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Review article

Quantifying the dynamic characteristics of indoor air pollution using real-time sensors: Current status and future implication

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ABSTRACT

People generally spend most of their time indoors, making indoor air quality be of great significance to human health. Large spatiotemporal heterogeneity of indoor air pollution can be hardly captured by conventional filter-based monitoring but real-time monitoring. Real-time monitoring is conducive to change air assessment mode from static and sparse analysis to dynamic and massive analysis, and has made remarkable strides in indoor air evaluation. In this review, the state of art, strengths, challenges, and further development of real-time sensors used in indoor air evaluation are focused on. Researches using real-time sensors for indoor air evaluation have increased rapidly since 2018, and are mainly conducted in China and the USA, with the most frequently investigated air pollutants of $PM_{2.5}$. In addition to high spatiotemporal resolution, real-time sensors for indoor air evaluation have prominent advantages in 3-dimensional monitoring, pollution peak and source identification, and short-term health effect evaluation. Huge amounts of data from real-time sensors also facilitate the modeling and prediction of indoor air pollution. However, challenges still remain in extensive deployment of real-time sensors indoors, including the selection, performance, stability, as well as calibration of sensors. In future, sensors with high performance, long-term stability, low price, and low energy consumption are welcomed. Furthermore, more target air pollutants are also expected to be detected simultaneously by real-time sensors in indoor air monitoring.

1. Introduction

Air pollution is the fifth leading risk factor for mortality worldwide which causes approximately 6.7 million premature deaths, 500,000 newborns deaths, and reduces life expectancy on average by 20 months globally in 2019 (Health Effects Institute, 2020). Continuous efforts have been made to control ambient air pollution in many counties. For example, China implemented clean air action in 2013 and three-year action plan in 2018 to control air pollutant emissions (The Central People's Government of the People's Republic of China, 2013, 2018), resulting in a decrease of annual average ambient $PM_{2.5}$ concentration from 72 μg/m^3 in 2013 to 33 μg/m^3 in 2020 (Clear Air Asia, 2021). Compared with ambient air pollution, indoor air pollution has received less attention partly due to the lack of measurement data. However, people generally spend 80 %–90 % of their time indoors (Klepeis et al., 2001), where air pollution can be more severe than that in outdoors due to extensive internal emissions (Han et al., 2015; Huang et al., 2022; Yang et al., 2021). Indoor air pollution exposure is responsible for 64 % of premature death associated with overall air pollution exposure (World Air Quality Report, 2020). Exposure to poor indoor air can also result in sick building syndrome and lower work efficiency of human (Laumbach and Kipen, 2005). Therefore, indoor air quality monitoring is of high significance for human health protection.

Conventionally, air pollution monitoring is based on fixed

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monitoring stations by passive or continuous sampling (Fig. 1). Data from these instruments are standardized with high quality. However, high price, large size, noisy, as well as high maintenance cost make these instruments are sparsely deployed and hinder their use in indoor air monitoring. With the development of sensor technology, real-time monitors are becoming more and more popular for air quality monitoring, which have deeply improved air pollution monitoring by providing high spatiotemporal data (Gozzi et al., 2016). Owing to the deployment of low-cost sensors, coverage of air quality data was expanded from 4,745 locations in 2020 to 6,475 locations in 2021 (World Air Quality Report, 2021). At first, real-time sensors were typically deployed to supplement ambient air quality data beyond fixed monitoring stations that were sparsely distributed (Chojer et al., 2020; Rai et al., 2017). In the past fifteen years, sensors with low price, portability, and acceptable precision broaden air quality monitoring from ambient to community or individual home (Clements et al., 2017) (Fig. 1). Recently, real-time sensors are now available in combination with communication technologies (Wi-Fi, ZigBee etc.) which can update air quality data to end users in time and further make real-time sensors popular in indoor air evaluation (Saini et al., 2020).

Mountains of literatures have evaluated indoor air quality using real-time sensors with various research objectives. Huang et al. (2022) investigated indoor air pollution levels, indoor/outdoor ratios, and the influencing factors on household $PM_{2.5}$ based on real-time monitoring. Li et al. (2022a) explored internal differences in various microenvironments and personal exposures to $PM_{2.5}$ based on low-cost sensors. Laurent et al. (2021) found cognitive function was associated with real-time indoor $PM_{2.5}$ concentrations. It was observed that per 8.8 μg/m^3 $PM_{2.5}$ increase would result in 0.82 % and 6.18 % increases in Stroop response time and Stroop interference time, respectively. However, some major deficiencies of real-time monitoring have also been reported, including but not limited to the need for sensor calibration, the reliability of data, and few types of target pollutants, which have hindered the further application of real-time monitoring indoors (Chojer et al., 2020; Kumar et al., 2015).

In view of the importance of real-time sensors, previous studies have discussed the development, challenges, and recent advancement of real-time sensors (Chojer et al., 2020; Morawska et al., 2018; Snyder et al., 2013). However, there are still knowledge gaps in indoor air evaluation using real-time sensors, including: 1) What is the current state of real-time sensors applied in indoors? 2) What are the special strengths/weaknesses of real-time sensors in indoor air evaluation? 3) What should be concerned when using real-time sensors? 4) What functions are expected for the future development of real-time sensors? To answer the above questions, related researches were systematically reviewed with the emphasis on the current status, strengths, challenges, and future research priorities of real-time sensors used for indoor air evaluation. This study is expected to provide comprehensive understanding of real-time sensors deployed indoors, and helpful information for sensor technology development.

Fig. 1. The comparison of indoor real-time monitor and conventional sampler.

2. The state of art of real-time monitoring

As shown in Fig. 2, literature search was conducted using three databases: Web of Science, Scopus, and PubMed. The search themes were: "indoor air pollution" or "household air pollution" or "indoor air quality" or "household air quality" or "indoor air monitoring" or "inhalation exposure" and "real time monitoring" or "real time" or "dynamic". A total of 6,991 records were observed. Among them, 1,523 records were from PubMed, 3,110 records were from Web of Science, and 2,358 records were from Scopus, respectively. After excluding duplicates, 4,657 records were found. Literature titles were firstly reviewed. 3,756 articles were removed due to inconsistent research objectives, and 901 records were selected for abstract reviewing. Then abstracts of these selected articles were reviewed, and 261 articles associated with the review scopes were read in full-text. 54 articles focused on chamber studies, sensor design, and modelling without measured data were further excluded. Finally, 207 literatures highly associated with the review scopes were used for analysis. All researches included in this review were published online from 8, January 1998 to 31, July 2022.

The selected researches usually have different foci, which can be classified as follow: 1) assessment of the impacts of influencing factors (e.g., ventilation, human activities) on indoor air quality; 2) spatial variations of indoor air quality in different locations or specific locations; 3) temporal variations of indoor air quality with different time resolutions (seconds, minutes, hours, days, etc.); 4) indoor and outdoor relationships including the comparison of pollutant levels in indoor and outdoor air or analysis of their interactions; 5) short-term health impact assessments associated with indoor air exposures; and 6) other objects such as vertical profiles of indoor air pollutants and indoor air pollution predicting using sensor data.

As shown in Fig. 3A, the publications of real-time sensors in indoor air quality measurement have shown an increasing trend in the past few decades. From 1998 to 2011, the number of publications was relatively small (0–6 publications per year), and the publications increased steadily during the years of 2012–2017 (8–12 publications per year). In the recent five years (since 2018), there has been a significant increase in publications (16–44 publications per year). Of these publications, the most were conducted in Asian (103 publications), followed by European (46) and North America (38), and only a few studies conducted neither in Africa (5) or South America (2) (Fig. 3B). However, severe indoor air pollution caused by solid fuel combustion in Africa has been reported in the existing studies. For example, the daily indoor $PM_{2.5}$ level in Malawi, southern Africa was 226 ± 206 μg/m^3 due to biomass fuel combustion (Fullerton et al., 2009), which was far higher than the WHO

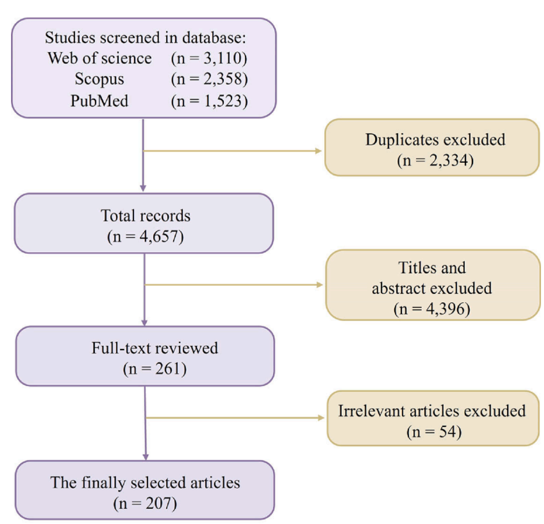

Fig. 2. Systematic review flowchart in this study.

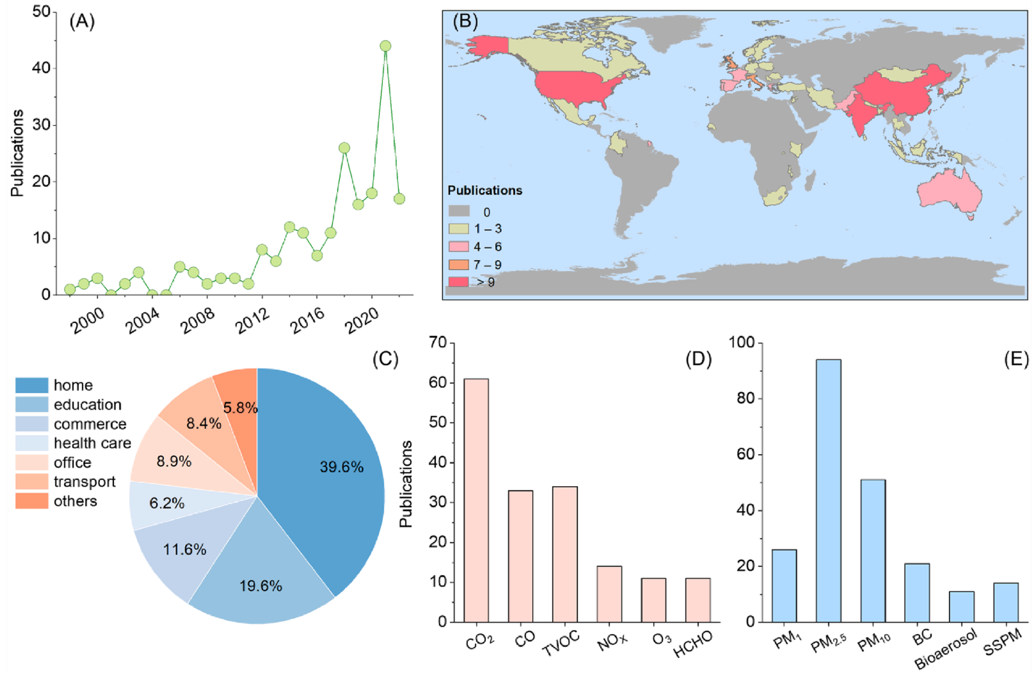

Fig. 3. The state of art of indoor real-time monitoring, SSPM in Fig. 3E refers to size segregated particles.

recommended level (15 μg/m^3), indicating the urgent need to improve indoor air pollution in these areas with less attention. As for the country level, China owns the most publications on indoor air quality evaluation using real-time sensors (49 publications), followed by the United States (34), and South Korea (16).

As shown in Fig. 3C, residential homes rank as the most interesting microenvironments for indoor air pollution studies, accounting for 39.6 % of total publications. Of these publications focusing on indoor air pollution in residential homes, 59 researches reported home locations, of which 31 studies were conducted in urban homes, 7 studies were in suburban homes, and 21 studies were in rural homes, indicating that rural homes received relatively less attention compared with urban homes. However, indoor air pollution can be more severe in rural homes due to extensive solid fuel combustion (Du et al., 2018; Huang et al., 2022). For example, the indoor $PM_{2.5}$ concentration of urban households in China was 123.9 ± 122.3 μg/m^3, significantly lower than that in rural households of 164.3 ± 104.5 μg/m^3 (Yang et al., 2021). Furthermore, Sun et al., (2022) revealed dose-dependent increasing patterns of reactive oxygen species (ROS) and Cellular interleukin-6 (IL-6) levels to $PM_{2.5}$ derived from solid fuel combustion, indicating that rural residents who exposed to high $PM_{2.5}$ might suffer from great health risks. Therefore, indoor air pollution in rural areas should be paid special attention. Educational places (i.e., school, classroom, and library) rank as the second popular microenvironments (19.6 %), followed by health care places (i.e., hospital, day-care center, and child-care center, 11.6 %). Indoor air pollution in transports was evaluated by 8.4 % publications. Even though people generally spend only 5.5 % of their daily time in traffic (Sa et al., 2022), indoor air quality evaluation in transportation is important, especially for drivers due to their generally longer working time (11.4 h) (Sekkay et al., 2021), and large population base (for example, 17.28 million truck drivers in China) (China News, 2021).

Conventionally, each real-time sensor has its specific target pollutants, and several sensors will be adopted simultaneously for multi-pollutant detection (Barkjohn et al., 2021; Canha et al., 2018; Gitau et al., 2019). In recent years, sensor monitoring system and multi-sensor array (or referred as electronic nose), which are capable of monitoring multiple pollutants, have developed rapidly and received increasing attention in indoor air monitoring (Ye et al., 2021). For example, Zheng et al., (2022) applied a highly accurate photoacoustic gas monitoring system which can monitor up to 5 gases (Carbon dioxide (CO_2), carbon monoxide (CO), formaldehyde, CH_4, and total volatile organic compounds (TVOCs)) to reveal the impact of Chinese cooking activities on indoor air quality. Tastan and Gokozan (2019) developed an electronic nose that can monitor various air parameters (CO_2, CO, PM_{10}, and nitrogen dioxide (NO_2)) and then applied it to monitor indoor air quality. In addition to pollutant concentrations, real-time sensors can also provide environmental parameters such as temperature and relatively humidity (RH) (Tran et al., 2017; Zhang et al., 2021), giving a more comprehensive understanding of indoor air quality.

The sampling periods of these researches varied from within 1 day to over 2 years with a median of 7 days, indicating relatively short sampling time using real-time sensors. Only a few studies conducted long-time samplings (over 1 years) (Cai et al., 2021; Huang et al., 2018; Liu et al., 2021a). Even though short sampling time is adequate to investigate the impact of human activities on indoor air, such short sampling time is unable to capture long-term variations in indoor air pollution.

3. Targeted air pollutants

For the purposes of human health protection and comfortable living, indoor air pollutants that have adverse health effects are always monitored. The target pollutants measured by real-time sensors can be simply classified into gaseous (e.g., CO, sulfur dioxide (SO_2), ozone (O_3), oxides of nitrogen (NOx), and TVOCs) and particulate pollutants (e.g., particles with aerodynamic diameters less than 10 μm (PM_{10}) and 2.5 μm ($PM_{2.5}$) and 1 μm (PM_1), and black carbon (BC)) (Rickerby and Skouloudis, 2014; Sa et al., 2022). As plotted in Fig. 3D, CO_2 is the most commonly detected gas in indoor air monitoring. In addition to monitoring CO_2 concentration, the relationship of CO_2 between indoor and outdoor can be used as an index of ventilation condition (Laurent et al., 2021). CO (33 publications) and TVOCs (34 publications) are also highly concerned gaseous pollutants in indoor air quality assessment. In addition to those frequently measured gaseous air pollutants (as shown in Fig. 3D), other gaseous pollutants such as ammonia (3 publications) and SO_2 (2 publications) were occasionally reported.

$PM_{2.5}$, which is regarded as the most harmful air pollutant to human health (World Air Quality Report, 2021), attracts the most attention in indoor air monitoring (94 publications, Fig. 3E). PM_{10}, PM_1, and BC are also frequently monitored particulate pollutants with 51, 26, and 21 related publications, respectively. In recent years (2017–2022), bioaerosol, including bacteria, viruses, molds, and fungi, etc. (Huang et al., 2017; Marcovecchio and Perrino, 2021), has become more and more popular in indoor air monitoring, in light of its adverse health effects (e.g., allergies, asthma, and lung cancer) and important contribution to indoor air pollution (5 %–34 %) (Kim et al., 2018; Morawska et al., 2017).

3.1. Gaseous air pollutant detection

Principles for gas sensors include: 1) chemical method based on measurable changes in properties of sensing element (e.g., conductivity) in response to target gases (White et al., 2012); 2) optical method based on general Lambert-Beer law; and 3) surface acoustic wave method which detects the subtle surface changes in amplitude or velocity of the wave induced by analyte gas exposure (Morawska et al., 2018; Kwak et al., 2019). Metal oxide semiconductors (MOS) and electrochemical gas sensors are frequently used in gas analysis (Barsan et al., 2007). For example, hydrocarbons and their derivatives, SO_2, H_2S, etc. are detectable for MOS sensors (Gebicki, 2016). Electrochemical sensors are usually used for toxic gas monitoring than other gas sensors partly due to their high accuracy and good selectivity (Khan et al., 2019). Amperometric gas sensor, an important branch of electrochemical sensors, is recognized as one of the most promising sensors for inorganic gas monitoring (Baracu and Gugoasa, 2021; Baron and Saffell, 2017). Furthermore, MOS and electrochemical gas sensors, which have miniaturized size, low power consumption and cost, are suitable for indoor air evaluation (White et al., 2012). Non-dispersive infrared sensor can detect gases with infrared activity, such as CH_4 and CO_2 (Thompson, 2016). Photo ionization detectors (PID) are commonly used for VOCs detection due to its low detection limits (ppb to ppm) (Thompson, 2016; Pang et al., 2019).

With the development of analytical technology, some unregular controlled pollutants have been monitored in real-time. For example, Wu et al. (2021) measured real-time gas-phase NCl_3 in an aquatic center based on a novel continuous analytical instrument. By open-path Fourier transform infrared spectroscopy, Chen et al. (2016) monitored the real-time concentrations of chloroform in an indoor swimming pool. In generally, as the development of technology, more and more gaseous pollutants in indoor air can be evaluated based on real-time measurement.

3.2. Particulate air pollutant detection

Particulate pollutants, particularly particulate matters (PMs), are always listed as the primary controlled air pollutants in many air protection actions. Principles for particle sensors include: 1) direct measurement by tapered element oscillating microbalance method (TEOM) according to changes of oscillation frequency (Patashnick and Rupprecht, 1991); 2) indirect detection by optical method which can be further divided into two categories. First, light scattering method that detects the intensity of scattered light when particle flow across a light beam (Seinfeld and Pandis, 1998). This method has been universally used in real-time particle monitoring (Molaie and Lino, 2021). Second, image processing-based method that analyzes particle number/mass distributions from pictures recorded by camera using image processing techniques (Molaie and Lino, 2021).

BC, as an important component of PMs, is also frequently measured in indoor air. Real-time BC can be quantified by optical absorption, photoacoustic, and laser induced incandescence methods (Yue et al., 2014). The principle of optical absorption method is to measure the light attenuation of transmitted light (880 nm) which is linearly proportional to the amount of filter-deposited BC (Delgado-Saborit, 2012). All studies monitored indoor BC adopted optical absorption-based monitors, of which MicroAeth AE51 was the most commonly used device (16 of 21 studies).

Several technologies are available for real-time bioaerosol monitoring such as fluorescence spectroscopy, Raman spectroscopy, elastic scattering, microscopy, and holography (Huffman et al., 2020). Among these techniques, laser/light-induced fluorescence (LIF) is commonly used (Huffman et al., 2020), which uses monochromatic light to investigate the fluorescent properties of individual biological particle after distinguishing biological aerosol from non-biological aerosol by the intensity of fluorescent signal (Pohlker et al., 2012). LIF monitors can also provide information on the concentration and size distribution of bioaerosol (Bhangar et al., 2014; Patra et al., 2021).

4. Characterizing indoor air pollution using real-time data

The way of air pollution analysis and management has changed from low to high spatiotemporal resolution due to the availability of real-time sensors (Kumar et al., 2016). Given such high spatial and temporal resolution data obtained from real-time monitoring, more detailed and in-depth contents can be analyzed, e.g., spatiotemporal characteristic and heterogeneity. Huge data from real-time monitoring also ensures sufficient input data for indoor air pollution simulation and prediction. The perspectives into indoor air pollution characterization based on real-time data are discussed below.

4.1. Temporal variation

The time resolution of real-time sensors generally ranges from seconds to minutes. The availability of such consecutive and high time resolution data allows the analysis of dynamic variations of indoor air pollution. Generally, dynamic variations of indoor air pollution can be classified into within-activity, diurnal, seasonal, and annual variations according to different time resolutions. Indoor activities can last from a few minutes (e.g., smoking and cooking) to several hours (e.g., air cleaner working and heating). These short-term activities have significantly positive/negative impacts on indoor air quality, which are crucial for indoor air evaluation. For example, cooking activities can increase $PM_{2.5}$ concentrations in kitchen from 4.1 μg/m^3 to 695.0 μg/m^3 within ten minutes, while can reduce 66.0 %–83.6 % of $PM_{2.5}$ emissions with using air cleaners (Sharma and Balasubramanian, 2020). Pollutant emission/removal rates are not stable in some activities, such as solid fuel combustion processes (Wang et al., 2022), resulting in variations in concentrations at different combustion stages. Ciuzas et al. (2015) compared the increase and decay rates of different indoor $PM_{2.5}$ sources based on real-time data, and found that the increase rate of heat sources (cooking, candle, and cigarette burning, etc.) was faster than that of personal care product sources (hair spray and furniture polishing machine, etc.), and the decline rate was determined by the duration of emission sources. He et al. (2021) reported distinct variations in CO_2 concentrations in aircraft cabins at different flight phases, with higher concentrations and large fluctuation peaks at boarding and landing phases than that at cruising phase.

Indoor air pollution varies acutely in different sampling days, seasons, and years. Long-term monitoring based on real-time sensors can better understand the variation patterns of indoor air pollution in time series with low cost and labor input. For example, the diurnal patterns of fluorescent biological airborne particles (FBAP) in an office building showed three evident stages: firstly, FBAP concentrations rapidly increased to high levels at 9:00 due to the occupancy of people, then maintained stably until 18:00, and finally decreased quickly to baseline after 18:00 when people gradually leaved the office (Li et al., 2022b). Elbayoumi et al. (2013) reported distinct seasonal variabilities of $PM_{2.5}$ and PM_{10} concentrations in classrooms by longtime monitoring, with higher pollution levels in winter than that in other seasons. Furthermore, higher daily variations of PM_{10} than $PM_{2.5}$ were observed from the real-time change curves due to shorter residence time of PM_{10} in the air than $PM_{2.5}$. Li et al. (2021b) compared indoor air quality in rural Beijing before and during the COVID-19 quarantine periods and confirmed that COVID-19 quarantine increased indoor $PM_{2.5}$ concentrations by 10 μg/m^3 due to stronger internal emissions.

4.2. Spatial variation

Spatial variation is another important aspect regarding air pollution monitoring and management. At the household level, indoor air quality evaluation and subsequent implementation of mitigation action require to identify emission hotspots. Portable real-time sensors make it possible to conduct intensive monitoring, which can clearly illustrate the spatial variations within household. Li et al. (2022a) reported that indoor $PM_{2.5}$ concentrations of urban households varied significantly in different microenvironments, with the highest in kitchen and the lowest in bedroom. Patel et al. (2017) quantified spatial variations in indoor PM by installing real-time sensors in multiple locations in households, founding that kitchen showed higher PM level and smaller variability than other rooms due to strong internal emissions, small size, and insufficient ventilation. Furthermore, similar high PM trends were observed in rooms adjacent to kitchen due to diffusion. Differences in household characteristics and indoor activities will result in large inter-household variations in indoor air pollution. Therefore, based on real-time monitoring, specific mitigation plans can be made for different households.

At the community level, people stay in a variety of indoor environments (Fig. 3C), where indoor air pollution in such microenvironment is substantially varied. Intensive sampling by portable sensors fills the gap of indoor air pollution map. By taking portable real-time $PM_{2.5}$ sensors, Hsu et al. (2020) investigated $PM_{2.5}$ concentrations in 18 kinds of indoor environments, and over 3 times of variations were found with the highest in the Taoist temple (62.5 μg/m^3) and lowest in office (18.1 μg/m^3).

At the regional scale, the deployment of real-time sensors can simultaneously investigate indoor air pollution in different areas or regions. For example, Chan et al. (2021) observed broadly similar temporal trends of indoor $PM_{2.5}$ in rural and urban households with peaks occurred in kitchen during cooking period. However, larger inter-home variations were observed in rural households than urban households due to the use of different residential energies. In the future, real-time sensors will play a more important role in regional indoor air evaluation.

4.3. Vertical variation

The recommended indoor air monitoring height is within the respiratory zone (GAQS, 2002), therefore, instruments for indoor air monitoring are mostly placed at a fixed height in the breathing zone, e.g., 1.45 m above the ground and 1.0 m away from the stove (IIAPIH, 2005). However, monitoring at certain height overlooks the vertical variations of air pollutants and is not suitable for health risk assessment of people with different heights (Fig. 4). For better health risk evaluation, measurements based on vertical gradients of indoor air pollutant are essentially needed. Unfortunately, only a few studies performed vertical measurement of indoor air pollution (Micallef et al., 1998a; Shen et al., 2020; Wu et al., 2021). Micallef et al. (1998b) firstly developed an auto-controlled lift system (kinetic sequential sampling system) with a single sensor that could move vertically and steadily at different positions. By adopting this system, Micallef et al. (1998a) measured the vertical PM concentrations in a non-smoking indoor environment and found the highest PM level was at ~1.3 m. Sensor arrays composed of several sensors at multiple heights, are commonly adopted in studies associated with vertical variations in indoor air pollution. Shen et al. (2020) monitored indoor gases (CO_2, CO, TVOCs, formaldehyde, and methane) by placing sensors at six different heights and found relatively high concentrations in the upper height due to hot air rising. Similarly,

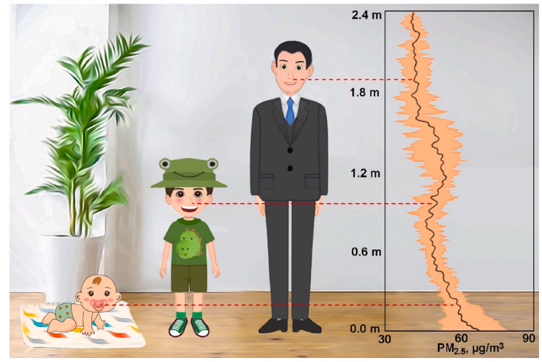

Fig. 4. Schematic diagram of indoor $PM_{2.5}$ exposures for people with different heights.

Ainiwaer et al. (2022) reported highly varied vertical profiles of indoor $PM_{2.5}$ with a high peak at 170–210 cm and a low peak at 110 cm height.

With the development of Lidar technology, Qiu et al. (2019) developed a portable indoor side-scattering Lidar (I-Lidar). Field test revealed that the newly developed I-Lidar had uniformly vertical resolutions, which was more effective and flexible than $PM_{2.5}$ sensor arrays. He et al. (2022) further expanded the I-Lidar technology to profile indoor $PM_{2.5}$ in three-dimensions by using I-Lidar arrays (3D I-Lidar). By adopting the 3D I-Lidars, the detailed trajectories of indoor $PM_{2.5}$ from cigarette smoking and incense burning were visualized and quantified in field, and stronger turbulence intensity of cigarette smoking was revealed. With the 3D I-Lidar, indoor $PM_{2.5}$ from different emission sources can be illustrated three-dimensionally and dynamically, as well as its emission, dispersion, and convection.

4.4. Peaks and source contribution

The high time resolution data from real-time sensors promotes the identification of peak concentrations in pollution events, which helps residents better understand indoor air pollution and then protect human health. Huang et al. (2022) reported that the daily average $PM_{2.5}$ concentration in rural kitchens using wood as cooking fuel was 60.1 ± 25.7 μg/m^3, while the peak $PM_{2.5}$ concentrations could be as high as 1,200 μg/m^3 during cooking period. Exposure to such high pollution levels may result in acute health effects, although the exposure duration is short. For example, exposure to high NO_2 (121.2 μg/m^3) during cooking period (~15 min) could lead to great falls in peak expiratory flow rates in women with asthma (Ng et al., 2001). Therefore, peak value may serve as a better indicator for short-term health effect evaluation (Delfino et al., 2002).

The identification and quantification of indoor emission sources is vital to implement pollution mitigations and clean interventions (Bari et al., 2015). The pollutant peaks recorded by real-time sensors contain information about durations and concentrations of each emission source, which are crucial to quantitatively analyze the contributions of different sources (Drewnick et al., 2012; Men et al., 2021). For example, Lu et al. (2020) calculated the contributions of three typical indoor activities (cooking, smoking, and mosquito coil combustion) to indoor $PM_{2.5}$ concentrations, of 0.55 ± 1.6, 0.34 ± 0.24, and 4.2 ± 4.0 μg/m^3 per activities, respectively, by extracting the pollution peaks. Men et al. (2021) developed a new peak extraction method to quantify the contributions of internal sources to indoor $PM_{2.5}$, showing indoor activities contributed ~70 % and 50 % to indoor $PM_{2.5}$ during heating and non-heating season, respectively. Meanwhile, the tangent line method is also used to identify $PM_{2.5}$ peaks in time series, and then the calculated peak areas are used to characterize the contributions of indoor activities and outdoor infiltrations (Shen et al., 2020; Shen et al., 2021). For example, Shen et al. (2020) quantitatively estimated the contributions of outdoor and indoor emission sources on various gases (CO_2, CO, formaldehyde, TVOCs, and methane) in an apartment, confirming that outdoor inputs contributed 15 % (formaldehyde) to 64 % (CO_2) to indoor air pollution.

4.5. Indoor and outdoor relationship

As mentioned before, both internal emissions and outdoor infiltrations can affect indoor air quality. The ratio of pollutant concentrations in indoor to outdoor (I/O) is wildly used to illustrate the relationships of indoor and outdoor air. I/O ratio calculated from filter-based sampling can hardly capture variations in I/O since the sampling resolution is low (e.g., 24 h average). Highly time-resolved data provided by real-time sensors makes it possible to explore dynamic variations in I/O based on simultaneous measurements in indoor and outdoor air, which is crucial to reflect the effects of various activities on the indoor/outdoor relationships (Qi et al., 2017). Huang et al. (2022) reported that the I/O ratios changed slightly (around 1.0) without human activities, while increased rapidly when indoor cooking and heating occurred. Men et al. (2021) found that the dynamic I/O ratios in rural households showed clear diurnal variations with higher in daytime than nighttime due to extensive human activities in daytime. The real-time I/O can serve as an indicator to improve indoor air quality through changing ventilation condition at proper time. For example, when the I/O increases, opening window will be helpful to alleviate indoor air pollution.

The diffusion of air pollutants from emission sources to other microenvironments needs time, which is defined as lag time (Chaloulakou and Mavroidis, 2002; Chaloulakou et al., 2003). Lag time is an important input parameter for modeling the impact of ambient air on indoor air, especially for those without internal emissions. Lag time is calculated by delayed correlation method, which shifts pollutant concentration data at various time intervals, calculates correlation coefficients and then identifies the time with maximum calculated correlation coefficients as lag time (Han et al., 2015), therefore, high time resolution data is necessary. Xu et al. (2020) reported a general lag time of 65 min for indoor CO diffusion to outdoors. Qi et al. (2017) reported significantly seasonal variations in lag time of household $PM_{2.5}$ in Beijing, in which the lag times were 12 ± 12 min and 78 ± 19 min in non-heating and heating seasons, respectively. Different lag times were found between rural and urban households; for urban households, indoor air pollution lagged to ambient, which was opposite to rural households (Qi et al., 2019), suggesting different patterns of indoor-outdoor relationships in rural and urban homes.

4.6. Indoor air pollution forecasting

As an important part of indoor air evaluation, the prediction of indoor air quality plays an important role for further countermeasure implement, especially when direct monitoring is not feasible (Yang and Wang, 2017). Indoor air models can be generally divided into physics-based mechanistic models and data-driven statistical models, of which statistic models are more popular due to their simplicity and easy-to-collect input variables (Li et al., 2021e; Tong et al., 2020; Wei et al., 2019). Generally, statistic models are used to simulate long-term averaged pollutant concentrations (e.g., 24-h average) (Milner et al., 2011), and the input data need to be used for training, validating, and testing models, resulting in a demand for large data set (Wei et al., 2019). Data from sensors are not only highly spatially- and temporally-resolved, but also own large data amount, which give a new chance to develop more sophisticated statistic models. Based on high spatiotemporal resolution $PM_{2.5}$ data from sensors, Shen et al. (2021) proposed a multivariate regression model to predict spatiotemporal variations of indoor $PM_{2.5}$, which considered source strengths, source-receptor pathway distances, and lag time. This simple model was possible to be applied to other internal sources, however, the large variations in household characteristics limited the large-scale expansion of this model. To quantify indoor $PM_{2.5}$ in the regional scale, Lu et al. (2020) developed a conceptual model by considering external infiltration and indoor contributions using simultaneous measured indoor and outdoor data, and then applied this model to predict indoor $PM_{2.5}$ levels in urban Beijing.

As a leading statistic method, machine learning plays an important role in indoor air quality forecasting. Since air pollutant concentrations are usually correlated with other parameters (Park et al., 2018), various parameters (e.g., temperature, RH) measured by real-time sensors further guarantee the development of predictive models using machine learning, of which artificial neural network (ANN) is the most popular method (Park et al., 2018; Wei et al., 2019). Khazaei et al. (2019) predicted indoor CO_2 levels by combing ANN with indoor temperature and RH, resulting in high accuracy of prediction with errors less than 17 ppm compared with actual concentrations. Liu et al., (2018) performed indoor airborne culturable fungi prediction by ANN models using indoor CO and PM concentrations, temperature, and RH as input, and the highest accuracy was 83 %. Furthermore, time-dependent data from sensors can be combined with time series models in machine learning, such as recurrent neural networks (RNN), to predict future sequences of pollutants more accurately through historical profiles (Wei et al., 2019). Ahn et al. (2017) reported indoor RNN-predicted CO_2 and $PM_{2.5}$ concentrations, founding that higher accuracy of RNN structures (70.13 % for long short-term memory (LSTM) and 84.89 % for gated recurrent unit (GRU), respectively) than that of single linear regression method (accuracy of 60.96 %). Similar results were also frequently reported in other studies (Kim et al., 2020; Lagesse et al., 2020; Loy-Benitez et al., 2019), indicating the great potential in indoor air pollution modeling in combination with sensor data and RNN methods.

4.7. Health effect assessments

Epidemiology studies have reported adverse health effects associated with air pollutant exposure, such as cardiovascular morbidity and mortality (Newby et al., 2015). Most of these studies are based on pollutant concentrations in ambient air (Chiarelli et al., 2011; Lelieveld et al., 2015; Shen et al., 2019). Only a few studies take indoor air pollution into consideration (Shan et al., 2014; Young et al., 2019), while most of the exposure occur indoors (Beko et al., 2015). Amongst the existing researches, daily (or longer duration) average values are usually adopted to assess long-term health effect (Genisoglu et al., 2019). However, short-term impacts as well as dynamic changes of health risk are rarely elucidated. Real-time data facilitates the evaluation of short-term health effects in response to pollutant exposures. Kim et al. (2020) investigated the correlations between indoor particles and phthalate metabolites based on real-time data, founding that PM_{10} showed higher effects on phthalate metabolites at 12 h cumulative intervals than those at 3 h and 6 h.

It is generally accepted that personal exposure concentration, which differs substantially from ambient and indoor pollutant concentrations (Barkjohn et al., 2021; Chan et al., 2021), is more suitable for health risk assessment. Estimation of daily air pollutant exposure can be achieved by time-weighted method which needs two key factors: time activity patterns and pollution levels in each microenvironment (Du et al., 2017; Kim et al., 2021). Differently, time series data can be combined with detailed time activity data to output more accurate results. For example, Fathallah et al. (2016) developed an Internet of Things (IoT)-based scheme to assess real-time personal formaldehyde and CO_2 exposures by combining real-time pollutant concentrations in various microenvironments and location information of people. Similarly, Li et al. (2022a) quantified real-time $PM_{2.5}$ exposure by integrating real-time $PM_{2.5}$ concentrations in various microenvironments when residents were attended. Moreover, wearable devices based on sensor technology can capture more detailed spatiotemporal variations in personal exposures to air pollutants at the individual level and provide more accurate air pollutant exposure concentrations than static monitoring sensors (Leaffer et al., 2019; Serrano and Licina, 2022), which makes wearable devices more suitable for personal exposure measurement (Shan et al., 2020).

The response of health indicators to air pollutant exposures may occur immediately or delay (Millers et al., 2016; Park et al., 2005). For example, the strongest impact of $PM_{2.5}$ exposure on heart rate increase was lagged at 3 h, while 0–3 h for fibrinogen increase (Li et al., 2021d). Liu et al. (2021b) reported that most metabolites responded to ozone exposure immediately; however, hysteresis effects were found for some metabolites (2 h to 2 days). The above-mentioned lag effects again highlight the need to measure indoor air pollution in real-time to better evaluate the impact of indoor air pollution on human health.

5. Challenges in real-time sensor application

In recent years, real-time sensors have been commonly used in indoor air monitoring and have shifted the indoor air pollution evaluation from static analysis into high spatiotemporal analysis. Meanwhile, real-time sensors promote the evaluation of indoor air quality at the individual household and community scale. Therefore, the application of real-time sensors has made remarkable achievements and shown promising outlook. However, wider adoption of real-time sensors in indoor air monitoring is limited by some challenges, such as data quality reliability and sensor performance, which is expected to be solved in the near future.

5.1. Sensor selection

Various types of sensors are now available; however, how to choose the most suitable sensor is the first challenge of sensor application. The selection of sensors depends on the purpose of study (Gillooly et al., 2019). Several studies have stated that real-time sensors are sufficiently accurate when the monitoring data is used for comparing with regulatory standards and/or qualitative analysis (Perez et al., 2018; Sa et al., 2022; Saini et al., 2021), while higher precision is needed for personal exposure evaluation and regulation purpose (Gillooly et al., 2019; Williams et al., 2014). Three major factors should be considered when selecting real-time sensors. First, the detectable range and limit of detection (LID) are varied for different sensors, and unreasonable use of sensors will introduce measurement errors. Sensors with large detectable ranges and high LID are more suitable for highly polluted area than those with low detectable ranges and low LID. For example, Afshar-Mohajer et al. (2018) found large variations in sensor performances under different pollutant concentrations, in which the tested low-cost electrochemical gas sensors showed poor performance at high CO (>12 ppm) and O_3 (>100 ppb), and at low NO_2 concentrations (<0.2 ppm). Zikova et al. (2017) reported LID of 10 μg/m^3 for Grimm portable laser aerosol spectrometer which limited its application in clean environments. Second, the response of PM sensor can be influenced by aerosol type (Sousan et al., 2016). Sousan et al. (2017) evaluated the response performance of PM sensors to several aerosols (salt, welding fume, and road dust), founding Footbot sensors had the highest performance than other two sensor types (Speck and AirBeam sensors), especially for dust aerosol monitoring. Similarly, Liu et al. (2020) reported variable sensitivity of Plantower $PM_{2.5}$ sensor to different aerosols, with higher sensitivity to organic particles than to inorganic particles (marine aerosols) and ultrafine particles (fresh traffic emissions). Therefore, the improper use of real-time sensors can lead to great measurement biases. However, not all sensor parameters (e.g., precision, LID, and source dependences) are well tested, which results in knowledge gaps in sensor selection (Zikova et al., 2017). Third, budget is also need to be considered. The cost of real-time sensors ranges from low (<$100 per sensor) to high (>$1000 per sensor) (White et al., 2012); furthermore, the maintenance cost of sensor may exceed the sensor itself (Gillooly et al., 2019), which will further limit the selection of sensors.

5.2. Sensor performance

Some real-time sensors have several weaknesses associated with their performances. For optical particle sensors, PM mass concentration is not directly monitored, but is inferred from determined number concentrations and particle sizes with the assumption that particles are uniformly distributed and spherical (Paprotny et al., 2013). Consequently, this will lead to inevitable deviations from the actual particle concentrations. The accuracy of light scattering-based optical particle sensors is also limited to "coincidence error", which is due to the overestimated size of particles when over one particle occurs in the observation volume (Lekhtmakher and Shapiro, 2004), and consequently underestimating the real particle number concentration and limiting the upper number concentration (Kuo et al., 2010; Sachweh et al., 1998). In addition, light scattering-based optical particle sensors are unable to detect ultrafine particle with particle size less than 0.3 μm due to they cannot scatter enough light (Väisänen et al., 2022), which further underestimates particle mass concentrations.

As for gas sensors, an important factor affecting their performances is their response to multiple variables. In other words, the cross-interference with other air pollutants is a crucial issue for chemical sensors, e.g., MOS sensors and electrochemical sensors (Chojer et al., 2020; Mijling and Jiang, 2017). The most significant cross interference was reported between O_3 to NO_2, possibly as high as 100 % (Mead et al., 2013). Meanwhile, it was reported that the downward bias was nearly 20 % in electrochemical sensors for NO_2 monitoring even after correcting the O_3 interference (Mead et al., 2013). The large cross interference of NO_2 to VOCs was found for MOS sensor due to the strong reaction between VOC and NO_3^- which was formed by the absorption of NO_2 of sensitive materials (Zhang et al., 2020). Furthermore, the cross interferences of CO and CO_2 to TVOCs were also reported (Baldelli, 2021), in which the increased interfering gas concentrations led to higher impact on TVOC sensors. The complex surface reaction inevitably results in defects of these sensors, and consequently leading to measurement errors (Zhang et al., 2020).

The reliability of data from real-time sensor is crucial for further analysis and is always a matter of concern (Jovasevic-Stojanovic et al., 2015). The inherent variability and discreteness among sensors during manufacturing process always leads to weak reproducibility of sensors, which means different responses may occur when using the same type of sensors to detect the same air pollutants (Carotta et al., 2001; Zhang et al., 2014). Crilley et al. (2018) assessed the accuracy of 14 optical particle counters of the same type and found that the average variance coefficients of PM_1, $PM_{2.5}$, and PM_{10} were 0.32, 0.25, and 0.22, respectively, indicating large internal differences between these sensors. Castell et al. (2017) compared the sensor performances in the field tests and also found that large intra-variations within the same series of sensors – the average inter-sensor correlations ranged from 0.49 for NO_2 sensors to 0.86 for NO sensors. Abdul-Wahab et al. (2015) and Afshar-Mohajer et al. (2018) reported the coefficient of variations ranged from 4.6 % to 18.2 %, 4.4 % to 24.6 %, and 0.4 % to 37.8 % for NO_2, O_3, and CO sensors, respectively. Weak reproducibility reduces sensor accuracy and comparability, which is crucial for sensor array-based studies (e.g., vertical variation studies). Furthermore, the sensors adopted in different studies are different, and the inconsistence within different sensors also challenges the comparability of results. A comparison of different particle sensors conducted by Manibusan and Mainelis (2020) found the inconsistent results from different PM sensors in the same place; this was due to the sensor response relied not only on particle composition, but also the specific algorithms for determining the values (Manikonda et al., 2016).

5.3. Sensor stability

Sensor stability is another important issue to maintain data reliability. First, real-time sensors generally lack long-term stability, which means the accuracy of sensor data will deteriorate over time. For example, Peterson et al. (2017) reported that the accuracies of NO_2 sensors decreased significantly after 4 months usage without calibration (the fractional error could rise up to ten). Another study by Gillooly et al. (2019) observed that the sensitivities of electrochemical gas sensors decreased approximately 21 %–29 % after monitoring over 18 months. The long-term instability of mobile sensor is majorly attributed to baseline drift (Tsujita et al., 2005), which is common in mobile sensors due to the tradeoff between drift resistance and low cost and portability (Xiang et al., 2013). The causes of sensor drift include heat output changes, degradation, and poisoning of sensors (Mijling and Jiang, 2017; Piedrahita et al., 2014; Romain and Nicolas, 2010). To compensate for drift errors, frequent recalibration is generally adopted. However, this method is time-consuming and burdensome. Some automatic calibration methods are proposed. For example, Xiang et al. (2012) developed collaborative calibration technique to adjust drift error based on sensor interactions, and successfully reduced the sensor errors to 2.2 %.

Second, sensor performances, such as sensitivity and baseline offset, can be interfered by meteorological conditions; furthermore, different sensors respond differently to meteorological conditions (Castell et al., 2017; Mead et al., 2013; Tsujita et al., 2005). For example, MOS and electrochemical gas sensors are more susceptible to the changes of RH, temperature, and pressure than non-dispersive infrared absorption sensors (White et al., 2012). Castell et al. (2017) reported the unique responses of individual sensors (with NO, CO, NO_2, O_3, PM_{10} and $PM_{2.5}$ as target pollutants) to the change in temperature and RH. Even though the correction factors for temperature and RH are available from generic data supplied by sensor manufacturers, these correlation factors are insufficient in field conditions where large differences of temperature and RH encountered (Castell et al., 2017). In addition, RH is an important influencing factor for the accuracy of optical particle counters, because particle refractive index and size are both associated with RH (Crilley et al., 2018; Hu et al., 2010). Crilley et al. (2018) reported significant decreases of accuracy of optical $PM_{2.5}$ sensors when RH > 90 % with the highest bias over 600 $\mu g/m^3$ compared with standard instruments. This calls for more sophisticated calibration methods, such as machine learning (Spinelle et al., 2015).

5.4. Sensor calibration

As mentioned before, data quality and accuracy for real-time sensors vary largely. Therefore, sensor calibration is needed to reduce the inter-sensor variability, and ensure data accuracy and sensor consistency (Jovasevic-Stojanovic et al., 2015). The biggest challenge in sensor calibration is standard guidance for real-time sensors is less available (Castell et al., 2017; Chojer et al., 2020). The available calibration methods usually include calibration with professional instruments or mutual calibration, as well as calibration under specific pollutant concentrations (Crilley et al., 2018; Kang et al., 2022; Kumar et al., 2017). Furthermore, most sensors are used directly without any calibration (Chojer et al., 2020). Saini et al. (2020) reported that only 22.5 % of studies performed sensor calibration before implementation.

Sensor calibration can be conducted both in the laboratory and in the field. Laboratory condition is important to test response time, LID, and inter-sensor variations (Piedrahita et al., 2014). Some researches pre-calibrated sensors with professional instruments in laboratory before field campaigns and good agreements were often reported (Liu et al, 2020). However, it is difficult to capture the confounding factors that can profoundly influence the accuracy of sensors (e.g., meteorological conditions, emission sources, and cross-sensitivity) under the well-controlled and stable laboratory condition (Morawska et al., 2018; Sauerwald et al., 2018). Some researchers compared laboratory and field calibration of sensors, and worse performance in field were reported. For example, Castell et al. (2017) reported good calibration result in laboratory condition with an average correlation coefficient of 0.99, which was significantly higher than that in field condition (average correlation coefficient: 0.60). Manibusan and Mainelis (2020) found the accuracy of PM sensor was site-depended, possibly due to the differences in PM composition, and suggested site-specific calibration to improve measurement accuracy. Furthermore, inter-sensor variations should be considered when calibration was conducted. Therefore, devices are more suitable to calibrate individually rather than using average calibration values for all devices in the same surrounding (Fritz et al., 2022).

The calibration methods are various, including but not limited to linear model, multi-linear regression model, exponential, logarithmic, and machine learning (Karagulian et al., 2019). How to choose the most suitable methods for each sensor is a challenge when taking large inter-variation of sensors into consideration. For example, some studies reported that PM sensors showed linear responses to the referenced methods (Baldelli, 2021; Sousan et al., 2017), while nonlinear responses were found in other studies (Jiang et al., 2021; Lee et al., 2020). Spinelle et al. (2015) compared the performances of various methods for sensor calibration, founding that good performance of simple regression for O_3 calibration, while ANN method was the most efficient method for NO_2 calibration.

5.5. Working time and life span of real-time sensors

Some real-time devices are powered by built-in batteries; therefore, the working time of these sensors is limited by the battery capacity. For example, the running time of MicroAeth AE51 is 22–24 h, which is only 7 h for Aeroqual handheld NO_2 monitor (Series 505) (Delgado-Saborit, 2012). Such short working time limits these sensors for long-term monitoring. Frequent replacement of battery is inefficient and burdensome, which will reduce the willingness of residents to use these sensors (Kuncoro et al., 2022; Xiang et al., 2012).

Relatively short life expectancy is a major issue for electrochemical sensors (only 1–2 years) (Jelicic et al., 2013). For example, the suggested lifetime (defined as the total working time when the sensor accuracy decreases by 50 %) of Alphasense oxidative gas sensors by manufacturer is 2 years. However, the field test conducted by Li et al. (2021c) showed that the performances of Alphasense NO_2 sensors degraded significantly after nearly 200–400 days of use, and become non-functional after ~400 days of deployment, far shorter than the suggested lifetime of 2 years.

6. Further development of real-time sensors

The ideal sensors are expected to be user friendly and have good performances. Therefore, further developed sensors require to have advantages such as high accuracy, long lifetime, strong resistance to environmental changes and drift, as well as silence, low power consumption, small size, and low cost (Holstius et al., 2014; Mead et al., 2013). As for the comparability of different sensors, standardized protocols should be developed, such as referenced instruments and methods, for various sensors which have the same target pollutants to evaluate their performances and ensure the comparability between sensors.

The indoor air monitoring system, which integrates monitoring with communication technologies for data analysis, transmission, and visualization, shows great potential in indoor environment enhancement, and is an essential part in smart city (Marques et al., 2020; Zhao et al., 2019). This system can provide users real-time updates of indoor air quality via communication technologies (Bluetooth, ZigBee, and Wi-Fi, etc.) and help users make decisions to alleviate indoor air pollution (Saini et al., 2020). Such system can be further used to work together with ventilation systems. For example, Chiesa et al. (2019) developed a multi-sensor system based on IoT to address indoor air pollution by integrating monitoring with ventilation system, which could adjust fan speed to control ventilation system based on sensor data and specific algorithms. However, some limitations are still existed, such as processing capabilities, energy consumption, and application scenarios. It is hoped that these limitations can be addressed in the future.

Technology to improve sensor performance is always demanded. On the one hand, sensor performance can be improved by developing highly responded and sensitive sensor materials, such as two-dimensional materials (Liu et al., 2017). On the other hand, in addition to monitoring multiple pollutants at the same time, electronic nose is one of the most efficient way to eliminate the influences of interfering gas and improve data accuracy (Speller et al., 2015). In addition, as the alternative and complementary method to electronic nose, virtual sensor array which can produce multiple analyte-specific signals by a single physical sensor is a very promising method in addressing cross-sensitivity issues (Li et al., 2021a; Zhao et al., 2018).

For particle monitoring, it is generally accepted that the hazardous effect of particles is up to not only mass concentrations, but also morphological features and bounded toxic components (such as polycyclic aromatic hydrocarbons and heavy metals) (Fubini and Fenoglio, 2007; Gozzi et al., 2016). The component analysis is always the main advantage of conventional filter-based sampling. Unfortunately, so far, most PM compositions cannot be determined by real-time sensors, which should be the focus of further development of PM sensors.

In addition to the development of sensor technology, the improvement of public awareness is necessary. The evaluation and visualization of indoor air pollution is an important part for improving indoor air quality, as well as the implementation of mitigation measures. However, the health impacts of air pollutants and ways to alleviate indoor air pollution are well known for researchers but not for the public. How to popularize these knowledges to public is important and remained to be solved in the future.

7. Conclusion

Indoor air quality improvement plays a crucial role in human health protection. The comprehensive analysis of indoor air pollution needs real-time monitoring. Herein, the state of art of real-time sensors used in indoor air monitoring is reviewed. The application of real-time sensors in indoor air quality evaluation has experienced three stages, and has shown a rapidly increasing trend in recent five years. Studies associated with the use of real-time sensors indoors are mainly conducted in China, and in residential homes. $PM_{2.5}$ is the most commonly investigated pollutant in indoor real-time monitoring. Real-time sensors can provide 3-dimensional pollutant data with high spatiotemporal resolution, which is hardly reflected by conventional static monitoring. Also, real-time sensors have prominent advantages in pollution peak analysis, source identification, and short-term human health evaluations. Data from real-time sensors is large and has temporal information which promotes indoor air quality modeling.

The available real-time sensors vary in performance, and how to choose the most suitable sensor is considerable. In addition, lack of long-term stability, weak reproducibility, and the need of frequent calibration of real-time sensors limit their wild application in indoor air monitoring. Future sensors are expected to have good performances, long-term stability, drift resistance, and can detect more air pollutants at low price, as well as interact with end users.

CRediT authorship contribution statement

Jinze Wang: Writing – original draft, Writing – review & editing. **Wei Du:** Writing – original draft, Writing – review & editing, Conceptualization, Funding acquisition, Supervision. **Yali Lei:** Writing – review & editing. **Yuanchen Chen:** Writing – review & editing. **Zhenglu Wang:** Writing – review & editing. **Kang Mao:** Writing – review & editing. **Shu Tao:** Writing – review & editing. **Bo Pan:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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