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Using low-cost particle sensors in HVAC ducts

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ABSTRACT

Low-cost sensors (LCSs) are increasingly used to measure particulate matter (PM). The possibility of using this kind of sensor within the HVAC system opens opportunities for improved control and management of indoor air quality and predictive maintenance of air filtration systems. This experimental study evaluates the effectiveness of LCSs in detecting particles within air ducts, employing three distinct types of LCSs under different testing aerosols, particle concentrations, and airstream velocities with particular emphasis non-statutory concentrations of $PM_{2.5}$ and PM_{10}. Data analysis includes statistical assessments to determine correlations and agreements to a reference laboratory-grade optical spectrometer (TSI OPS 3330). The findings underscore the suitability of LCSs for relative measurements, especially for $PM_{2.5}$ concentrations, with varying degrees of accuracy for PM_{10} concentrations. In particular, one LCS did not perform well for PM_{10} for either a standardized test aerosol or for measurements of outdoor aerosol, potentially owing to the lack of a sampling fan in the sensor. The other two sensors generally had a linear response with the reference instrument for $PM_{2.5}$ under test conditions with both the standardized aerosol and outdoor aerosol and at different velocity conditions. However, the agreement was generally worse at higher velocity conditions, especially for PM_{10}, suggesting challenges associated with accurate PM_{10} assessments with the tested LCSs. This investigation highlights opportunities and constraints for using LCSs in HVAC systems.

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1. Introduction

Exposure to Particulate Matter (PM) strongly correlates with several health effects (Bräuner et al. 2008; Chen, Zhao, and Weschler 2012; Ji and Zhao 2015; Logue et al. 2012). Despite the serious consequences of human exposure to PM, measuring airborne particles in indoor environments is historically rarer than in outdoor environments because of the complexity, cost, and regulations that emphasize ambient concentrations. In recent years, the availability of portable monitoring devices, including low-cost PM sensors (LCSs), has increased, and their further development and deployment offer an opportunity for new applications (Feng, Zheng, Zhang, et al. 2024; Hapidin et al. 2020; Munir et al. 2019; Piedrahita et al. 2014; Snyder et al. 2013; Thakur et al. 2024; Weekly et al. 2013; Williams et al. 2014). Low-cost sensor elements generally cost less than 100 USD and are thus a fraction of the price of a traditional PM monitor. The low cost enables the deployment of multiple devices simultaneously, allowing for a more distributed network of sensors across the monitored space. This approach enhances spatial resolution and provides a more comprehensive understanding of the variability in particle concentrations. Compared to a scenario with a single, more expensive, and sophisticated sensor limited to one or few locations, this distributed approach improves the accuracy of describing PM's spatial and temporal distribution while increasing data coverage (Bulot et al. 2019; Giordano et al. 2021; Rogulski and Badyda 2020; White et al. 2012). In contrast to air pollution monitoring with a reference-grade measurement that requires skilled operators for maintenance and frequent calibration, LCSs can work without human intervention, making it possible for unskilled users to monitor PM concentrations relatively easily (Karagulian et al. 2019). However, the low cost of LCSs and their ease of use comes with the perception (and reality) of reduced accuracy, especially

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compared to research-grade instruments (Palmisani et al. 2021).

For this reason, LCS performance has been tested under many circumstances, including different PM sources, types of aerosols, ambient conditions, seasons, and locations (He, Kuerbanjiang, and Dhaniyala 2020; Kim, Park, and Lee 2019; Malings et al. 2020; Pawar and Sinha 2020; Rogulski and Badyda 2020; Sayahi, Butterfield, and Kelly 2019; Tryner et al. 2020; Levy Zamora et al. 2019; Zheng et al. 2018). Recent studies have reflected heightened interest in the indoor application of LCSs and have demonstrated their ability to serve as reliable monitoring tools for detecting pollution events originating from diverse indoor and outdoor sources (Aix, Schmitz, and Bicout 2023; Connolly et al. 2022; Feng, Zheng, Ren, et al. 2024; Kang et al. 2022; Palmisani et al. 2021; Shen et al. 2021; Wang, Delp, and Singer 2020; Zafra-Pérez et al. 2023). This potential holds promise for revolutionizing indoor air quality management (Demanega et al. 2021; Mohammadshirazi et al. 2022).

However, the use of LCSs in heating, ventilation, and air conditioning (HVAC) systems remains largely unexplored. During operation, HVAC systems experience highly variable air flow rates and velocities, temperatures, and relative humidities, which can significantly degrade the quality of data provided by LCSs, particularly for coarse particles (Park et al. 2023). Common environmental factors contributing to this challenge include moving air as LCSs are often designed for static air conditions (Mui et al. 2021), highly variable concentration levels (e.g., the concentration difference between upstream and downstream of a filter), and varying particle composition and optical properties. The integration of LCSs into HVAC systems fulfills a critical need for real-time PM monitoring in dynamic and complex environments. LCSs enable enhanced control of ventilation systems by allowing demand-controlled ventilation strategies, which adjust airflow based on PM concentrations rather than control strategies using proxies such as CO_2. LCS adoption aims to improve IAQ by addressing harmful particulate pollutants and allows for balancing energy use against IAQ goals. Furthermore, integrating LCSs into HVAC systems can optimize maintenance by providing continuous data on air cleaning performance and directly monitoring filter/air cleaner efficiency instead of relying on proxies such as pressure drop, which can be only weakly correlated with efficiency. While challenges remain, such as ensuring sensor accuracy in high-velocity environments and mitigating errors in PM_{10} measurements (Budde et al. 2018; Kuula et al. 2020; Ouimette et al. 2024; Ouimette et al. 2022), the scalability, affordability, and ease of deployment of LCSs make them a promising solution for advancing IAQ management, energy efficiency, and filter performance evaluations.

In this investigation, we assess the performance of three different models of LCSs installed and operated in a controlled air stream to analyze their output. We compared the data to a laboratory-grade instrument and assessed their potential use inside HVAC systems. We evaluated LCS performance by comparing sensor output with $PM_{2.5}$ and PM_{10} measured with a reference instrument at different aerosol concentrations and airspeeds. Our overall goal is to provide insight into how these sensors would perform for controlling (e.g., modulating ventilation) and *in situ* evaluation of air cleaning performance.

2. Methods

The study is rooted in an experimental analysis encompassing three distinct types of low-cost sensors (LCSs) evaluated under two separate aerosol testing conditions. Subsequently, statistical methodologies are employed to compare the PM_{10} and $PM_{2.5}$ data from LCSs, compared to data from a reference laboratory-grade optical spectrometer. Typically, PM_{10} and $PM_{2.5}$ outputs from LCSs mean the particle concentration for the fraction smaller than 10 and 2.5 µm, respectively.

The statutory definitions of PM_{10} and $PM_{2.5}$ extend beyond particles "smaller than x µm," as these metrics are based on aerodynamic diameters and adhere to regulatory sampling conventions (e.g., US EPA 40 CFR part 53.62 and 53.43 or EN 12341). However, by their very nature, low-cost sensors (LCSs) do not comply with such methodologies. This study does not aim to achieve equivalence with regulatory-grade instruments but instead investigates the performance of LCSs relative to a laboratory-grade instrument in controlled duct conditions.

In this study, we used the TSI OPS 3330 as a laboratory-grade instrument within a controlled duct environment according to ISO 16890 standards as a reference to evaluate LCS performance. The TSI OPS 3330 measures optical particle size distribution and provides equivalent optical diameters based on spherical particles calibrated with PSL spheres. For atmospheric aerosols, where particle shape and refractive index are unknown, the TSI OPS 3330 and the LCSs may provide data of uncertain accuracy. For DEHS aerosol, the situation is slightly different, as the

particles are spherical, and their refractive index is known, allowing for more accurate measurements with the TSI OPS 3330. However, most LCSs do not incorporate such adjustments for refractive index differences.

The focus of this study is not to achieve high accuracy on absolute values but rather to examine whether LCSs maintain a predictable relationship with the reference instrument under controlled conditions. Specifically, we aim to determine (1) whether LCSs exhibit differing inaccuracies relative to the TSI OPS 3330 at higher airflow velocities and (2) whether these inaccuracies can be corrected using a mathematical relationship, such as a linear model.

The methodology used in this study ensures that the calculation of PM_x concentrations is broadly consistent with the scientific literature and the definition of outputs from particulate matter low-cost sensors. Therefore, the reference measurements in this study are specifically designed to provide outputs comparable to those of LCSs, allowing for meaningful analysis and calibration.

2.1. Experimental setup

Our investigation examined two samples, each of three models of low-cost sensors (LCSs), designed primarily for measuring PM mass concentration in calm air conditions (air velocity <1 m/s). The LCSs generally pull the aerosol flow into an integrated optical chamber within the device. Inside this chamber, the aerosol is illuminated with a light source and scatters light. A photodiode then records the scattered light's strength, generating a pulsating signal processed by a microcontroller. The signal intensity depends on the particle number concentration, particle size distribution, and the particles' refractive index. A particle density is assumed (either explicitly or inherently within the manufacturer's calibration process). The sensors provide an output based on proprietary algorithms derived from Mie Theory (Li 2019).

We tested three different LCS types, the NovaSensor-SDS011, Sensirion-SPS30, and Sharp-GP2Y1010AU0F, respectively labeled as sensors type A, B, and C. Table 1 details the characteristics of each LCS type. During the experimental campaign, we simultaneously used two sensors of the same type (A, B, and C) in each test to increase data reliability and understand sample variation. Sensors A and B use a suction fan to direct the flow toward an optical chamber containing a laser-emitting diode (Chen et al. 2022; Sousan, Regmi, and Park 2021). In particular, in the case of sensor A, the inlet and outlet sections are located at the opposite sides of the sensor, while for sensor B, they are adjacent on the same face. However, eventual bypass and/or recirculation that can occur, especially in the second case, are reduced in a flow regime characterized by higher velocities. These sensors report PM_x as particles "smaller than x μm" based on optical diameters, not aerodynamic diameters. The datasheet of the sensor type B (Sensirion SPS30) explicitly defines PM_x in this manner. The datasheet of the sensor type A (SDS011) does not explicitly provide the meaning of its outputs; we assumed that its output has a similar meaning.

Sensor type C uses an infrared emitting diode (Khan et al. 2021) directly on the air stream naturally entering through an opening. Sensor type C uses a heating element, creating a negative pressure inside the chamber and natural air convection within the measuring volume. This approach simplifies the operation and reduces the energy demand but may lead to variations in airflow and, thus, decreased sensor accuracy.

The reference laboratory-grade instrument is the TSI OPS 3330 (labeled *Ref*), an optical spectrometer measuring airborne particles ranging from 0.3 μm to 10.0 μm with a sampling flow rate of 1 L min^{-1}. We treated the TSI OPS 3330 data to obtain a format

Table 1. Characteristics of the LCSs used in this investigation.

	NovaSensor	Sensirion	Sharp
Number of tested sensors	2	2	2
Labels	A-1, A2	B-1, B-2	C-1, C-2
Model	SDS011	SPS30	GP2Y1010AU0F
Light source	Laser diode	Laser diode	Infrared emitting diode
Digital resolution	8 bit	8 bit	N/A
Presence of a suction fan	Yes	Yes	No
Supply voltage [V]	5 ± 0.3	5 ± 0.5	5 ± 0.5
Supply current [mA]	70 ± 10	<80	<20
Dimensions [mm]	70x71x23	41 × 41 x 12	46 × 34 x 17.6
Mass concentration range [μg/m3]	0 – 999.9	0 – 1000	0 – 580
Smallest detectable particle size [μm]	0.3	0.3	N/A
Max air velocity [m/s]	0.5	0.75	–
Data provided	$PM_{2.5}$; PM_{10}	PM_1; $PM_{2.5}$; PM_4; PM_{10}	TSP*

*Total Suspended Particles (TSP). The test aerosol has a particle size lower than 10 μm in the following experiments. Hence, TSP and PM_{10} are assumed equivalent.

comparable with the LCSs, $PM_{2.5}$, and PM_{10} information. We programmed the *Ref* instrument to count and size particles within the 0.3–10 μm in 12-size channels. Based on the discrete distribution of particles measured with the *Ref* instrument, the $PM_{2.5}$ and PM_{10} were evaluated, integrating all the particles below 2.5 and 10 μm, respectively. The particle density was assumed to be 1.65 g/cm^3 when using outdoor air (as in other investigations in Turin, Italy [Tittarelli et al. 2008; Tuch et al. 2000; Weijers et al. 2004]) and 0.912 g/cm^3 for tests using di-ethyl-hexyl-sebacate (DEHS) aerosol as ISO Standard 16890-2 specified.

We mounted all the LCS sensors (two per kind, A, B, and C) close to the isokinetic probe inside the test duct. The *Ref* sensor was connected directly to the isokinetic probe using an electrically conductive rubber tube (Figure 1a). The purpose was to reproduce a testing environment close to a ventilation duct to evaluate the behavior of LCSs exposed to an airstream in controlled conditions. For this reason, we employed a standardized test duct compliant with ISO 16890-2 (ISO 2016) requirements. These conditions guaranteed the uniformity of test aerosol across the duct section where we placed the sampling nozzle connected to the reference instrument and the two sets of LCSs. The airspeed was uniform across the test rig, having a coefficient of variation within 10%. More specifications about the qualification tests of the test duct are in ISO 16890-2 (ISO 2016). The sensor modules containing a sample of the three sensors under study were attached to the upstream probe (model TSI 1130011) (Figure 1b).

We tested the LCSs with two different PM sources: outdoor air and di-ethyl-hexyl-sebacate (DEHS) synthetic aerosol. DEHS was selected as the test aerosol prescribed by ISO 16890 (ISO 16890-2 2022), ensuring consistency with standardized methodologies for air filtration performance evaluations. This selection aligns with the long-term perspective of using LCSs to monitor air filters in ventilation systems as specified in ISO 29462 (ISO 29462 2022). Furthermore, low-cost PM sensors often exhibit good performance when measuring smaller particle sizes (PM $<$ 1) (Kuula et al. 2020; Ouimette et al. 2024; Ouimette et al. 2022; Tryner et al. 2020), i.e., the fraction of particles that is more difficult to control with air-cleaning technologies. Using DEHS allowed providing controlled conditions to assess the suitability of LCSs for detecting these smaller particles. The DEHS aerosol was generated by a Laskin nozzle and directly introduced into the plenum upstream of the measuring points (Figure 1a). Atmospheric aerosol was obtained from an air intake located in the plenum of the test rig, 11 m from the ground level, and 90 m from road traffic (Inlet 2 in Figure 1a) (ISO 16890-2 2022). The test rig is connected to an air treatment unit (ATU) capable of conditioning the air stream from *Inlet 1* (Figure 1a). It can adjust the air temperature and relative humidity and remove the particles in the air stream when passing through a bank of high-efficiency particulate air (HEPA) filters. In addition, maintaining a constant airflow rate is possible by controlling the fans' rotational speed through a programmable logical controller (PLC). We maintained the temperature and relative humidity constant (within 0.5 °C and 3%, respectively) during the tests with DEHS aerosol. When testing with outdoor aerosol, both temperature and humidity were not controlled but were measured using HD4817ET temperature and humidity transmitter from DeltaOhm.

2.2. Testing conditions

When using DEHS aerosol, we maintained an overpressure within the test duct relative to the laboratory

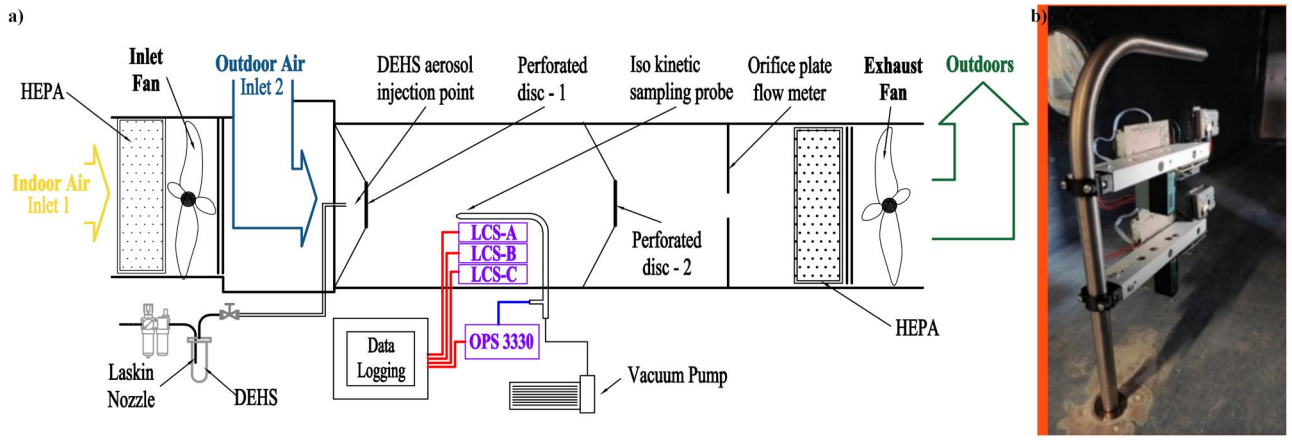


Figure 1. On the left is the schematic of the experimental setup employed in the dynamic characterization of LCSs. On the right is a picture showing the sampling probe installed upstream of Ref and the tested LCS modules attached.

environment by controlling the airflow and pressure in the duct. This approach prevented the infiltration of ambient air into the duct, ensuring that the generated aerosol concentration and particle size distribution remained undisturbed. Incoming air was first filtered with a HEPA filter bank, and the test duct was at a higher pressure than the laboratory room. In the case of the outdoor air, we obtained the desired airflow rate using only the downstream fan to draw the sample from *Inlet 2* inside the test rig, avoiding the passage through the inlet HEPA filter bank. Consequently, the portion of the test duct before the fan may have experienced a small negative pressure. Hence, some aerosol intake from the laboratory environment might be mixed with the outdoor aerosol downstream of the measuring points.

The particle size distribution of outdoor air varies depending on various factors such as location, weather conditions, and sources of pollution. However, the particle size distribution in outdoor air in Northern Italy is generally similar to that of particles found in other urban or industrialized areas (Wu and Boor 2021). Specifically, in the Piedmont region, the mass distribution as a function of particle size in outdoor air is typically bimodal. The distribution has two main peaks: around 0.4 µm and about 3 µm. In addition, residential heating causes higher PM concentration values during winter (Malandrino et al. 2016; Rovelli et al. 2017).

The maximum air velocities suggested by the manufacturer to operate sensors A and B were 0.50 m/s and 0.75 m/s, respectively. However, we also conducted experiments at higher air velocities using unfiltered outdoor air. The duration of the tests with DEHS was 20 min. Section S9 of the online supplementary information (SI) indicates the test duration's suitability for evaluating average values in stationary flow rate and particle generation conditions. In the case of outdoor air, because of the absence of direct control on particle generation, the testing duration increased to 1 h to capture fluctuations. Table 2 summarizes the tests performed with their conditions.

2.3. Data analysis

After evaluating the particle mass concentration (Görner et al. 2012) in each dimensional range (as reported in the SI, S1), we compared data obtained from two datasets, the *Ref* and LCS instruments. The lab grade reference instrument has a logging interval equal to 20 s, while the data from the LCSs are logged approximately every 1.2 s. We established a quantitative relationship between the LCS data and *Ref* measurements, including measuring metrics like the coefficient of determination R^2, slope, and intercept *via* linear regression (detailed results in SI, S2). We also assessed the root square mean error (RSME) at four concentrations of DEHS to gauge the agreement between LCSs and *Ref* data.

Determining the statistical significance of data from each sensor model required the evaluation of hypotheses, based on comparisons with the TSI OPS 3330 reference device and across these four DEHS concentrations. The null hypothesis posited no statistical difference between the mean concentrations. We opted for Welch's t-test (Taeger and Kuhnt 2014), which accommodates potential variations in

Table 2. Test conditions.

Test number	Test duct air velocity	PM_{10} from Ref	Test aerosol	Temperature	Relative humidity	Test duration
#	[m/s]	[µg/m3]	–	[°C]	[%]	[h]
1	0.75	106 ± 14	DEHS	22 ± 0.5	31 ± 3	0.33
2	0.75	79 ± 12	DEHS	22 ± 0.5	31 ± 3	0.33
3	0.75	47 ± 6	DEHS	22 ± 0.5	32 ± 3	0.33
4	0.75	22 ± 4	DEHS	22 ± 0.5	32 ± 3	0.33
5	1.50	42 ± 4	Outdoor air	21-23*	22-30*	1
6	2.53	43 ± 14	Outdoor air	15-21*	22-30*	1
7	1.5	171 ± 11	DEHS	20 ± 0.5	36 ± 3	1
8	1.5	81 ± 7	DEHS	20 ± 0.5	36 ± 3	1
9	1.5	26 ± 3	DEHS	20 ± 0.5	36 ± 3	1
10	1.5	137 ± 9	DEHS	20 ± 0.5	36 ± 3	1
11	2.5	41 ± 9	DEHS	20 ± 0.5	36 ± 3	1
12	2.5	30 ± 3	DEHS	20 ± 0.5	36 ± 3	1
13	2.5	8 ± 4	DEHS	20 ± 0.5	36 ± 3	1
14	2.5	27 ± 4	DEHS	20 ± 0.5	36 ± 3	1
15	2.5	14 ± 2	DEHS	20 ± 0.5	36 ± 3	1
16	2.5	77 ± 6	DEHS	20 ± 0.5	36 ± 3	1
17	2.5	165 ± 11	DEHS	20 ± 0.5	36 ± 3	6
18	2.5	94 ± 5	DEHS	20 ± 0.5	36 ± 3	1
19	1.5	10 ÷ 70	Outdoor air	15-21*	22-60*	60
20	2.5	15 ÷ 60	Outdoor air	15-21*	22-60*	88

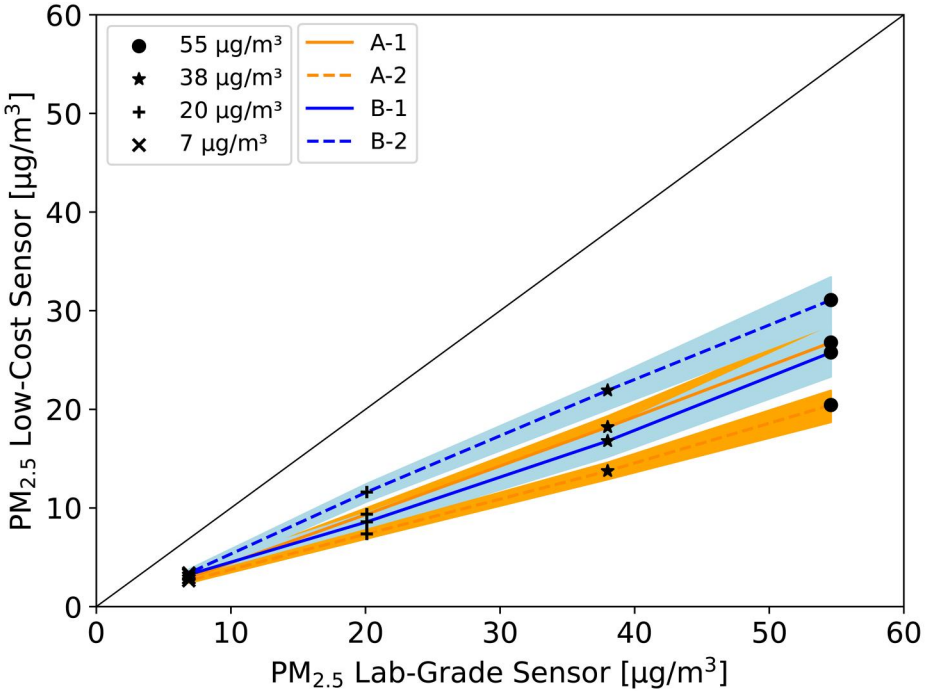
*During these tests, the ATU was in free mode, and temperature and humidity were not controlled.

population variances within the TSI and LCS datasets, presenting a more robust alternative to the conventional two-sample t-test (Taeger and Kuhnt 2014) (detailed results in SI, S4). However, it's worth noting that the application of Welch's *t*-test assumes a normal distribution of the underlying populations. To ensure the validity of this assumption, we evaluated both the sensor data and the reference instrument data with two normality assessments. First, we examined the histograms and calculated the skewness to assess the distribution shape (SI S3). The second assessment employed the Shapiro-Wilk hypothesis test (Taeger and Kuhnt 2014), which assesses the dataset's adherence to a normal distribution. Detailed values are reported in the SI Table S1 (*Ref*), Table S2 (LCS, $PM_{2.5}$), and Table S3 (LCS, PM_{10}).

3. Results

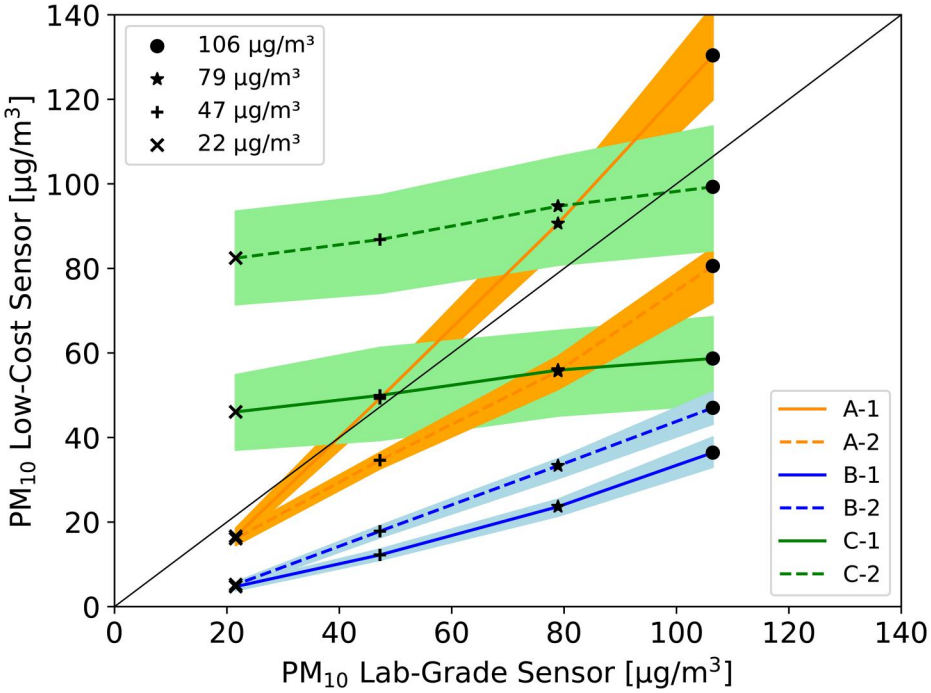
Figures 2 and 3 present $PM_{2.5}$ and PM_{10} data correlated with the reference instrument at different average concentrations of DEHS aerosol. The table to the right of each graph summarizes the linear interpolation metrics, the coefficients of determination (R^2), intercepts (b), and slopes (m). The observed linear relationship between LCSs and *Ref* data across this wide concentration range (corresponding RSME values reported in Table 3) supports the suitability of LCSs for obtaining data useful for relative measurements for the sensors type A and B sensors for $PM_{2.5}$ (Figure 2). However, both the A and the B showed slightly worse agreement with a linear fit for the PM_{10} relationships than for $PM_{2.5}$ (Figure 3). The third type of LCS sensor (C) exhibited a significant variation, especially in slope, raising concerns about its ability to measure PM_{10}, even in relative applications. Since this sensor exploits natural buoyancy, any disturbance capable of influencing the local airflow close to the sensor (e.g., duct curves, turbulent eddies, section variations, or obstructions) affects the sampling of particles. This can especially limit the possibility of larger particles reaching the detection chamber of the sensor. The presence of a fan in the LCSs type A and B can reduce this influence, reducing the disturbance and the difference in velocities between the sampled stream in the probe and the air stream in the duct.

Linear interpolation metrics highlight, in general, a reduced ability of the LCS sensor to correctly assess PM_{10} compared to $PM_{2.5}$. This fact is inherent in the sensing technology typical of this kind of system, as reported elsewhere (Molina Rueda et al. 2023; Tryner et al. 2020, 2021). Indeed, larger particles (such as PM_{10}) interact differently with light than smaller particles (such as $PM_{2.5}$). In the case of forward scattering, which is the scattering of light at small angles



	R²	b	m
A-1	0.92	0.14	0.47
A-2	0.96	0.38	0.35
B-1	0.91	0.22	0.45
B-2	0.94	0.1	0.57

Figure 2. Comparison of $PM_{2.5}$. DEHS concentration between LCSs and reference instrument (left). On the right, the table summarizes linear interpolation metrics for each tested sensor. R2 is the coefficient of determination, and b and m are the linear interpolation's intercept and slope, respectively.



	R²	b	m
A-1	0.89	-6.76	1.24
A-2	0.92	2.63	0.68
B-1	0.87	-2.65	0.34
B-2	0.92	-4.08	0.47
C-1	0.56	43.52	0.14
C-2	0.62	77.88	0.21

Figure 3. Comparison of PM_{10}. DEHS concentration between LCSs and reference instrument (left). On the right, the table summarizes linear interpolation metrics for each tested sensor. R2 is the coefficient of determination, and b and m are the linear interpolation intercept and slope, respectively.

Table 3. RSME value [$\mu g/m^3$] of each sensor compared to the reference concentration of $PM_{2.5}$ and PM_{10} measured with the OPS-3330.

Ref $PM_{2.5}$ [$\mu g/m^3$]	55	38	20	7
A	29	20	11	4
B	30	22	12	4
Ref PM_{10} [$\mu g/m^3$]	106	79	47	22
A	32	15	9*	7
B	72	56	36	17
C	50	26	7	25

*According to the Welch's Test, there is no significant difference between the sensor and the reference instrument having a $p_{T\text{-}Test} > 0.05$.

relative to the incident light direction, larger particles tend to scatter light less efficiently. Larger particles have less surface area per unit volume compared to smaller particles. Hence, they generate a lower intensity of scattered light, resulting in a lower count for the LCSs. Additionally, larger particles may have different optical properties and shapes than the smaller ones, increasing the share of absorbed and refracted light and generating additional challenges for their detection with the LCSs.

In addition, we configured the *Ref* instrument to sample airborne particles in isokinetic conditions. LCS sensors do not have any sampling system to achieve isokinetic conditions when exposed to an airstream with a certain velocity. Their orientation can affect the measured data. The greater the difference between the LCS sampling conditions and the isokinetic sampling of the *Ref*, the greater the influence on the capacity of the sensor to sample larger particles compared to the smaller ones (<1 µm). Indeed, as the velocity increases, the imbalance increases, causing an underestimation of the reference concentration (Hinds and Zhu 2022).

Figure 4 shows the experimental data obtained with DEHS aerosol at higher air velocities (1.25 m/s and 2.5 m/s). It shows that the linear trend between LCSs and the reference instrument remains consistent for both $PM_{2.5}$ and PM_{10} measurements. However, a minor deviation associated with increased velocity is evident, particularly for $PM_{2.5}$. As the velocity increases, the slope of the traces for $PM_{2.5}$ and PM_{10} increases, reducing the mismatch between the LCS and the reference optical instrument. This behavior is observed for both sensors (type A and B). For PM_{10}, while the general trend is similar, the change in slope with velocity moves data closer to unity, indicating potentially different mechanisms affecting particle detection at higher velocities. However, the small fraction of particles larger than 2.5 µm (see cumulative distributions included in the SI S1) limits our confidence in this finding.

Figures 2–4 highlighted a slight divergence between the sensor types A and B, which can likely be explained by sample-to-sample variation. Potential contributing factors might include manufacturing inconsistencies,

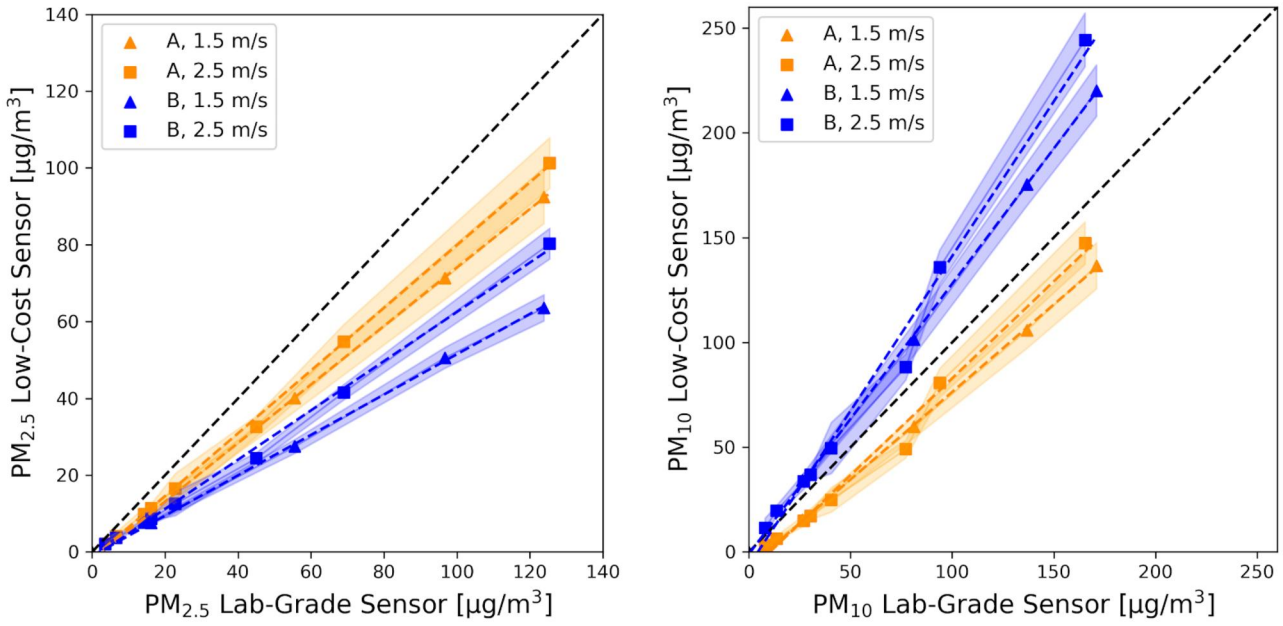


Figure 4. Comparison of $PM_{2.5}$ (left) and PM_{10} (right) DEHS concentrations between LCSs and reference instrument at 1.5 m/s and 2.5 m/s air velocities (left).

calibration differences, and slight deviations in sensor placement relative to the airflow in the duct. The two LCSs of each type were positioned approximately 0.1 m apart, and variations in air velocity at their respective locations could result in different particle sampling efficiencies. This effect is consistent with the results presented in Figure 4, where testing with DEHS aerosol at velocities of 1.5 and 2.5 m/s revealed that air velocity influences the slope of the linear correlation between the laboratory-grade instrument and the LCSs. Figure 5 illustrates the stability of sensor data over time, showing small deviation at low concentrations throughout the 20-minute test duration. However, the deviation becomes more pronounced as DEHS concentration increases for both $PM_{2.5}$ and PM_{10}. In addition, Figure 4 includes simultaneous measurements from two LCS samples of each type, revealing that increasing the average concentration level of $PM_{2.5}$ and PM_{10} results in larger differences between similar sensors. Some of these differences may be sample variation across LCSs of the same type. However, non-isokinetic influences stemming from differences in sensor alignment with the air streamlines inside the duct may also contribute to this effect. The alignment of the *Ref* instrument is optimal to minimize particle sampling loss at the sampling probe location. Again, this aspect impacts more particles with higher inertia and is likely why PM_{10} shows higher deviations than $PM_{2.5}$.

Because the research goal of assessing the suitability of LCS usage in real HVAC applications, using DEHS test aerosol is limiting. Ambient particle variability may generate additional uncertainty on LCS output. Additional tests evaluating LCS output with outdoor aerosol compared to the same lab-grade *Ref* filled this knowledge gap. Further, if positioning sensors inside a duct as in a real application, LCS sensors might likely experience higher air velocities. For this reason, tests reported in Figures 6 and 7 show comparisons for outdoor aerosol for $PM_{2.5}$ and PM_{10} at two velocities, 1.5 and 2.5 m/s, respectively. The graphs show a weaker linear relationship between LCS and *Ref* with a higher variability than for DEHS test aerosol, particularly at 2.5 m/s. A large contributing factor is the variations in aerosol composition, morphology, and optical properties. The difference is pronounced for PM_{10} aerosols for all LCSs. Another contributing factor is velocity. The strongest linear relationship is for $PM_{2.5}$ at 1.5 m/s, and the weakest is for PM_{10} at 2.5 m/s (interpolation metrics reported beneath each graph of Figures 6 and 7). The results for PM_{10} at 2.5 m/s are particularly interesting as all LCSs have almost flat slopes with high degrees of variability (low R^2 values). Since the LCSs studied here have either a fan working at a fixed speed or no fan, their sampling operation will likely be non-isokinetic. The aerosol sample analyzed by the LCSs may have a particle size distribution different from that in the test duct. This difference also depends on the airspeed inside the test duct and the properties of the aerosol under study, as shown in Figures 6 and 7 (online SI, S5 contains detailed results related to airstream velocity influence on linear regression when compared with the

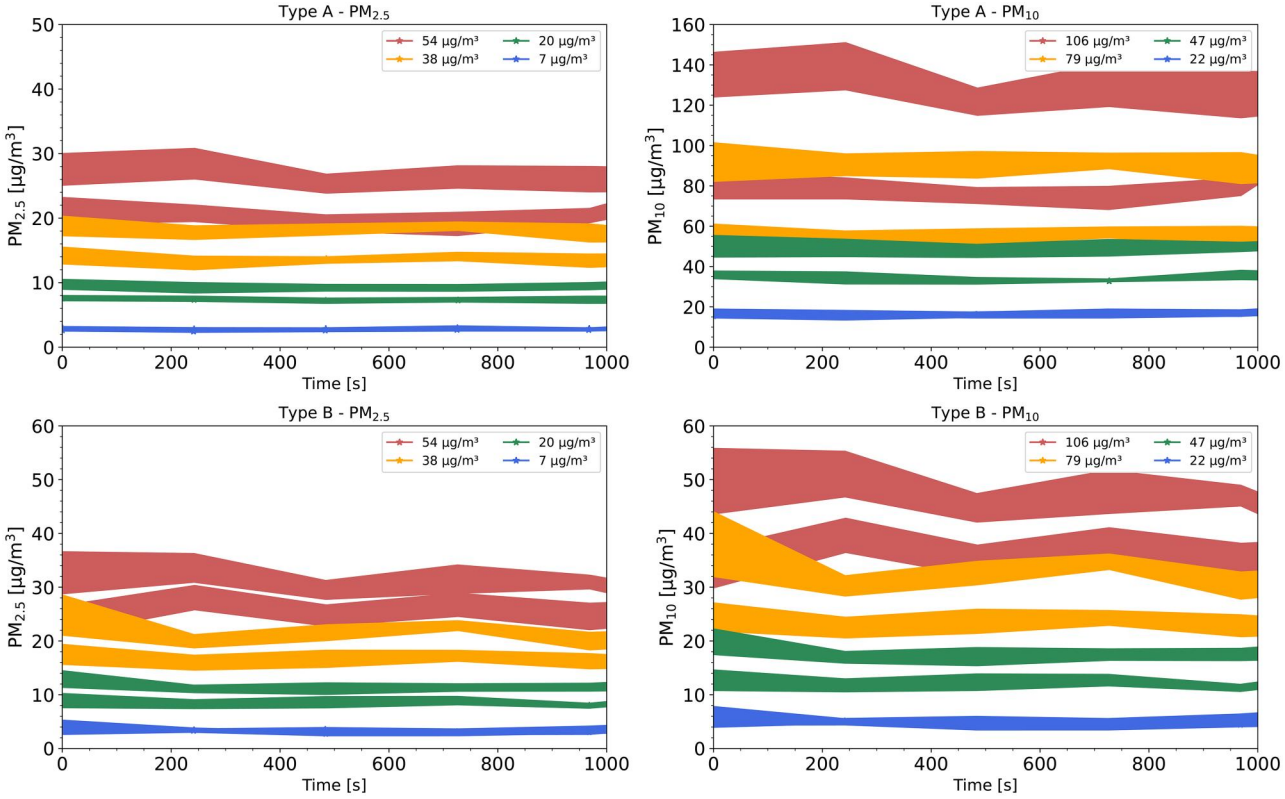
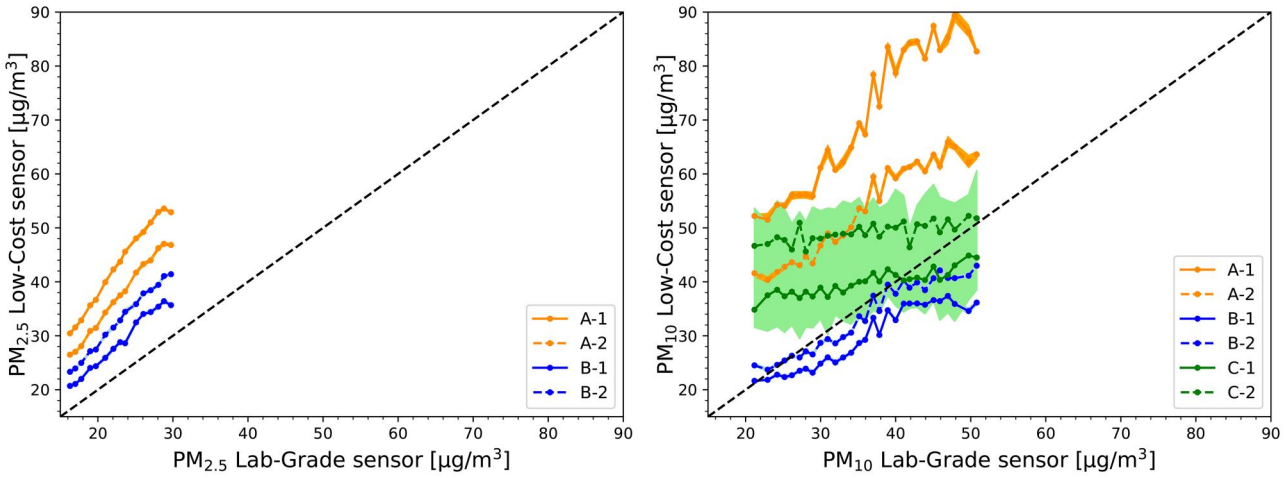


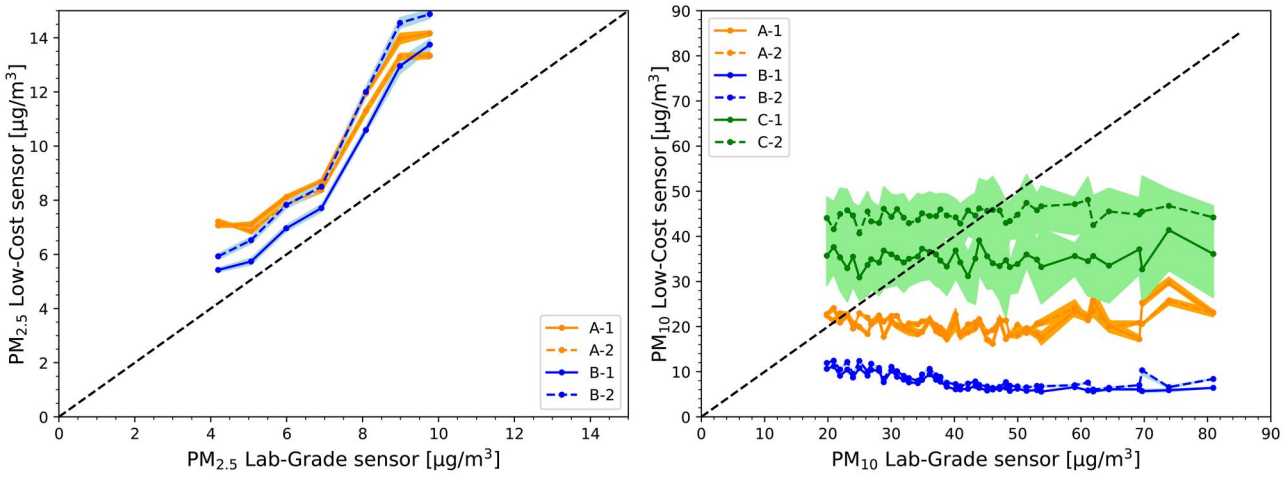
Figure 5. Temporal stability of the DEHS aerosol measurement from sensors types A and B during 1000 s of test duration at different $PM_{2.5}$ and PM_{10} concentrations at 0.75 m/s. Figure S10 in the SI reports the same information for the sensor type C.



	R^2	b	m
A-1	0.99	1.01	1.83
A-2	0.96	-0.66	1.65
B-1	0.98	-0.13	1.26
B-2	0.99	-0.19	1.41

	R^2	b	m
A-1	0.91	18.3	1.45
A-2	0.93	18.62	0.97
B-1	0.91	6.64	0.64
B-2	0.94	7.0	0.74
C-1	0.8	31.08	0.24
C-2	0.5	43.76	0.15

Figure 6. Influence of the airstream velocity with outdoor aerosol for $PM_{2.5}$ (left) and PM_{10} (right) at 1.5 m/s. Beneath each graph, the table containing the linear interpolation metrics related to each tested sensor, coefficient of determination (R^2), intercept (b), and slope (m).



	R²	b	m
A-1	0.93	-0.13	1.47
A-2	0.91	0.55	1.31
B-1	0.96	-2.33	1.62
B-2	0.95	-2.4	1.78

	R²	b	m
A-1	0.07	18.35	0.04
A-2	0.01	20.91	0.01
B-1	0.63	11.33	-0.09
B-2	0.46	12.12	-0.08
C-1	0.02	34.33	0.02
C-2	0.14	43.24	0.04

Figure 7. Influence of the airstream velocity with outdoor aerosol for $PM_{2.5}$ (left) and PM_{10} (right) at 2.5 m/s. Beneath each graph, the table containing the linear interpolation metrics related to each tested sensor, coefficient of determination (R^2), intercept (b), and slope (m).

reference instrument). However, the information obtained by the better-performing LCSs (type A and B) is valuable even if the sampling is not isokinetic. Indeed, it is still possible to assess the trend of $PM_{2.5}$ concentration as a function of time and its reduction due to the presence of air-cleaning equipment in these conditions. However, these results suggest caution when using LCSs for PM_{10}, even for relative measurements, especially at higher air speeds.

Another crucial consideration is the variability among samples. Sensor-to-sensor variation can significantly impact the reliability of LCS data when used for relative evaluations. The placement of sensors within a duct can be pivotal for the quality of the relative measurements. Illustrated in Figure 8 is the correlation between air stream velocity and the relative concentrations measured by LCSs, showcasing discrepancies among equivalent outputs normalized against the *Ref* value at 1.5 and 2.5 m/s for both $PM_{2.5}$ (Figures 8a–c) and PM_{10} (Figures 8d–f).

Figures 8a and d depict the temporal evolution of the sensor-to-sensor relative uncertainty normalized against the *Ref* output at the corresponding acquisition time. The comparison of the normalized uncertainty trends between equivalent LCS types and equivalent velocities reveals higher uncertainties for PM_{10} (Figure 8d) when compared to $PM_{2.5}$ (Figure 8a). The relative positioning of equivalent sensors significantly impacts the output value for types A and B, with this positioning uncertainty being more pronounced for particles with higher inertia. Furthermore, comparing trends at 1.5 and 2.5 m/s indicates a reduced significance of sensor positioning as air stream velocity increases. Sensor-to-sensor differences are less than 10% of the *Ref* value for $PM_{2.5}$ and PM_{10} at 2.5 m/s. However, the impact of sensor positioning and corresponding error is less relevant for sensor type B. Conversely, sensor type C shows minimal influence of air stream velocity on sensor positioning, with a normalized sensor-to-sensor error for PM_{10} oscillating between 20–40% of the *Ref* value during the 1 h of testing for both velocities.

Figures 8b, c, e, and f show the sensor-to-*Ref* differences normalized against the same *Ref* value. Points closer to the 1:1 line indicate lower differences between equivalent sensors, suggesting reduced variability. Datapoints closer to the 1:1 line mean lower discrepancies with *Ref*, indicating better agreement with the *Ref* value. However, this proximity does not eliminate the influence of sensor location. Variations in local airflow conditions can still generate differences in sensor outputs, even after normalization. As air velocity increases, points shift closer to 1:1 in all four plots, suggesting that higher airflow velocities reduce the dependence of discrepancies on sensor location. However, the data spread widens at higher velocities, indicating less consistency in relative measurements. This trend highlights the tradeoff between reduced location dependence and increased variability in

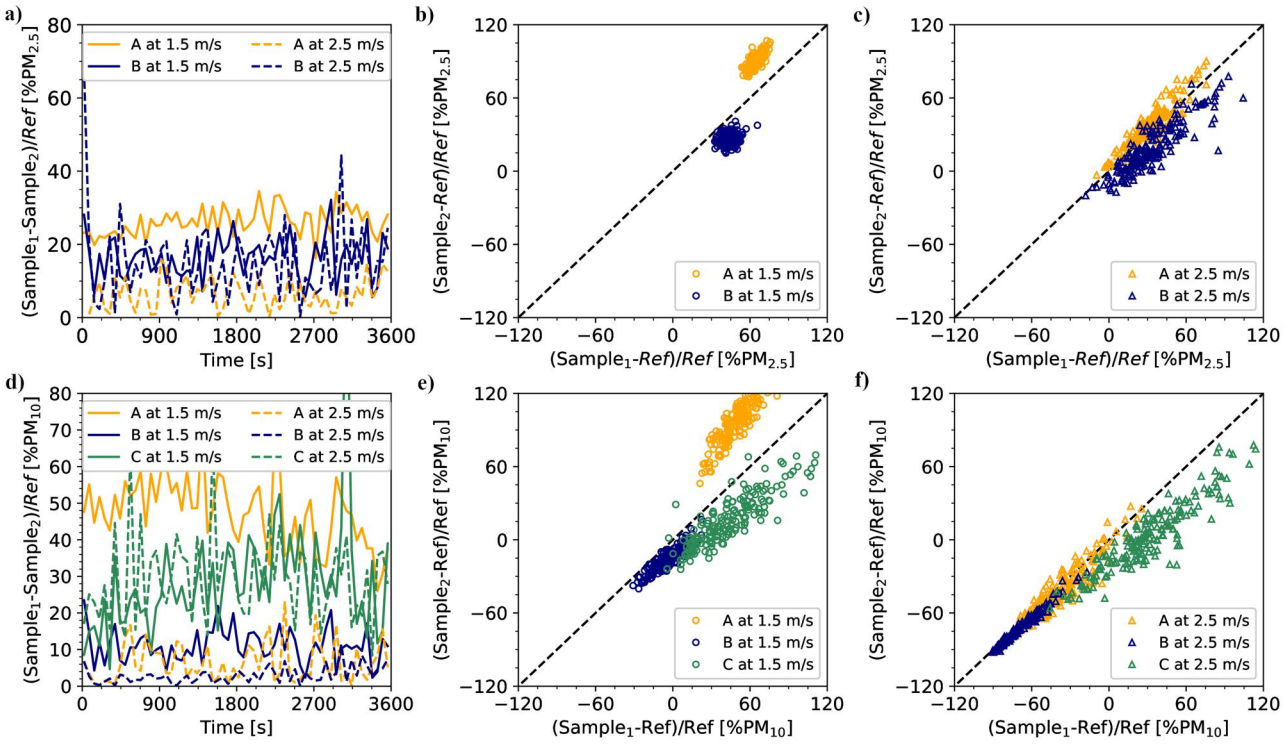


Figure 8. Cross comparison between sensors of the same type A, B, and C when exposed to higher airflow velocity, at 1.5 and 2.5 m/s for $PM_{2.5}$ (top) and PM_{10} (bottom).

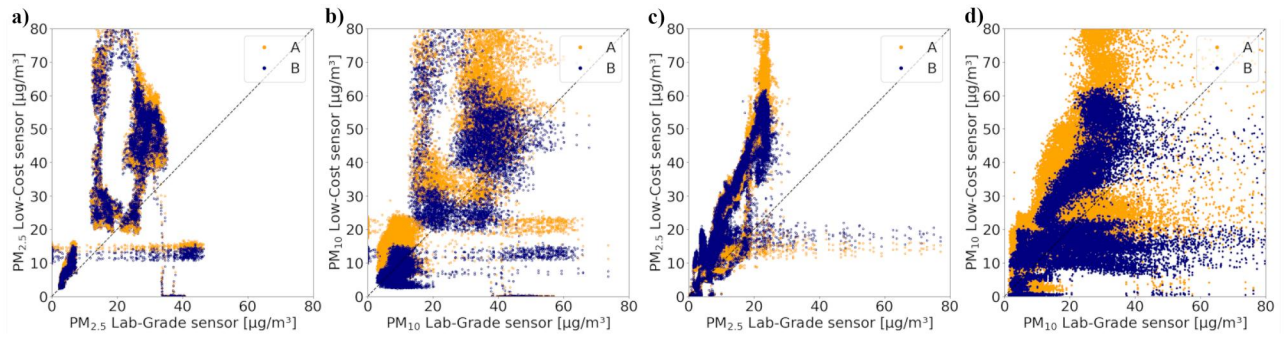


Figure 9. Comparison of $PM_{2.5}$ and PM_{10} data between sensor type A and B with the lab grade sensor when exposed to outdoor air at higher airflow velocity: 1.5 m/s (a and b) and 2.5 m/s (c and d).

relative measurements as air velocity increases. Additionally, for $PM_{2.5}$, there is a general overestimation, as seen in the densification of points in the positive quadrant of both velocity regimes. For PM_{10}, a consistent underestimation is clear, highlighting differences in particle behavior due to inertia and aerodynamic properties. These observations underscore the importance of carefully considering sensor placement and airflow characteristics when integrating LCSs into HVAC systems. While increased velocity can mitigate the location dependence of measurements, it may also introduce variability in relative data quality, necessitating additional calibration and placement considerations.

Figure 9 compares the LCSs and the lab-grade sensor during two long-duration tests with outdoor air. The tests lasted 60 h at an air velocity of 1.5 m/s (Figures 9a and b) and over 88 h at an air velocity of 2.5 m/s (Figures 9c and d). The mismatch between LCSs and lab-grade sensors increases as the concentration increases, as in the DEHS results. PM_{10} comparisons show greater dispersion than $PM_{2.5}$ comparisons for both airflow regimes. Notably, the $PM_{2.5}$ comparisons reveal distinct discrepancies between the LCSs and the lab-grade sensor, which appear as random occurrences rather than systematic errors or consistent mismatches. Despite this, the densification of data points along a linear correlation, as observed in earlier

tests, is still evident at both velocities. PM_{10} measurements also display a similar trend but with higher variability.

The LCS type B also provides two additional outputs, PM_1 and PM_4, i.e., the concentration of particles smaller than 1 µm and 4 µm, respectively. Figure 10 shows all four PM measurements at four different concentrations of DEHS aerosol. On one hand, the absolute difference from the reference instrument is higher when estimating $PM_{2.5}$, PM_4, and PM_{10} than PM_1, suggesting more accuracy for submicron aerosols. On the other hand, the absolute sensor-to-sensor difference is larger for PM_1, heightening the importance of two types of calibration: *(i)* calibration of LCS to a reference instrument at the same concentrations and velocities (particularly important for absolute concentrations and for $PM_{2.5}$ and larger particle size) and *(ii)* calibration of one sensor relative to another for relative measurements (important for all sizes, but particularly important for PM_1).

4. Discussion

The experimental outcomes presented in the study shed light on various aspects pertinent to the suitability of LCSs in different scenarios. One overall finding is that a standardized approach for assessing and qualifying LCSs for use in duct measurements would allow these results to be expanded to other LCSs than those tested here, as well as provide an approach for manufacturers to develop sensors that work well in moving air flows/HVAC duct applications.

4.1. Factors influencing sensor-to-sensor comparisons

The inherent light-scattering properties of particles also contribute to this variability, particularly forward scattering connected to Mie theory plays a major role (Molina Rueda et al. 2023; Tryner et al. 2020, 2021). The lower surface area per unit volume of PM_{10} compared to $PM_{2.5}$ reduces the intensity and efficiency of light scattering, resulting in lower signal intensity for PM_{10} and increasing their uncertainty and variability (Kuula et al. 2020; Ouimette et al. 2024; Ouimette et al. 2022). Sensors such as the NovaSensor SDS011, the Plantower PMS5003, and the Sensirion SPS30 are inaccurate in detecting particles in the coarse mode (Budde et al. 2018; Kuula et al. 2020; Ouimette et al. 2024; Ouimette et al. 2022; Zikova, Hopke, and Ferro 2017). Variability in particle composition, morphology, and optical properties can differ significantly between $PM_{2.5}$ and PM_{10}. PM_{10} particles are more likely to include a wider range of particle types, such as dust and other larger particulate matter resulting from mechanical mechanisms (e.g., erosion from natural agents and wind transport), which can vary more in shape and optical characteristics. $PM_{2.5}$ particles are more likely the result of combustion processes. This variability in particle properties generates greater disturbances in particle detection for larger particles than smaller particles and can lead to inconsistencies in sensor-to-sensor comparisons.

The sensor-to-sensor variability observed for PM_{10} compared to $PM_{2.5}$ is also due to the aerodynamic properties of larger particles like PM_{10}, which exhibit higher inertia than smaller particles like $PM_{2.5}$. This increased inertia affects the particles' ability to follow air streamlines, leading to more significant discrepancies in particle sampling, especially under non-isokinetic conditions. When the air stream velocity is inconsistent with the sensor's design specifications, larger particles are less likely to be accurately captured by the sensors. This effect is particularly pronounced in environments with varying air speeds and directions, such as within HVAC ducts. Different LCS models have varying

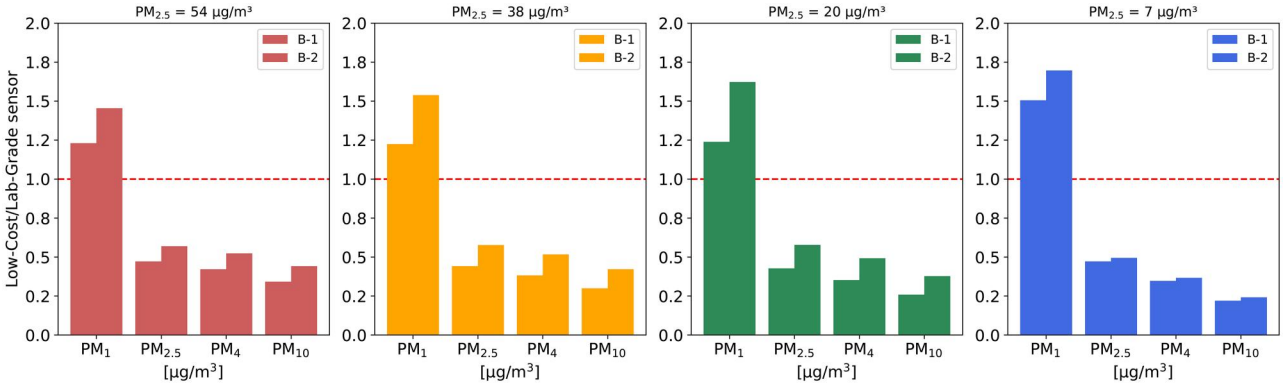


Figure 10. The ratio between the different outputs (namely PM_1, $PM_{2.5}$, PM_4, PM_{10}) from each sample of sensor type B over the Ref value at different aerosol concentrations.

designs and operational mechanisms, such as the presence or absence of fans. Sensors with built-in fans can partially mitigate the effects of airflow disturbances, reducing variability. However, sensors without fans, which rely on natural convection, are more susceptible to local airflow variations, significantly affecting PM_{10} measurements. The positioning of these sensors about airflow patterns within a duct can further exacerbate this variability. Additionally, LCS sensors are not typically designed for isokinetic sampling, meaning their sampling rate does not match the velocity of the airstream. This mismatch leads to sampling bias, particularly for larger particles like PM_{10}, which are more prone to deviations due to their higher inertia. Differences in sensor alignment and orientation within the duct can also contribute to this effect, as larger particles are more affected by these variations than smaller particles.

4.2. Suitability for test-duct/standardized aerosol

The observed linear relationship between LCSs and *Ref* data across a broad concentration range underscores the applicability of LCSs for PM measurements where relative values are important. Particularly, the inherent linearity, evident for precise relative comparisons of $PM_{2.5}$ concentrations, emphasizes the value of LCSs for such assessments. However, disparities in linear PM_{10} relationships, notably among sensor types, highlight challenges in achieving consistent measurements for larger particle sizes. This discrepancy indicates potential limitations in applying these devices to assess the efficiency of low-performing filters, like prefilters, which primarily impact the concentrations of larger particles. The results described in this paper are for DEHS and are likely valid for similar oily particles. Aerosols with different optical properties, particularly those with properties that change with a particle size distribution, may yield different results, highlighting the need for calibration and their coordinated location (colocation), as discussed below. Evidence shows that higher velocities also cause relative discrepancies, suggesting the value in developing LCSs that can sample isokinetically or using external isokinetic samplers with LCSs.

4.3. Value of relative measurements and importance of colocation

Discrepancies in agreement levels among different LCS samples emphasize the need for instrument correlation factors. Several factors influenced these disparities. They include variability in sensor calibration, positioning within the duct, differences in airflow field, and environmental conditions such as air humidity and temperature. The significance of these factors advocates for standardized colocation procedures and quality control measures. Colocation allows for direct comparison of sensor outputs in controlled environments, enabling the identification of systematic biases and the development of correction factors to improve measurement accuracy. For instance, properly positioning LCSs sensors with reference instruments under different environmental conditions, such as varying humidity and temperature, can help evaluate and compensate for biases caused by hygroscopic growth or infrared absorption. Regular calibration and maintenance schedules for LCSs and robust data validation protocols can ensure consistent performance over time.

In addition, the tests here with outdoor aerosol show that more complex aerosol mixtures may need periodic calibration with reference instruments, particularly when aerosol composition changes and at higher velocities. We did not explore this in detail (beyond any variations in humidity in the outdoor air measurements), but high humidity conditions can be challenging for many LCSs (Lewis, Schneidemesser, and Peltier 2018). Further, humidity can be high in outdoor air streams and downstream of cooling coils and humidifiers in HVAC systems. A factor responsible for the impact of humidity is the hygroscopic growth of the aerosol particles, leading to particle size changes (Crilley et al. 2018; Hagan and Kroll 2020; Malings et al. 2020). Also, water vapor absorbs infrared radiation and can cause an overestimation of particle mass concentrations (Wang et al. 2015). High humidity may even affect relative measurements with LCSs (if humidity is different at different measurement points or particle distributions are different because of hygroscopic growth). This is an important area for future research requiring a more robust and standardized methodological approach.

4.4. Challenges with variation over time and influence of velocity

The stability of sensor data over time, showcased by minimal deviation at low concentrations, contrasts with more pronounced deviations at higher DEHS concentrations for both $PM_{2.5}$ and PM_{10} with two tested sensors. A third tested sensor that did not use a sampling fan showed worse agreement for PM_{10}, indicating that such a design may not be well-suited for HVAC measurements. Additionally, higher velocities contribute to reduced linear correlations between LCS data and *Ref*

measurements, especially noticeable for high-inertia particles at 1.5 m/s, emphasizing the impact of anisokinetic sampling conditions and potential challenges associated with varying velocities. Positioning LCSs in a duct is pivotal in making good relative measurements, and matching air velocity and measurement locations is important for any relative measurement.

4.5. Suitability for in situ testing

In situ filter or ventilation performance testing and some HVAC control using PM measurement are appealing applications for LCSs. Because these applications require relative measurement, they avoid some of the absolute inaccuracies of LCSs. However, differences in aerosol properties and particle concentration variations across a duct and in different LCS locations may affect measurement consistency. A specific example application where relative errors might be important is filtration testing. The performance of air filters for general ventilation depends on the ratio of upstream and downstream particle concentrations. Therefore, the evaluation of filtration efficiency will still be correct by making the same (i.e., the same non-isokinetic conditions) measurement errors in both sections, particularly for $PM_{2.5}$ measurements.

For larger particles (the PM_{10} in our measurements) at higher velocities and with outdoor aerosol, all the LCSs tested would lead to considerable uncertainty in any *in situ* efficiency measurement. However, for the DEHS aerosol, two of the three LCSs would introduce small uncertainties, especially if they were colocated/cross-calibrated before use. The concentration measurements were generally quite accurate for $PM_{2.5}$ (and PM_1, when available) for both DEHS and outdoor aerosol, suggesting that LCSs (at least those tested) might be better suited to smaller particle measurements than PM_{10}. Although both sensors in filtration testing generally see the same velocity (unless there are duct size changes or non-uniformity in flow across the duct cross-section), care should be taken to confirm similar velocities when using LCSs to measure filter efficiency. As part of best practices for measuring filter efficiency with LCSs, doing a no-filter test (when the filter is removed) will allow for correcting any sensor differences (Li and Siegel 2020).

4.6. Integration of LCS into building management systems

The integration of Low-Cost Sensors (LCSs) into Building Management Systems (BMS) can significantly enhance indoor air quality (IAQ) management and energy efficiency.

LCSs can provide real-time monitoring of $PM_{2.5}$, enabling dynamic control of ventilation rates based on actual particulate matter (PM) concentrations as an improved approach to CO_2 sensor-based ventilation strategies. $PM_{2.5}$ sensors can supplement CO_2 sensors if the goal is to preserve human health, as they can detect harmful particulate matter more effectively. However, CO_2 sensors remain indispensable when indoor air quality is assessed based solely on olfactory comfort or for ultrafine PM and gas-phase compounds, which are not measured by the optical LCSs used in this work. This approach allows for increased ventilation during high PM events, such as outdoor pollution spikes or indoor activities, and reduced ventilation when PM levels are low, saving energy. This demand-controlled ventilation (DCV) strategy improves IAQ and reduces energy consumption, aligning with sustainability goals and potentially enhancing occupant health and productivity.

The reproducibility of our experiments is crucial for broader applications. Our setup, involving LCSs and a reference-grade instrument, is designed to be straightforward and replicable, with stable aerosol generation, consistent sensor placement, and controlled airflow conditions. The commercially available LCSs and detailed calibration and data collection procedures ensure the methodology can be easily replicated.

The setup can be expanded for larger-scale studies or commercial testing by increasing the number of sensors and sampling points, covering more extensive areas or multiple zones within a building. The modular nature of LCSs allows for flexible deployment across various environments, and integration with existing BMS infrastructure can be achieved through standard communication protocols like Wi-Fi or Zigbee, which many LCSs support. Overall, the integration of LCSs into BMS offers a practical and scalable solution for improving IAQ management and energy efficiency. Our study demonstrates the feasibility of using LCSs for real-time PM monitoring in air ducts, especially for $PM_{2.5}$ monitoring, providing a foundation for future research and practical applications. Ensuring the reproducibility and scalability of our experimental setup is essential for advancing this technology from research to widespread commercial adoption.

5. Conclusions

This study demonstrates the feasibility of using various low-cost sensors (LCSs) in air ducts where airflow

velocities range from 0.75 to 2.5 m/s. When comparing LCS output with measurements from a laboratory-grade optical spectrometer, two sensors (types A and B) exhibited a strong linear relationship across a wide range of PM concentrations. Linear fitting of $PM_{2.5}$ measurements (representing the total number of particles with an optical diameter smaller than 2.5 µm) for sensors A and B yielded very high R^2 values, indicating a proportional agreement with the reference instrument. The experimental data confirmed the suitability of these sensors for relative measurements, such as those typically used to assess filtration efficiency following ISO 16890 in a standardized test duct or for continuous monitoring in ventilation systems as specified in ISO 29462. However, for PM_{10} measurements, the linear relationship is less reliable, presenting challenges in accuracy.

In contrast, sensor type C, which lacks an internal fan for aerosol sampling from the main air stream, demonstrated poor performance under varying air velocities and PM concentrations for both $PM_{2.5}$ and PM_{10}. The lack of a linear correlation with the optical spectrometer's output makes this sensor unsuitable for measurements in air ducts under the tested conditions. Test at higher air velocity also revealed that it impacts LCS accuracy more noticeably for $PM_{2.5}$. This suggests that sensors A and B are better suited for smaller particle measurements in dynamic air environments. Still, at higher air velocities, the accuracy of PM_{10} measurements is compromised, especially under non-isokinetic sampling conditions.

To ensure the reliability and significance of our findings, we applied the methodology detailed in Section 4.1, providing insights into the linear relationship between particle concentration and the output signal of the sensor at higher air velocities. The results highlight that, with this approach, sensors can be calibrated according to a specific velocity field, expanding their usability and ensuring more accurate measurements in diverse conditions. This methodology offers a practical framework for researchers aiming to adapt low-cost sensors to specialized environments, such as air ducts or HVAC systems, where a variety of velocity regimes may exist.

We observed sensor-to-sensor variation, particularly for PM_{10}, with differences in sensor positioning and alignment potentially contributing to measurement inconsistencies. Such differences highlight the importance of calibration and co-location procedures to ensure reliable and consistent results across multiple sensors in real-world applications. Furthermore, aerosol properties and environmental conditions, such as aerosol composition and humidity, introduced additional variability, underscoring the need to consider these factors when assessing LCS performance carefully. While LCSs show promise for *in situ* applications, such as filter efficiency testing and HVAC system monitoring, uncertainties at higher velocities limit their effectiveness for PM_{10} measurements in real-time monitoring. Therefore, further research is needed to improve sensor calibration and should focus on fine particle monitoring, such as $PM_{2.5}$ and PM_1, in HVAC systems.

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Disclosure statement

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