NSW Parliament Clean indoor air inquiry - Australian Academy of Science post hearing responses

1. Role of natural ventilation in the context of outdoor air pollution

The Hon. SUSAN CARTER: This is a question to all of the witnesses. Forgive me; I'm not a scientist. A common theme appears to me to be the difficulty of stopping outdoor pollution becoming indoor pollution. Is it your evidence that we shouldn't be using natural ventilation? Is it your evidence that we should always be using artificial ventilation? As a practical thing, how do we address particulate matter in the outside environment in our homes? Any clarification of that would be helpful.

The Hon. SUSAN CARTER: Dr Robinson, I wonder if I wasn't clear. I suppose what I was asking was is it your submission that we should be trying to stop natural ventilation coming into the house and should rely entirely on artificial ventilation?

To be clear, the Academy's responses related to public buildings not private homes or dwellings. Some of the research is relevant to private homes, but it is important to not draw a direct link between them.

Natural and mechanical ventilation are two ways to manage indoor air quality. The management of indoor air quality is context dependent, including what risks are being managed and what approaches are available in the building.

There are three general approaches for managing indoor air quality, ventilation, source control and air cleaning.

Source control

Source control is the most effective method to prevent exposure to pollutants, including particulate matter from outside. For example, Australia's wider policy framework for outdoor air quality and planning decisions (e.g., restrictions on tobacco smoking areas, not building childcare centres or schools on major roads) impact the quality of the air which enters a building.

Ventilation

Ventilation is achieved by supplying air to or removing air from a space. Ventilation with outdoor air is the most prevalent method for improving indoor air quality. Ventilation can also include the supply of appropriately sourced (away from outdoor sources, e.g. parking lots or air vents) and cleaned recirculated air. Bringing in outdoor air or cleaned recirculated air can dilute pollutants, preventing accumulation in an indoor space.

Ventilation can be achieved through natural forces (by opening windows or designing openings to allow outdoor air to flow indoors) or mechanical forces (using fans to introduce and circulate air, such as in HVAC systems). Hybrid ventilation systems are a combination of natural and mechanical ventilation.

Natural ventilation may not be sufficient nor reliable. For example, it may require windows to be opened to their full extent and conflict with the thermal comfort requirements of occupants. Further, natural ventilation generally requires occupants to manually manage ventilation and is thus more reliant on individual knowledge and behaviour change.

Advanced HVAC systems with embedded air cleaning technologies that automatically respond to indoor air quality monitoring can better manage indoor air quality for public buildings. New buildings should be built with systems to manage indoor air quality. Ideally, existing buildings would also be retrofitted with mechanical or hybrid systems that allow for improved indoor air quality management. However, this may not be feasible in all buildings and in many buildings natural ventilation is currently the only form of ventilation. When conditions allow, natural ventilation should still be used to manage indoor contaminants such as infectious respiratory particles.

Air cleaning

Air cleaning is achieved by removing or neutralising contaminants. The effectiveness of air cleaning technologies depends on many factors including, but not limited to, their design, the settings they are used in, how they are maintained, and where they are positioned.

Filtering the air is the best-established method to remove particulate matter. Filters with different removal efficiencies are used in both fixed HVAC systems and in many portable air cleaners.

2. Responsibility for monitoring and calibration of low-cost sensors

The Hon. SUSAN CARTER: We heard evidence before about air monitoring, and I notice the low-cost monitors have been raised in the submissions. The question I have that keeps being raised is—and the issue of calibration was discussed earlier—can the average person monitor their own air, and who should take responsibility for the results of the monitoring and acting on those results?

For public buildings, monitoring and acting on the results of monitoring should be the responsibility of building operators. The burden of monitoring should not be on individuals in public buildings.

Ideally, indoor air quality monitoring would be integrated with HVAC control systems to support automated responses based on real-time occupancy and indoor air quality levels.

3. Calibration of low-cost sensors

The Hon. EMILY SUVAAL: There was some discussion earlier on about calibrating them. I'm keen to understand what is involved in that and who can do it.

To be clear, the Academy's responses related to public buildings not private homes or dwellings. Some of the research is relevant to private homes, but it is important to not draw a direct link between them.

The calibration of low-cost sensors used to monitor indoor air quality requires specialist technology and training.

The responsibility to ensure that sensors used to monitor indoor air quality are functioning correctly should fall on building operators, however, the calibration itself would need to be undertaken by trained personnel. For example, a building operator could contract a specialist supplier of this service, much like many organisations contract specialist providers to assure other aspects of work health and safety like fire panels.

A framework to use PM2.5 low-cost sensors for compliance monitoring of indoor air proposed by Morawska et al. (2025) provides an example of what would be involved in calibration.

Morawska et al. (2025) describe the following requisite monitoring infrastructure:

- nomination of a reference sensor to act as the 'ground truth' for the other sensors in the computer network
- one sensor on the exterior to provide a reference for the local environment
- using low-cost sensors from the same model, and ideally from the same batch
- connecting all sensors to the building management system.

With that base infrastructure in place, a calibration framework can be applied including:

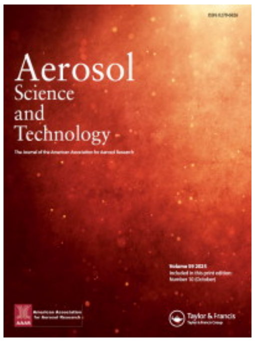
- regular comparisons between the sensors in the network at times when they would be expected to read similar concentrations – for example, when the building is unoccupied
- co-location of the reference sensor and external sensor with reference instruments once a year (at minimum), either by taking them to the nearest ambient air quality monitoring station or by bringing reference instrumentation to the building.

Based on these calibration activities, correction factors can be established. These are numbers that can be used in calculations applied to the sensor readings to correct the readings to account for different optical properties of particles emitted from different sources in different environments.

Morawska et al. (2025) recommends correction factors should be openly shared in a database alongside metadata like building type and occupancy levels. This database could be hosted by the relevant regulatory authority for use by the wider community where custom correction factors cannot be established.

The journal article referenced in this response and noted by Professor Lidia Morawska during the hearing is attached.

Reference: Lidia Morawska, Christof Asbach & Hamesh Patel (2025) Application of PM2.5 low-cost sensors for indoor air quality compliance monitoring*, Aerosol Science and Technology,* 59:10, 1210-1220, DOI: 10.1080/02786826.2025.2457326



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AAAR PLENARY LECTURE PAPER

Application of $PM_{2.5}$ low-cost sensors for indoor air quality compliance monitoring

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ABSTRACT
The importance of indoor air has come into the spotlight in recent years with attempts being made to address the challenges surrounding indoor air quality (IAQ). In order to legislate IAQ, compliance monitoring guidelines and frameworks are needed to support regulation. Current compliance monitors are expensive and complex, and it is not feasible to install them in every indoor space; however, the emergence of $PM_{2.5}$ low-cost sensors (LCS) provide an avenue for IAQ compliance monitoring. As $PM_{2.5}$ LCS' mature, there has been a significant development into our understanding of these sensing technologies which has enabled us to improve their data. However, a significant proportion of this learning is within an ambient setting, not indoors. Therefore, in this paper, we provide a framework to use $PM_{2.5}$ LCS for compliance monitoring of indoor air. An indoor reference sensor must be allocated as a ground truth for the neural network and this sensor must be taken to a monitoring station to be collocated with reference instrumentation or reference instrumentation taken to the sensor at regular intervals. A database of correction factors should be established and shared with the wider community. It is apparent that the use of $PM_{2.5}$ LCS is a realistic way forward for compliance monitoring of IAQ. The framework outlined in this paper, provides a starting point to gather high-quality data for effective IAQ compliance in the future. With improved active management of indoor air, environments will become safer and healthier for all.

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1. Background

The awareness for the role of indoor air quality (IAQ) has strongly increased over recent years and particularly during the COVID-19 pandemic. The importance of IAQ is underlined by the fact that people in western industrial countries spend more than 90% of their time in indoor environments (Klepeis et al. 2001). For many decades experts have called for regulations on IAQ (Corsi 2000; Morawska 2000) on par with regulations for ambient air quality. There are numerous significant challenges, making this much more complex than ambient air regulations. However, attempts are being made from various angles to address and resolve these challenges for IAQ regulations (Chojer et al. 2022; Fanti et al. 2021; Morawska et al. 2024).

A lack of appropriate compliance monitors remains a challenge. Traditional monitoring strategies from ambient air pollution monitoring such as Federal Reference Method (FRM) and Federal Equivalent Method (FEM) are not suitable for IAQ compliance monitoring. This is due to their large, costly and complex setups as well as, in some cases, their coarse data resolution. Coarse data resolution is due to specific measurement principles of certain instruments which limits sub-daily or even sub-hourly data reporting. However, $PM_{2.5}$ low-cost sensors (LCS) can address this issue. The inexpensive, low-power, easy-to-use nature of $PM_{2.5}$ LCS have resulted in a paradigm shift in the way air quality specialists monitor air pollution in both ambient and indoor environments and provide a possible solution for regulating indoor air

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quality (Snyder et al. 2013). Therefore, a scientific bridge must be developed between the light scattering intensity, monitored by sensors as the primary measurand and particle gravimetric mass concentrations to relate to the existing health guidelines. In this paper, the authors use the terms 'regulation', 'compliance' and 'legislation' throughout. The reason for this is that in different jurisdictions, various words can hold varying meanings, limiting the uptake of research being applied in the real world. In the context of this paper: 'Legislation' refers to the legal framework that underpins the regulations. 'Regulations' are the official directives that are determined by government agencies on how business and entities can operate, whilst 'compliance' is adherence to the regulations. The authors have also referred to reference method instrumentation (FEM/FRM) as 'instruments' and all other monitors without Federal approval or certification, as 'sensors'.

A recent paper provided scientific and technological basis for IAQ standards that could be mandated. It recommended for parameters to be included in IAQ standards, one of them being $PM_{2.5}$ (Morawska et al. 2024). Exposure to airborne particulate matter (PM) is one of the ten leading risks by the Global Burden of Disease study (Ardon-Dryer et al. 2020; Stanaway et al. 2018) and in 2021, it was the leading contributor to disability adjusted life years (DALY) (HEI 2024).

Exposure to ambient PM is most commonly assessed in terms of the particle mass concentrations in different size fractions (PM_{10} or $PM_{2.5}$). The World Health Organization provides guidelines for $PM_{2.5}$ and PM_{10} (WHO 2021) and most countries include $PM_{2.5}$ and/or PM_{10} in their ambient air quality standards. Legislation across the European Union focuses mainly on the PM_{10} fraction, whilst most other regions of the world prescribe measurement of $PM_{2.5}$. The current state of LCS to monitor $PM_{2.5}$ is adequate to serve for wide-scale regulatory purposes within IAQ applications (Ródenas García et al. 2022; Jayaratne et al. 2020; Liu et al. 2020). Major advances in LCS for PM monitoring based on optical particle detection (Morawska et al. 2018) opens new possibilities for monitoring air pollution with a high spatio-temporal resolution. Owing to the better quality of LCS for measuring $PM_{2.5}$ and the much larger worldwide dataset of ambient $PM_{2.5}$ concentrations, we only focus on $PM_{2.5}$.

So far, most applications of LCS have been for ambient air monitoring of $PM_{2.5}$ and consequently, most published studies focus on the use of $PM_{2.5}$ LCS in ambient air quality monitoring sensor networks (Jiao et al. 2016; Sousan et al. 2018). One example of a $PM_{2.5}$ LCS network is the one operated by PurpleAir, since 2015. With more than 30,000 registered around the world, the sensor utilizes the Plantower PMS5003 which provides estimates for PM_1, $PM_{2.5}$ and PM_{10} (IQ Air 2018). Advanced data treatment methods have been designed and validated, to reduce the root mean square error of the raw data from 8 $\mu g\ m^{-3}$ to 3 $\mu g\ m^{-3}$, with an average FRM or FEM concentration of 9 $\mu g\ m^{-3}$; this correction procedure along with developed data cleaning criteria, has been applied to PurpleAir $PM_{2.5}$ measurements across the US on the AirNow "Fire and Smoke Map" (Ardon-Dryer et al. 2020; Barkjohn, Gantt and Clements 2021; Stavroulas et al. 2020; Tryner et al. 2020).

However, the potential of $PM_{2.5}$ LCS extends much beyond ambient measurements and applications such as occupational exposure monitoring (Cheriyan and Choi 2020; Ruiter et al. 2023), on-demand and thus energy-efficient control of HVAC systems (Rashid et al. 2019) or for monitoring the emissions from cleanable filters have been proposed (Schwarz, Meyer and Dittler 2018). With the increasing awareness of, and need for IAQ monitoring, the use of $PM_{2.5}$ LCS for monitoring IAQ has come more and more into the focus of research activities (Bousiotis et al. 2023; Kelly and Fussell 2019; Kumar et al. 2016; Li et al. 2018; Sá et al. 2022; Tryner et al. 2021). So far, however, low-cost $PM_{2.5}$ sensors have been used more as a research tool. A recent US study monitored around 10,000 indoor spaces (Barkjohn, Gantt and Clements 2021). There are also a few low-cost indoor air quality monitors on the market (e.g., one marketed by IKEA) that are based on $PM_{2.5}$ LCS and can provide residents with estimates of what they are exposed to. Scientifically sound investigations in support of indoor $PM_{2.5}$ control and IAQ compliance are yet lacking.

The stability and durability of LCS for measuring particulate matter have been demonstrated in numerous studies, including Jayaratne et al. (2020), Liu et al. (2020), and Ródenas García et al. (2022). However, Castell et al. (2017) pointed out that the data quality can vary from location to location, depending on the local sources, and depending on meteorological conditions. Snyder et al. (2013) also highlighted that rigorous sensor evaluations are needed to understand sensor performance when exposed to particles of varying characteristics. Stability and durability are essential qualities in sensors to be used for large-scale monitoring, beyond scientific research, and in particular in support of regulatory monitoring. In addition, data from the sensors can help identify sources of air pollution and in turn aid in their control.

Historically, a key challenge in terms of compliance monitoring has persisted: optical sensor data is not equivalent to gravimetric. However, recently, laser based optical instruments have been approved by the US EPA and EU regulatory authorities for ambient compliance monitoring (CEN 2017; EPA 2016) removing the restriction of optical instruments for compliance monitoring. However, care must still be taken with the use of factory calibrated LCS. LCS calibrations are calculated by coefficients set by sensor manufacturers. In most cases, sensors are calibrated with synthetic test dusts and typical ambient air which can be considerably different to those which they are exposed to in the real world (Morawska et al. 2018). Particles in the real-world are a heterogeneous mixture of different particle shapes, sizes, refractive indices and densities, which may vary from location to location. In particular, these properties of indoor particles may differ significantly from those in ambient air, especially if indoor sources like cooking or candle burning affect the indoor air quality. This impacts the sensors' ability to accurately assess $PM_{2.5}$ concentration which will have impacts on compliance and regulation. Various studies have highlighted significant error due to the nature of sensor calibration and have recommended in-situ co-location and calibrations (Sá et al. 2022; Sousan et al. 2018). Options for establishing variation are based on equivalency tests (which are labor intensive) or based on data from the literature.

The neural network approach discussed in the calibration framework will depend on a number of factors including, but not limited to building type and use as well as pollutant exposure and loadings. The number of nodes and their spatial relationship within the network will also impact how the network functions and how machine learning algorithms and models are applied. Neural networks have been successfully used in a number of applications to forecast and manage IAQ and building ventilation (Lei et al. 2019; Li et al. 2022; Zhang et al. 2023). The neural network-based approach has also been successful used in a number of ambient air quality forecasting applications (Elangasinghe et al. 2014; McKendry 2002; Prasad, Gorai and Goyal 2016; Sun et al. 2013).

With increasing interest in IAQ and push for setting IAQ standards for public buildings (Morawska et al. 2024; Morawska et al. 2021), it's becoming clear that surveillance of these IAQ standards by means of instrumentation, used for regulatory ambient air quality monitoring is not feasible. Instead, it is apparent that the use of LCS for $PM_{2.5}$ monitoring presents the only realistic way for compliance monitoring in support of forthcoming IAQ legislated standards. In this paper we discuss the challenges and suggest ways in which to address them, providing a path forward for IAQ compliance monitoring. There are, however, several scientific challenges that still need to be resolved to enable application of this technology for IAQ regulatory control of indoor PM.

2. The current state of low-cost $PM_{2.5}$ sensors

2.1. Principles of operation

Basically, all $PM_{2.5}$ LCS are based on optical detection of light scattered by particles inside an illuminated measurement volume. The available $PM_{2.5}$ LCS can be sub-grouped into three different sensor categories. The simplest type of $PM_{2.5}$ LCS uses a photometric measurement principle, in which the total intensity of light, scattered by a cloud of particles inside the large measurement volume is measured. The intensity of the scattered light depends on various particle characteristics (e.g., the number concentration and size distribution of the particles, their shapes, refractive indices and density). In order to calculate a $PM_{2.5}$ mass concentration from the scattered light intensity, average values for particle characteristics need to be assumed during sensor calibration. Accurate results can only be achieved as long as the characteristics of the measured aerosol do not significantly differ from these assumptions.

In contrast, the most sophisticated $PM_{2.5}$ LCS apply a spectrometric measurement principle, i.e., they measure the light intensity, scattered by individual particles inside a small measurement volume. With the measured height of the light pulses as a measure for the particle size and counting of the pulses as a measure for the number concentration, this type of LCS is capable of measuring the number size distribution of the airborne particles as a function of the optical equivalent diameter. In order to transfer the measured number size distribution into a $PM_{2.5}$ mass concentration, the particle characteristics mentioned above need to be assumed. Unlike in pure photometers, spectrometers require the aerosol to flow through the measurement volume at a known and constant flow rate.

Most currently available LCS use a mixture of the two types and are also termed "advanced photometers" (CEN 2024). These LCS measure the light intensity scattered by a cloud of particles with high time resolution and distinguish between an "offset" of the intensity and short individual spikes sticking out of the offset signal

(Ouimette et al. 2024; Wang et al. 2009). The offset is caused by the large number of small particles as a measure for the overall concentration, whereas the spikes are caused by a small number of large particles that dominate the mass concentration. The sizes of these particles is determined by measuring the height of the peaks and used to differentiate between mass concentrations in different PM_x size fractions.

2.2. The impact of particle characteristics

There are two particle characteristics that have the most significant impact on the accuracy of LCS PM measurement: particle size and particle optical properties. Firstly, a general downside of optical aerosol measurements is the strongly decreasing intensity of the scattered light with decreasing particle size in the so-called Rayleigh regime, e.g., for particle sizes much smaller than the wavelength of the light source (the wavelength of visible light ranges from about 0.4 to 0.7 µm). As a rule of thumb, particles smaller than approximately half the wavelength of light cannot be detected. Most LCS manufacturers therefore specify the lower size detection limit of the sensors to be at 0.3 µm, but without specifying for which material or refractive index. Studies have shown that various particle sensors can behave significantly differently than outlined by the manufacturer (Kuula et al. 2020; Molina Rueda et al. 2023).

It has further been shown that larger particles in the micron size range are detected with a decreasing efficiency with increasing particles size (Budde et al. 2018; Jayaratne et al. 2020; Kuula et al. 2020) and that the maximum efficiency is typically obtained for particle sizes between 1 and 2 µm. The former will typically be less of a problem in environments, not impacted by fresh combustion or secondary particles (both types of particles are very small (between 50-200nm)). Both these types of particles can be present in indoor environment and their presence and contribution should be quantified for typical indoor environments. This limitation results in an underestimation of the actual gravimetric mass. However, due to their small size, particles below 0.3 µm typically only have a small contribution to the total $PM_{2.5}$ mass concentration. The latter problem is less important for the $PM_{2.5}$ range, because the decrease of the efficiency is strongest for particles >2.5 µm. This change in detection efficiency is one of the main reasons why the sensors have been reported to be much less accurate for PM_{10} compared with $PM_{2.5}$ (Molina Rueda et al. 2023). Secondly, particles of the same size will be detected with different efficiency if they differ in optical properties, i.e., refractive index (Jayaratne et al. 2020). Since composition of indoor particles is unknown at the time of sampling, we cannot use a correction factor for that specific type of particles. A correction based on ambient particle characteristics is also questionable, since it can change, unless we demonstrate that typical urban ambient air at that location has reasonably stable characteristics. Nevertheless, it will be possible to provide a range of variations for typical indoor environments (such as schools, offices, etc.), where no unusual particle sources operate, however, this is outside the scope of this work.

A recent study on the suitability of $PM_{2.5}$ LCS for monitoring occupational exposure to airborne particles found a strong dependence of the sensors' response to different particle materials. The study was carried out as pre-normative research for the European standardization authority CEN by member if CEN/TC137 WG3. The results are included in the recently released Technical Specification CEN/TS 18086 (CEN 2024). The study investigated five different $PM_{2.5}$ LCS models (Alphasense OPC-R2, Groupe Tera Next-PM, NovaFitness SDS011, Plantower PMS7003, Sensirion SPS30) with at least five specimens per sensor model and exposed them to TiO_2 and fumed silica test aerosols at various concentrations. They found that all sensors showed a linear response to the reference $PM_{2.5}$ concentrations, but none of them was capable of quantifying the $PM_{2.5}$ concentrations correctly. While for TiO_2, the observed differences of the results from the different sensor models and the reference concentrations ranged from an underestimation by a factor of 2.5 to an overestimation by a factor of 2, the $PM_{2.5}$ concentrations of fumed silica were all strongly underestimated by factors between 4 and 18. These differences are mainly caused by the differences in the properties of the test aerosols, mainly refractive index and particle density, and those assumed for the calibration. This problem is inherently caused by the indirect optical measurement technique and was observed similarly for research-grade optical aerosol spectrometers. The study also looked at a potential fouling of the sensors that could lead to a drift of their response but did not find a significant effect. This is in contrast to various ambient long-term studies which have identified drift within their sensor networks and offered numerous correction approaches (Datta et al. 2020; Sá et al. 2022; Weissert et al. 2023).

2.2. The impact of relative humidity

It has been shown in various studies that $PM_{2.5}$ LCS tend to overestimate particle concentrations at due to water vapor, generally as a result of high humidity (Crilley et al. 2018; Jayaratne et al. 2018; Nothhelfer et al. 2023; Tagle et al. 2020). The overestimation is caused by the growth of hygroscopic particles, such as ammonium sulfate ($(NH_4)_2SO_4$) or sodium chloride (NaCl). The hygroscopic particle growth as a function of relative humidity shows a hysteresis, e.g., starting with a dry aerosol, water uptake by the particles only starts when then relative humidity exceeds the material specific deliquescence level, which for $(NH_4)_2SO_4$ and NaCl is at around 75%. Above this level, the particles grow quickly, and their mass can increase by a factor of 10 or more. When the aerosol is dried again, the particles retain water down to the efflorescence level, which is lower than the deliquescence point, in case of $(NH_4)_2SO_4$ and NaCl around 45%. When hygroscopic particles are exposed to high humidity, they are detected in an optical aerosol measurement device as particles larger than their dry size, which is thus interpreted as a higher mass concentration.

The effect of hygroscopic particle growth can generally affect any aerosol measurement. Direct-reading aerosol measurement devices for the regulatory measurement of ambient particles are therefore equipped with upstream aerosol dryers or dynamic heating systems. Since the use of commercial aerosol dryers is not feasible for LCS, due to their high costs and often high pressure drop, it is often advised to exclude from the analysis data collected at RH levels exceeding 70%. This problem is, however, of less significance indoors, as under normal conditions indoor RH remains below the deliquescence point. If the indoor environmental conditions exceed the deliquescence point, care should be taken when using this data for compliance monitoring. However, if for the purpose of the identification of particle sources (indoor versus ambient – discussed below), indoor and ambient $PM_{2.5}$ concentrations are to be compared, we need to assure that ambient $PM_{2.5}$ measurements are not affected by the presence of water vapor (either high humidity or fog).

As of now, no commercial low-cost aerosol dryer is available, but simple and low-cost solutions have already been proposed (Chacón-Mateos et al. 2022; Nothhelfer et al. 2023; Samad et al. 2021). These solutions all use heated inlet tubes. Consequently, these dryers only reduce the relative, but not the absolute humidity, as they do not remove any vapor. Since the hygroscopic water uptake by particles only depends on the relative and not the absolute humidity level, this is fully sufficient, provided that the aerosol does not significantly cool down on its way to the measurement volume of the LCS. The dryer, developed by Nothhelfer et al. (2023) has been operated continuously and reliably for a two-year period without intervention.

2.3. Calibration of low-cost $PM_{2.5}$ sensors

The two major challenges in application of $PM_{2.5}$ LCS for regulatory monitoring of IAQ is that their primary measurement is not equivalent to gravimetric mass (as discussed above), and, that the calibration should be done in-situ. These two challenges are discussed below and how they can be addressed.

Advanced photometers are capable of distinguishing between mass concentrations in different size fractions based on the measurement of the height of the detected peaks (Wang et al. 2009). In some cases, they also provide number concentrations in different size fractions. However, such derived mass concentrations can differ significantly from gravimetric mass concentrations, if the assumptions made during the calibration are not met (Rivas et al. 2017). With typical LCS factory calibrations for ambient aerosols, quantitative estimates of indoor air pollution would have higher uncertainty. More quantitative, in-situ calibrations are required (discussed below) against reference methods (since we refer to WHO AQG for $PM_{2.5}$).

The second challenge is the in-situ calibration of $PM_{2.5}$ LCS. Proper calibration is a key requirement for any compliance with standards, but because of the scale of monitoring (every public indoor space), the current costly and labor-intensive methods used to calibrate existing regulatory monitors will not be practical. Significant progress has been achieved in calibration of ambient $PM_{2.5}$ LCS. These calibrations have mostly been carried out by collocating the LCS with reference measurement techniques in monitoring stations for extended periods (Gao, Cao and Seto 2015; Holstius et al. 2014; Jiao et al. 2016). While in general, station locations are carefully chosen to provide data representative of the area in which they operate, the relatively small number of stations cannot provide air quality information at the individual building or street level scale. However, advanced modeling techniques allow pollution assessment at the required fine scale, using monitoring stations and meteorological data (Özkaynak et al. 2013). However, for indoor monitoring we cannot rely on an ambient monitoring network, because this does not take into consideration the attenuation of the ambient air pollution levels by the buildings themselves and potentially ventilation systems with filters and more importantly, indoor sources of (particulate) air pollutants (Goldstein et al. 2021).

Large-scale monitoring networks are the only solution as monitoring in only selected indoor public spaces is insufficient for epidemiology, as every space is different and utilized differently. We cannot use modeling to predict pollution concentration in one space based on the concentrations measured in other spaces. So, the question is how to calibrate $PM_{2.5}$ LCS, in-situ, such that the procedure is stringent on the one hand but also not prohibitively labor demanding. The calibration method applied to the use of LCS for ambient PM monitoring cannot simply be transferred to indoor monitoring, due to the lack of suitable (regulatory) monitoring stations, cost, labor constraints and variability in particle chemistry between indoor and ambient locations**.**

The CEN study (data yet unpublished) found that individual sensors of the same type, always showed comparable results, so that an individual calibration of each sensor is not generally necessary. Instead, calibration factors per sensor model and test aerosol were derived. It was shown that for the investigated sensor models (Alphasense OPC-R2, NovaFitness, SDS011, Plantower PMS7003, Sensirion SPS30, Groupe Tera NextPM) the agreement between sensor results and the reference after applying these calibration factors was mostly well within ±10% (PM_1) and ±25% ($PM_{2.5}$), respectively, for data with 1 s time resolution and even higher for longer averaging times. Field measurements, carried out in workplaces and simulated workplaces showed that field calibration of $PM_{2.5}$ LCS for the specific aerosol in a workplace is possible through side-by-side measurements with a reference instrument (FRM/FEM). The results of this study show that individual calibration of the sensors for the relevant indoor aerosols is necessary. The $PM_{2.5}$ LCS calibration could be carried out by co-locating one or more $PM_{2.5}$ LCS with a regulatory instrument. Such a calibration shall ideally be carried out over several days for each relevant condition. Different relevant conditions may apply during summer and winter due to the effect of heating and/or air conditioning or seasonal changes due to changes in PM composition. Since indoor temperature and humidity typically vary much less than outdoors, meteorological influences are not expected to significantly affect indoor $PM_{2.5}$ LCS performance. If such an indoor calibration is feasible, a calibration may also be carried out at a regulatory ambient monitoring station (it is not expected that every building will have its own team for calibration purposes) during periods with similar temperature and relative humidity as expected indoors. However, the quality and applicability of this approach is limited due to the differences of the composition of ambient PM monitored by the regulatory instrument and the composition of indoor PM, which means indoor particles originating from different sources than ambient particles may have different density and/or refractive index than indoor particles (this is addressed below). Based on the findings of the pre-normative CEN project, it is assumed that, at least for the tested sensor models, a yearly calibration and if necessary, adjustment or replacement would be sufficient, independent of which calibration method is pursued. If the main contribution is ambient air (as in typical office buildings), little variation is expected. If there is a strong indoor source, the variation will depend on the characteristics of the source, e.g., in the case of schools, dust, buildings near roads (combustion particles) (Morawska et al. 2017).

3. A Framework for $PM_{2.5}$ LCS measurements indoor

3.1. Establishing infrastructure

Before we can proceed with calibration, there are a number of prerequisites that must be met. These include the following:

1. One sensor is nominated as the ‘reference’ sensor which will act as the ground truth for which the rest of the sensors within the neural network can be compared. The reference sensor should have two particle sensors to understand whether that data from each reference sensor is accurate. This sensor must be in a location that is representative of population exposure and pollutant loading. The calibration factor remains constant within a given monitoring zone indoors and also across time.
2. One sensor must be located on the exterior, in a well-ventilated area, that is representative of the local environment. This sensor will act as the external ground truth, measuring ambient $PM_{2.5}$ concentrations. The sensor fitted with a heater or drying system to combat the aforementioned effects of moisture as discussed above. It is recommended that temperature and humidity algorithms not be used as this may be a source of error when performing sensor calibration.
3. All $PM_{2.5}$ LCS located in the building (both indoor and outdoor) should be of the same type/

model and ideally from the same batch. This will minimize the introduction of uncertainty and error due to differences in factory calibration between different sensor manufacturers. It will also mean that sensor precision and accuracy will be of similar, allowing for easier calibration of the neural network. This will not always be feasible; however, it is recommended that the number of different sensor types is kept to a minimum. In the case of various different sensors being used within the building, inter-sensor variability must be robustly understood via co-location of these sensors.

4. All sensors must be connected to the building management system (BMS) (either hardwired, connected through the internet of things (IoT), or through local networks such as LoRaWAN. This will allow for dynamic user control of indoor ventilation to manage indoor air quality through the BMS; regular quality checks can also be performed as detailed below.

3.2. Calibration framework

Once the infrastructure has been established, the following calibration framework can be implemented.

For regular quality checks, dynamic intercomparisons of the sensors can take place at times when the sensors could be expected to be reading similar concentrations (e.g., when the building is unoccupied or during extreme events). This will allow for a quantitative estimate of uncertainty of the neural network and allow for further statistical testing to determine whether individual nodes are reading as expected and fall within an acceptable criterion compared to: (a) a 'reference' sensor, and (b) other sensors located in the network.

Once a year (at a minimum), the 'reference' sensor and the external sensor will be collocated with reference instruments. This can be undertaken in two ways with the decision up to the building manger/owner/occupier's discretion. Either (1) the co-located instrumentation can be taken to the nearest air quality monitoring station or (2) reference instrumentation can be taken to the building. The selection will be dependent on $PM_{2.5}$ sources at given sites. If the building is naturally ventilated or regularly experiences penetration of external pollution, the users undertake a monitoring station co-location. If the building is mechanically ventilated and experiences less penetration of external pollution, a local co-location should be undertaken.

The co-location duration will be dependent on the minimum usable time resolution of the reference instruments (e.g., 24-h for filter samplers; as a rule of thumb and tapered element oscillating microbalance (TEOM) – 1-hr; optical instrument – sub-hourly). It shall be noted that although some optical aerosol spectrometers have received type approval as an FEM, atmospheric monitoring, they suffer from the same shortcomings for indoor measurements as the $PM_{2.5}$ LCS and therefore may need to be calibrated for the specific location against a gravimetric reference. The co-location should also cover an appropriate dynamic range of concentrations that the sensors will usually be exposed to. Data should be compared over both a 24-h and 1-h timescale to understand sensor performance (Duvall et al. 2021). As discussed above, the characteristics of indoor particles vary from those of ambient air, and the variation depends on the indoor source (Morawska et al. 2017). Care must be taken when selecting the co-location site that particle sources and composition remains similar to the particle composition within given buildings. This is to limit the error induced due to differences in particle properties.

Ideally, data should be logged at high resolution (1 s) and aggregated into averages (1 h, 24 h). At least 75% data capture must be achieved to form averages. Concentrations should not differ by more 10% or the measurement uncertainty of the sensors (whichever is greater). Performance metrics must fall within the boundaries outlined by the US EPA's performance testing protocols. Sensor precision measured as standard deviation should be $\leq 5\,\mu g\ m^{-3}$, bias should fall between slope and intercept limits of $1.0 \pm 0.35\,\mu g\ m^{-3}$ and -5 to $5\,\mu g\ m^{-3}$ whilst linearity, measured as the coefficient of determination (R^2) should be ≥ 0.7 (Duvall et al. 2021). Individual outliers may be omitted from this analysis, if they can be explained by e.g., instrument/sensor malfunctioning or short-term spatial inhomogeneity of the concentration. Under each scenario, a suitable correction factor can be established and should be logged as discussed under *Correction Factors*.

3.3. Correction factors

We suggest that a database be established, hosted by the competent regulatory authority, to host correction factors. The data should be shared freely amongst the wider community for use where correction factors cannot be established. Associated meta-data that should also be captured and shared alongside the correction factor includes building type, ventilation type, patronage, co-location instruments and meteorological data. It should be noted that correction factors will not be universal but can be grouped into rooms and buildings of particular uses. Correction factors can be loaded into the BMS, and automated error statistics can allow for updated dynamic control of the building ventilation system.

4. Management of indoor air

To protect the occupants of buildings from unsafe air due to $PM_{2.5}$ pollution, this paper addresses the challenges of regulating indoor $PM_{2.5}$ concentrations and provides a framework for regulatory management. It is apparent, that the only feasible, technological solution for the regulatory management of indoor air is with the use of $PM_{2.5}$ LCS. The framework outlines real-world application of $PM_{2.5}$ sensors with a number of prerequisites that must be met. The calibration framework outlines dynamic intercomparisons of sensors, appropriate statistical testing and calibration criterion in the form of co-locations. Determination of correction factors can be loaded into relevant systems to provide automated error statistics and alerts. There are a number of limitations associated with this work that still need to be addressed which include: the application of this approach is specifically for $PM_{2.5}$ variances in the approach to managing humidity and moisture control within measurement devices, the number of different brands of sensors within the neural network, an agreed correction protocol and the differences in the calibration of the sensors. However, the framework provides a starting point for researchers, building owners, managers and occupants to make efforts to gather high-quality data that is comparable and suitable for compliance purposes. We encourage the initiation of routine IAQ monitoring based on the proposed framework in anticipation of upcoming regulations requiring IAQ monitoring, and to provide momentum for such regulations: if IAQ monitoring is technically possible, it means that introducing regulations is possible as well.

Future research should focus on improving the reliability of $PM_{2.5}$ LCS for use in IAQ applications, mitigate the impacts of environmental factors on the performance of $PM_{2.5}$ LCS, understand the variances of $PM_{2.5}$ LCS within a wider range of indoor settings, test varying neural network approaches whilst varying the number of brands of sensors within the networks and develop agreed correction protocols and templates to further reduce the barrier to using $PM_{2.5}$ LCS for regulatory IAQ compliance monitoring in the future. Efforts must also be made in sensor data interpretation to enable determination of the origin of the particles, from indoors or outdoors, to inform control measures (in simple terms, whether to open or close the windows). Depending on the type of the building, its use and sources operating, these contributions vary (Morawska et al. 2017). If these steps are taken, we can ensure that indoor spaces are actively managed to provide safe and healthy air for all.

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Author contributions

Lidia Morawska: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Funding acquisition. Christof Asbach: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Funding acquisition. Hamesh Patel: Methodology, Writing - Original Draft, Writing - Review & Editing.

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