data point of \( \text{PM}^{\text{Ref}} \); \( \hat{y}_i \) denotes a data point of \( \text{PM}^{\text{Cal.LCS}} \) (\( \text{PM}^{\text{LCS}} \) to which a CF is applied); \( \bar{y} \) represents the average of all data points of \( \text{PM}^{\text{LCS}} \); \( \text{MR} \) has different implications depending on the configuration of variables \( a \) and \( b \). When \( a = \hat{y}_i \) and \( b = y_i \), Eq. (16) represents the \( \text{MR} \) of \( \text{PM}^{\text{LCS}} \) for \( \text{PM}^{\text{Ref}} \). When \( a = \hat{y}_1 \) and \( b = \hat{y}_2 \), Eq. (16) represents the \( \text{MR} \) between the two LCSs (subscript 1 = Plantower PMS3003, subscript 2 = Plantower PMS7003). The performance of the model is better when \( R^2 \) is closer to 1, \( \text{RMSE} \) is closer to 0, and the \( \text{MR} \) is closer to 100%.
3 RESULTS AND DISCUSSION

3.1 Laboratory Evaluation

To determine the performance of LCSs, laboratory evaluation was conducted with two size distributions of PSL: mono-disperse (0.56 µm) and poly-disperse (1.3, 1.5, 1.8, and 2.0 µm). Fig. 7 shows the results of this evaluation.

First, mono-disperse PSL particles were sprayed into the chamber using an atomizer until the concentration did not increase further (based on GRIMM 11-D, 279.52 µg m⁻³). Thereafter, the gradually falling concentration was measured until each LCS showed zero (based on GRIMM 11-D, 2 µg m⁻³) (Fig. 7(a)). As a result, the correlation ($R^2$) between each LCS and GRIMM 11-D was over 0.99 (PMS3003: 0.9968 and PMS7003: 0.9986). The ratios (= LCS/GRIMM 11-D) were 1.0772 (± 0.2055) and 1.2686 (± 0.1572), respectively, for PMS3003 and PMS7003 (Fig. 7(b)). Therefore, the results showed high correlation and low deviation.

Second, poly-disperse PSL particles were sprayed into the chamber using the atomizer until the concentration did not increase further (based on GRIMM 11-D, 60.26 µg m⁻³). Thereafter, the gradually falling concentration was measured until each LCS showed zero (based on GRIMM 11-D, 10 µg m⁻³) (Fig. 7(c)). As a result, the correlation ($R^2$) between each LCS and GRIMM 11-D was over 0.98 (PMS3003: 0.9815 and PMS7003: 0.9876). The ratios (= LCS/GRIMM 11-D) were 0.2462 (± 0.1091) and 0.3129 (± 0.1439), respectively, for PMS3003 and PMS7003.

Therefore, each LCS was significantly lower than GRIMM 11-D and showed higher deviations than in the case of mono-disperse PSL particles (Fig. 7(d)). To explain these trends, we hypothesized two possible causes: 1) owing to the internal structure of LCSs, larger particles may not fully reach the measurement part of the LCS (Fig. 2); 2) as larger particles can block smaller particles, the light scattering caused by smaller particles remains undetected, resulting in underestimation or noise generation (Figs. 1(b) and 1(c)).

![Fig. 7](image-url) Results of the laboratory evaluation: (a) Time series graph in mono-disperse PSL test; (b) Correlation analysis graph for PM$_{2.5}$ in mono-disperse PSL test; (c) Time series graph in poly-disperse PSL test; (d) Correlation analysis graph for PM$_{2.5}$ in poly-disperse PSL test.
3.2 Field Evaluation

The measured data are shown in Fig. 8. The average room temperature was 15.91°C (± 2.16) while the average indoor relative humidity was 34.83% (± 11.32), showing a large variation. The ranges of PM$_{2.5}^{\text{Ref}}$ and PM$_{10}^{\text{Ref}}$ were 1.33–72.92 µg m$^{-3}$ (20.45 ± 12.55 µg m$^{-3}$) and 1.65–119.27 µg m$^{-3}$ (29.07 ± 17.52 µg m$^{-3}$), respectively. Likewise, in the case of PMS3003, the ranges of PM$_{2.5}^{\text{LCS}}$ and PM$_{10}^{\text{LCS}}$ were 1.00–137.54 µg m$^{-3}$ (39.28 ± 28.46 µg m$^{-3}$) and 1.04–153.03 µg m$^{-3}$ (42.88 ± 31.02 µg m$^{-3}$), respectively. In the case of PMS7003, the ranges of PM$_{2.5}^{\text{LCS}}$ and PM$_{10}^{\text{LCS}}$ were 1.29–129.72 µg m$^{-3}$ (38.40 ± 26.71 µg m$^{-3}$) and 1.65–172.33 µg m$^{-3}$ (50.71 ± 34.95 µg m$^{-3}$), respectively. The PM$_{LCS}$ generally showed higher mass concentrations than PM$_{Ref}$.

Prior to constructing the calibration model, the ability of each LCS needed to be evaluated to discriminate between PM$_{2.5}$ and PM$_{10}$ as PM$_{10}^{\text{LCS}}$ had a significantly lower correlation than PM$_{2.5}^{\text{LCS}}$. Fig. 9 shows the correlation between PM$_{10}$/PM$_{2.5}$ of GRIMM 11-D (PM$_{10}$/PM$_{2.5}^{\text{Ref}}$) and that of LCS, (PM$_{10}$/PM$_{2.5}^{\text{LCS}}$). As (PM$_{10}$/PM$_{2.5}^{\text{LCS}}$)$_{\text{Ref}}$ increased, (PM$_{10}$/PM$_{2.5}^{\text{LCS}}$) tended to increase, and PM$_{10}^{\text{LCS}}$ had a non-linear relationship with PM$_{2.5}^{\text{LCS}}$. Therefore, PM$_{10}^{\text{LCS}}$ was determined as reliable data.

![Fig. 8. Results of the field evaluation: (a) Time series graph of temperature/humidity and PM$_{2.5}$ output data of GRIMM 11-D, PMS3003, PMS7003; (b) Time series graph of temperature/humidity and PM$_{10}$ output data of GRIMM 11-D, PMS3003, PMS7003.](image-url)
3.2.1 Simple calibration model

Fig. 10(a) shows the relationship between PM\(_{1.0}^{\text{LCS}}\) and PM\(_{1.0}^{\text{Ref}}\). The slope for PMS3003 was higher and closer to unity than the slope for PMS7003. However, no difference in slope was observed in Fig. 10(b), which shows the relationship between PM\(_{1.0}^{\text{Cal.LCS}}\) and PM\(_{1.0}^{\text{Ref}}\). PM\(_{1.0}^{\text{Cal.LCS}}\) was a result of applying CF1 to PM\(_{1.0}^{\text{LCS}}\). As a result, even if the simple calibration model was applied, PM\(_{1.0}^{\text{Cal.LCS}}\) was close to PM\(_{1.0}^{\text{Ref}}\). In cases of PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\), some PM\(_{x}^{\text{LCS}}\) were different from PM\(_{x}^{\text{Ref}}\) (black and red circles of Figs. 10(c) and 10(d)). Fig. 10(e) shows the relationship between PM\(_{2.5}^{\text{Cal.LCS}}\) (obtained with CF1) and PM\(_{2.5}^{\text{Ref}}\). Fig. 10(f) shows the relationship between PM\(_{10}^{\text{Cal.LCS}}\) (obtained with CF1) and PM\(_{10}^{\text{Ref}}\).

Table 4 shows R\(^2\), RMSE, and MR values obtained with CF1 for PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\). The results are shown for both PMS3003 and PMS7003. For PMS3003, the RMSE and MR values of PM\(_{2.5}^{\text{Cal.LCS}}\) were significantly lower and higher than those of PM\(_{2.5}^{\text{LCS}}\), respectively, implying performance improvement after calibration. In contrast, the RMSE and MR values of PM\(_{10}^{\text{Cal.LCS}}\) were not that different from those of PM\(_{10}^{\text{LCS}}\), implying that the calibration with CF1 did not significantly improve performance.

When RMSE and MR were used as indicators for calibration performance, the performance seemed to improve with the use of CF1 for PM\(_{2.5}^{\text{LCS}}\). However, when R\(^2\) was used as an indicator, no performance improvement was observed for both PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\) (Table 4 shows almost the same R\(^2\) values of PM\(_{x}^{\text{LCS}}\) and PM\(_{x}^{\text{Cal.LCS}}\) for both PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\). We surmise that this lack of improvement was due to the data shown in the black and red circles (Figs. 10(c) and 10(d)).

In addition, the use of CF1 for PMS3003 caused the minimum detectable concentration (in other words, LOD) to increase from 1.33 to 3.98 µg m\(^{-3}\) for PM\(_{2.5}^{\text{LCS}}\) and from 1.65 to 10.48 µg m\(^{-3}\) for PM\(_{10}^{\text{LCS}}\) (Figs. 10(e) and 10(f)). For PMS7003, similar trends were obtained.

3.2.2 Calibration model with (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\)

For PMS3003 and PMS7003, CF\(_{\text{Ref}}\) (= PM\(_{x}^{\text{Ref}}\)/PM\(_{x}^{\text{LCS}}\)) values for PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\) were calculated from the results of Fig. 8 and plotted, respectively, in Fig. 11(a) and Fig. 11(b), which also show the (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\) variation with time. For both PM\(_{2.5}^{\text{LCS}}\) and PM\(_{10}^{\text{LCS}}\), CF\(_{\text{Ref}}\) increased with (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\).

To better understand the relationship between CF\(_{\text{Ref}}\) and (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\), the results were re-plotted in Figs. 11(c) and 11(d). Fig. 11(c) shows a linear correlation between CF\(_{\text{Ref}}\) for PM\(_{2.5}^{\text{LCS}}\) and (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\), whereas Fig. 11(d) shows a second-order polynomial correlation between CF\(_{\text{Ref}}\) for PM\(_{10}^{\text{LCS}}\) and (PM\(_{10}^{\text{LCS}}/PM_{2.5}^{\text{LCS}}\))\(_{\text{API}}\). Using these correlations, CF2 in Eq. (10) was determined and then PM\(_{2.5}^{\text{Cal.LCS}}\) values were obtained for each case (Eq. (9)). Finally, Fig. 11(e) shows the relationship between PM\(_{2.5}^{\text{Cal.LCS}}\) (obtained with CF2) and PM\(_{2.5}^{\text{Ref}}\) for both LCSs. Similarly, Fig. 11(f) shows the relationship between PM\(_{10}^{\text{Cal.LCS}}\) (obtained with CF2) and PM\(_{10}^{\text{Ref}}\) for both LCSs.
Table 4 shows $R^2$, RMSE, and MR values obtained with CF2 for PM$_{2.5}$LCS and PM$_{10}$LCS for both PMS3003 and PMS7003. The RMSE values of PM$_{2.5}$Cal.LCS were significantly lower than those of PM$_{2.5}$LCS, whereas the $R^2$ and MR of PM$_{2.5}$Cal.LCS values were significantly higher than those of PM$_{2.5}$LCS. This finding indicated that the performance improved with the use of CF2 for PM$_{2.5}$LCS. Similarly, the performance significantly improved for PM$_{10}$LCS.

Fig. 10. Processes and results of deriving a calibration model using CF1: (a) CF1 for PM$_{1.0}$; (b) PM$_{1.0}$Cal.LCS; (c) CF1 for PM$_{2.5}$; (d) CF1 for PM$_{10}$; (e) PM$_{2.5}$Cal.LCS; and (f) PM$_{10}$Cal.LCS. ** In the figure, PM$_{Cal.LCS}^{Cal} =$ CF1*Slope*PM$_{LCS}$ + CF1*Intercept **
Moreover, the use of CF2 showed higher performance than the use of CF1 (Table 4). In particular, the data shown in the black and red circles were corrected for PM1.0 and PM10 (Figs. 10(c) and 10(d)). In addition, the use of CF2 did not increase the minimum detectable concentration. However, some data points of PM2.5 and PM10 still deviated from the trend-line in the concentration range of 30–90 μg m⁻³ (Figs. 10(e) and 10(f)).

### 3.2.3 Calibration model with (PM10/PM2.5)AP by dividing concentration sections

For both PMS3003 and PMS7003, the data shown in Fig. 10(a) were re-plotted to show the relationship between CF₁₀ᵣₑₐⱼ = PM₁₀ᵣₑⱼ/PM₂.₅ᵣₑⱼ and PM₁₀ᵣₑⱼ. As a result, the following relationships were derived:

\[
y = \begin{cases} 
1.3171x^{-0.174}, & \text{PM3003} \\
0.8836x^{-0.15}, & \text{PM7003}
\end{cases}
\]  

\[(17)\]

where \(x \) and \(y \) denote PM₀ᵣₑⱼ and CF₁₀ᵣₑⱼ, respectively. The \(y \) value rapidly decreased as the \(x \) value increased until \(x \) was approximately 6–7, and then converged after \(x = 6–7 \). This rapid decrease suggests that the LCS is less sensitive than GRIMM 11-D at concentrations below \(x = 6–7 \), likely due to the difference in LOD between LCS and GRIMM 11-D. This changing point value \((x = 6–7) \) became the threshold point in Eqs. (12a) and (12b). If the changing point was defined as the \(x \)-value when the \(y′ \) is equal to the \(y'' \) (an average of \(y'' \); \(y'' = 0.0036 \) for PM3003, \(y'' = 0.0026 \) for PM7003), the changing points were 7.3355 μg m⁻³ and 5.8269 μg m⁻³, respectively, for PM3003 and PM7003.

For PM2.₅, Figs. 12(b) and 12(c) show linear correlations between CF₁₀ᵣₑⱼ and (PM₁₀/PM₂.₅)AP in low and high concentration sections, respectively. For PM₁₀, Figs. 12(d) and 12(e) show second-order polynomial correlations between CF₁₀ᵣₑⱼ and (PM₁₀/PM₂.₅)AP in low and high concentration sections, respectively. Using these correlations, CF3 in Eqs. (12a) and (12b) were determined, after which PM₁₀ᵣₑⱼ values were obtained (Eq. (12)). Finally, Fig. 12(f) shows the relationship between PM₁₀ᵣₑⱼ and PM₂.₅ᵣₑⱼ (obtained with CF3). Fig. 12(g) shows the relationship between PM₁₀ᵣₑⱼ and PM₁₀ᵣₑⱼ (obtained with CF3).
Fig. 11. Processes and results of deriving a calibration model using CF2: (a) Time series graph of \((\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}\) and \(\text{CF}^\text{Ref}\) for \(\text{PM}_{2.5}\); (b) Time series graph of \((\text{PM}_{10}/\text{PM}_{2.5})_{\text{API}}\) and \(\text{CF}^\text{Ref}\) for \(\text{PM}_{10}\); (c) \(\text{CF}^2\) for \(\text{PM}_{2.5}\); (d) \(\text{CF}^2\) for \(\text{PM}_{10}\); (e) \(\text{PM}_{2.5}^\text{Cal.LCS}\); and (f) \(\text{PM}_{10}^\text{Cal.LCS}\). ** In the figure, \(\text{PM}_{\text{Cal.LCS}} = \text{CF}^2\cdot\text{PM}_{\text{LCS}}\)**.
Fig. 12. Processes and results of deriving a calibration model using CF3: (a) Correlation with $C_{\text{Ref}}$ according to $\text{PM}_{1.0}$LCS; (b) CF3 in $\text{PM}_{2.5}$ low conc. section; (c) CF3 in $\text{PM}_{2.5}$ high conc. section; (d) CF3 in $\text{PM}_{10}$ low conc. section; (e) CF3 in $\text{PM}_{10}$ high conc. section; (f) $\text{PM}_{2.5}^{\text{Cal-LCS}}$; and (g) $\text{PM}_{10}^{\text{Cal-LCS}}$. ** In the figure, $\text{PM}^{\text{Cal-LCS}} = \text{CF3-PM}^{\text{LCS}}$ **
Table 4 shows $R^2$, RMSE, and MR values obtained with CF3 for PM$_{2.5}$LCS and PM$_{10}$LCS. The results are shown for both PMS3003 and PMS7003. Considering the decrease in LCS sensitivity at low concentrations, the use of CF3 showed improved performance compared with the use of CF2.

3.2.4 Calibration model with (PM$_{10}$/PM$_{2.5}$)$_{API}$ and RH by dividing concentration sections

Figs. 13(a) and 13(b) show the correlations between $C_{\text{Ref}}$ ($= PM_{\text{Ref}}/PM_{\text{LCS}}$) and RH for PM$_{2.5}$ and PM$_{10}$, respectively. When the RH was higher than 40%, $C_{\text{Ref}}$ slightly decreased with increasing RH, indicating that the hygroscopic effect was not significant. However, when the RH was lower than 40%, no correlation and data points showed significant deviation from the trend-line ($y = ax + b$). Nonetheless, using these correlations, CF4 in Eq. (13a) and (13b) were determined (Table 5), and then $PM_{\text{Cal.LCS}}$ values were obtained (Eq. (13)). Consequently, Figs. 13(c) and 13(d) show that $PM_{\text{Cal.LCS}}$ values were well correlated with those of $PM_{\text{Cal.LCS}}$ obtained with CF4, respectively, for PM$_{2.5}$ and PM$_{10}$. Considering that the red and black circle data shown in Figs. 10(c) and 10(d) were obtained at a RH lower than 40%, we expected that the challenge of data point deviation was solved by using calibration models, including (PM$_{10}$/PM$_{2.5}$)$_{API}$.

Table 4 shows $R^2$, RMSE, and MR values obtained with CF4 for PM$_{2.5}$LCS and PM$_{10}$LCS. The results are shown for both PMS3003 and PMS7003. The use of CF4 showed practically insignificant improvement compared with the use of CF3. However, if the RH was higher than 70%, the effect of RH could not be neglected (Magi et al., 2020; Jayaratne et al., 2018; Badura et al., 2019; Zheng et al., 2018).

![Fig. 13. Processes and results of deriving a calibration model using CF4: (a) Correlation between RH and $C_{\text{Ref}}$ for PM$_{2.5}$; (b) Correlation between RH and $C_{\text{Ref}}$ for PM$_{10}$; (c) PM$_{2.5,\text{Cal.LCS}}$; and (d) PM$_{10,\text{Cal.LCS}}$. ** In the figure, PM$_{\text{Cal.LCS}} = \text{CF4} \cdot PM_{\text{LCS}}$ **](image)
Fig. 14 shows the time series graph of PM$_{\text{Ref}}$ and PM$_{\text{Cal.LCS}}$ (obtained with CF4). Therefore, compared with the time series graph before calibration in Fig. 8, a remarkable performance improvement was observed. Considering the performance evaluation using CF4 and lower susceptibility to hygroscopic effects, we determined that the PMS7003 showed a higher performance than the PMS3003 did (Table 4).

Table 5. Table of regression coefficients for multiple regression model correction factor (CF4).

<table>
<thead>
<tr>
<th>Node</th>
<th>Sections</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
</tr>
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<tr>
<td>PMS3003 (PM$_{2.5}$)</td>
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<td>0</td>
<td>0.1373</td>
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<td>0.1259</td>
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<td></td>
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<td>0.2738</td>
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<tr>
<td>PMS7003 (PM$_{2.5}$)</td>
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<tr>
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<td>0.0007</td>
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<tr>
<td></td>
<td>CF$_4$High</td>
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<td>0.2105</td>
<td>-0.0004</td>
<td>0.1443</td>
</tr>
</tbody>
</table>

Fig. 14. Time series graphs of PM$_{\text{Ref}}$ and PM$_{\text{Cal.LCS}}$ (CF4 calibration model): (a) PM$_{2.5}$ case; (b) PM$_{10}$ case.
Fig. 15 shows the MR between PMS3003 and PMS7003 before and after calibration (Raw, CF1, CF2, CF3, and CF4), and the MR of PM$_{Cal.LCS}$ between PMS3003 and PMS7003 was higher than those of PM$^{LCS}$ between PMS3003 and PMS7003. While using CF4, the MR was highest for both PM$_{2.5}^{Cal.LCS}$ (96.1%) and PM$_{10}^{Cal.LCS}$ (96.1%).

4 CONCLUSIONS

In the field evaluation, LCSs (PMS3003 and PMS7003) show generally higher PM mass concentrations than GRIMM 11-D; however, some data points of LCSs show different trends. Outdoor PM$_{10}$/PM$_{2.5}$ and relative humidity have notable impacts on the LCSs data. In addition, LCS sensitivity depends on the quantity of PM concentrations. Based on these observations, regression-based calibration models were constructed using the selected independent variables (outdoor PM$_{10}$/PM$_{2.5}$ and relative humidity) after dividing the PM concentration into low and high sections. As a result, PMS7003 show better performance than PMS3003 (RMSE: 2.03 µg m$^{-3}$, 4.89 µg m$^{-3}$ for PM$_{2.5}$ and PM$_{10}$, respectively; MR: 91.43%, 86.39% for PM$_{2.5}$ and PM$_{10}$, respectively).

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