Science of the Total Environment 807 (2022) 150797

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale

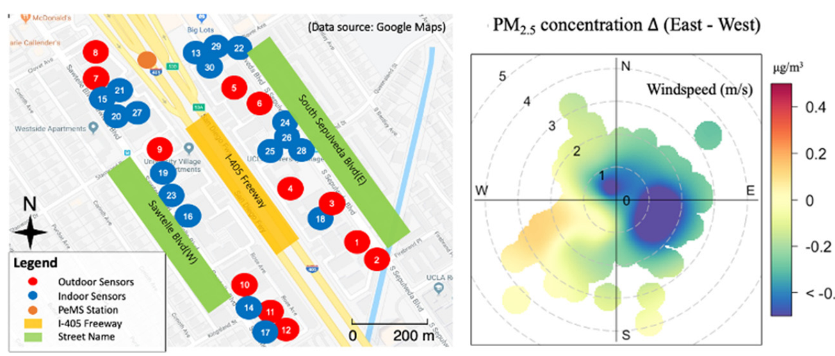
Rachel E. Connolly [a], Qiao Yu [a], Zemin Wang [a], Yu-Han Chen [a], Jonathan Z. Liu [a], Ashley Collier-Oxandale [b], Vasileios Papapostolou [b], Andrea Polidori [b], Yifang Zhu [a,*]

[a] Department of Environmental Health Sciences, Jonathan and Karin Fielding School of Public Health, University of California, Los Angeles, CA 90095, United States
[b] South Coast Air Quality Management District, Diamond Bar, CA 91765, United States

HIGHLIGHTS

- Evidence on real-world performance of low-cost sensors for community use is limited.
- Data quality and performance of 30 indoor and outdoor low-cost sensors was assessed.
- Main data quality concerns resulted from outdoor sensor data incompleteness.
- Indoor and outdoor air sensors detected resident activities and traffic pollution.
- Community-maintained low-cost sensors can produce accurate $PM_{2.5}$ pollution data.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 14 June 2021
Received in revised form 30 September 2021
Accepted 30 September 2021
Available online 6 October 2021

Editor: Philip K. Hopke

Keywords:
Community air monitoring
Particulate matter
Low-cost sensors
Optical particle counter
Traffic emissions
Indoor air quality

ABSTRACT

Given the growing interest in community air quality monitoring using low-cost sensors, 30 PurpleAir II sensors (12 outdoor and 18 indoor) were deployed in partnership with community members living adjacent to a major interstate freeway from December 2017- June 2019. Established quality assurance/quality control techniques for data processing were used and sensor data quality was evaluated by calculating data completeness and summarizing $PM_{2.5}$ measurements. To evaluate outdoor sensor performance, correlation coefficients (r) and coefficients of divergence (CoD) were used to assess temporal and spatial variability of $PM_{2.5}$ between sensors. $PM_{2.5}$ concentrations were also compared to traffic levels to assess the sensors' ability to detect traffic pollution. To evaluate indoor sensors, indoor/outdoor (I/O) ratios during resident-reported activities were calculated and compared, and a linear mixed-effects regression model was developed to quantify the impacts of ambient air quality, microclimatic factors, and indoor human activities on indoor $PM_{2.5}$. In general, indoor sensors performed more reliably than outdoor sensors (completeness: 73% versus 54%). All outdoor sensors were highly temporally correlated ($r > 0.98$) and spatially homogeneous (CoD<0.06). The observed I/O ratios were consistent with existing literature, and the mixed-effects model explains >85% of the variation in indoor $PM_{2.5}$ levels, indicating that indoor sensors detected $PM_{2.5}$ from various sources. Overall, this study finds that community-maintained sensors can effectively monitor $PM_{2.5}$, with main data quality concerns resulting from outdoor sensor data incompleteness.

* Corresponding author.
E-mail address: yifang@ucla.edu (Y. Zhu).

https://doi.org/10.1016/j.scitotenv.2021.150797

1. Introduction

Exposure to fine particulate matter ($PM_{2.5}$), a prevalent ambient air pollutant, is associated with adverse health effects such as respiratory illness, cardiovascular disease, and premature mortality (Anderson et al., 2012; Brunekreef and Holgate, 2002; Mukherjee and Agrawal, 2017; Pope and Dockery, 2006). The World Health Organization reports that more than 90% of people worldwide live in regions in exceedance of $PM_{2.5}$ standards (World Health Organization, 2021), and a 2018 study developed from the global burden of disease project estimated almost nine million deaths in 2015 were caused by long-term $PM_{2.5}$ exposure (Burnett et al., 2018). Recent studies in the United States and other regions have provided substantial evidence of both acute and chronic health impacts from $PM_{2.5}$ (Anenberg et al., 2019; Fajersztajn et al., 2017; Horne et al., 2018; T. Wang et al., 2019), even at concentrations under regulatory standards (Pascal et al., 2014; Schwartz et al., 2017). Additionally, ambient $PM_{2.5}$ exposures occur simultaneously with exposure to other hazardous air pollutants, resulting in an added risk of cumulative negative health effects (Farraj et al., 2015; Ku et al., 2017; Ljungman et al., 2016; Siddika et al., 2019; Thompson et al., 2019). Indoor air pollution is an established health concern as well (Tran et al., 2020); a recent meta-analysis found that 1.8 million global deaths in 2017 were associated with household air pollution (including $PM_{2.5}$) (Lee et al., 2020). The capacity to efficiently identify $PM_{2.5}$ sources and quantify outdoor (ambient) and indoor concentrations can facilitate the development of control measures to reduce exposures and resulting health impacts (Mukherjee and Agrawal, 2017).

Attempts to collect both outdoor and indoor real-time and high-resolution air quality data are often encumbered by the limitations of air monitoring devices (Snyder et al., 2013). Air pollution is measured outdoors by a limited number of stationary air quality monitoring stations; ubiquitous placement of these regulatory-grade air monitoring instruments is cost-prohibitive (Faridi et al., 2018; Guo et al., 2017; Pun et al., 2017; Snyder et al., 2013). Until recently, air pollutant concentrations measured by the Federal Equivalent Method (FEM) or Federal Reference Method (FRM) at Environmental Protection Agency (EPA) or other regulatory air quality monitoring stations were the primary source of data available for use in exposure assessment. However, the use of air pollution data with inadequate spatial and temporal coverages for such analyses can limit the potential to examine exposures to specific populations and identify communities to target for emission reduction efforts. These FRM/FEM monitoring stations may fail to identify hotspots or significant pollution events (Kelly et al., 2021; McLaughlin et al., 2020). Moreover, these existing air quality monitoring networks are not intended to provide indoor air quality information for households. Considering that people spend 80-90% of their daily time in the indoor environment (Klepeis et al., 2001; Simoni et al., 2003), this is a critical factor as well.

With technological advancements in the areas of electrical engineering and wireless networking, "low-cost" air quality sensors have been developed and expanded air monitoring in a more affordable and portable direction (Snyder et al., 2013). In the last several years, evidence has begun to emerge about the utility of low-cost sensors. Studies have demonstrated various applications and limitations of low-cost air sensors, such as improving the resolution of concentration coverages (Ahangar et al., 2019; Kelly et al., 2021; Mead et al., 2013), detecting wildfire emissions (Gupta et al., 2018; Holder et al., 2020; Kaduwela et al., 2019), and classifying sources of emissions in an airport setting (Popoola et al., 2018). Studies have also identified that low-cost sensors have a limited capacity to detect ultrafine particle emissions from residential sources (Z. Wang et al., 2020). The EPA (Barkjohn et al., 2021) and the South Coast Air Quality Management District (South Coast AQMD) have both investigated the accuracy and utility of low-cost sensors. The South Coast AQMD Air Quality Sensor Performance Evaluation Center (AQ-SPEC) has developed both ambient (field) and controlled (laboratory) sensor testing protocols (Polidori et al., 2016, 2017) and conducted an extensive evaluation of dozens of commercially available low-cost air quality sensors, finding that several low-cost sensors perform well under both conditions (Feenstra et al., 2019; South Coast Air Quality Management District, 2021).

One popular low-cost sensor is the PurpleAir II (PA-II) device, which was designed for monitoring both outdoor and indoor particulate matter (PM) levels. Many recent studies have focused on PA-II sensors, testing the validity of the sensors for assessing both indoor and outdoor $PM_{2.5}$ levels (Kim et al., 2019), quantifying the detection of wildfire emissions (Gupta et al., 2018), using measurements for large-scale exposure modeling (Bi et al., 2020), and developing correction factors for various conditions (Delp and Singer, 2020; Magi et al., 2020; Malings et al., 2020). A study conducted by the South Coast AQ-SPEC found that PA-II sensors perform well when comparing $PM_{2.5}$ measurements to FEM in ambient settings and discussed how establishing sensor correction factors can further improve the data (Feenstra et al., 2019). The study also identified that the need for such corrections may limit the utility of the sensors for the general public (Feenstra et al., 2019). Soon thereafter, research conducted by EPA scientists compared PA-II data with FEM and FRM across 16 states and found that the PA-II sensors overestimated $PM_{2.5}$ concentrations by approximately 40%, which can be corrected with an optimized linear regression equation (Barkjohn et al., 2021).

While several long-term studies have identified the evident utility and benefits of PA-II sensors, such as filling significant local air quality monitoring data gaps (Magi et al., 2020; Malings et al., 2020), there is limited research on real-world performance of the PA-II sensors and potential applications for the general public, including individual households, local environmental organizations, and communities. One of the chief benefits of the accessibility of low-cost sensors is building the capacity for communities to play a central role in air pollution monitoring, which can empower and educate them (Snyder et al., 2013); however, there are no existing studies evaluating the performance of a PA-II sensor network implemented and maintained by communities themselves. To fill these knowledge gaps, this study uses one and a half years of PA-II data to evaluate long-term sensor performance and explore the potential applications of PA-II devices in a community residential setting. This is achieved through assessing the data quality and performance of 30 indoor and outdoor sensors installed and maintained in partnership with community residents. This study was part of a larger effort supported by an EPA STAR grant (Grant Number: R836184) to engage, educate, and empower communities through the use of low-cost air sensors. There were 300 PurpleAir sensors (primarily outdoor sensors) installed across 14 communities throughout California. This particular study is focused on one of the 14 study sites, which utilized both indoor and outdoor sensors.

2. Materials and methods

2.1. Study site and sampling details

The study area is a University of California, Los Angeles (UCLA) University Village housing community located on the eastern and western sides of Interstate 405 (I-405). Located four miles from the shoreline, the study area typically experiences steady onshore sea breeze each day beginning in the mid-morning. The sea breeze reaches its maximum in the early to mid-afternoon and recedes in the early evening. A weaker offshore sea breeze prevails during the night.

Occupants of apartments for indoor installations were recruited based on location, and they gave consent for data collection. The study participants residing in this community are UCLA graduate students with families (domestic partners, spouses, and children). Community outreach was one of the key components of the implementation of the sensor network. The research team worked in partnership with the community residents throughout this entire study, training and

Table 1
Quality assurance/quality control process and sensor data completeness statistics.

Step		Description	Source	Data completeness (Mean ± SD)	
				Outdoor sensor	Indoor sensor
1		Delete missing data (missing value from both channels)	EPA (Barkjohn et al., 2021)	62 ± 29%	86 ± 20%
2		Delete observations with data from only one channel	EPA (Barkjohn et al., 2021)	43 ± 21%	62 ± 13%
3		Delete data with abnormal temperature (T) and relative humidity (RH) readings. (T < -200 °F, or > 1000 °F; RH >100% or < 0%)	EPA (Barkjohn et al., 2021)	40 ± 21%	62 ± 13%
4	*4a*	Delete data if $\overline{PM_{2.5}}$ < 100 μg/m^3 and Δ > 10 μg/m^3, or if $\overline{PM_{2.5}}$ ≥ 100 μg/m^3 and Δ > 10%.[a,b]	PA-II Manufacturer (Yong and Haoxin, 2016)	40 ± 21%	61 ± 13%
	4b	Delete data if Δ > 5 μg/m^3 and Δ > 61%[a]	EPA (Barkjohn et al., 2021)	40 ± 21%	61 ± 13%

Note: [a] Δ = Difference between 80 or 120 s data from channel A and B; [b] $\overline{PM_{2.5}}$: Arithmetic mean of $PM_{2.5}$ reading from channel A and B. Step 4a was recommended by the PurpleAir manufacturer (Yong and Haoxin, 2016), and Step 4b was implemented by Barkjohn et al. (EPA) (Barkjohn et al., 2021).

empowering them to maintain the sensors and review their personal sensor data to understand drivers behind air quality trends. Throughout the course of this study, three workshops for the community residents were held to guide them through sensor installation, maintenance, and troubleshooting, as well as report and reflect on preliminary findings. The study was performed in accordance with the guidelines and approval of the UCLA Institutional Review Board.

A total of 30 PA-II sensors were installed and equally distributed on the two sides of the freeway; indoor sensors were installed inside 18 apartments, and 12 outdoor sensors were installed, with 11 on the roof of the apartment buildings at approximately the same height as I-405 and one at roof-level attached to a single-story building (Sensor 4). A map of the study site and sensor locations is included in Appendix A (Fig. A.1). Sampling data were collected from December 2017 to June 2019. Data were nominally defined as spring (March-May), summer (June-August), fall (September-November), and winter (December-February).

2.2. Data acquisition and quality assurance/quality control

The PA-II sensor is a low-cost optical particle counter. Each sensor contains two particle counters (Channel A and Channel B) to verify intra-model consistency. Particle counters inside the sensors provide the mass concentration (in μg/m^3) of PM_1 (particles with a diameter < 1 μm), $PM_{2.5}$, and PM_{10}, and particle number counts for various sizes ($PN_{0.3}$, $PN_{0.5}$, $PN_{1.0}$, $PN_{2.5}$, $PN_{5.0}$ and PN_{10}, where each number represents the maximum particle diameter in μm for that size group). Each device is equipped with an enclosed meteorological sensor to provide temperature, relative humidity (RH), and barometric pressure within the sensor. All the data collected by PA-II sensors are automatically uploaded to and recorded on the PurpleAir server through a Wi-Fi connection. All sensor data were downloaded (on the scale of 80 to 120 s per measurement) from the PurpleAir website.

As shown in Table 1, four quality assurance/quality control (QA/QC) measures were implemented in sequence. The U.S. EPA recently developed a nationwide correction factor for PurpleAir sensors and implemented data processing techniques, including matching Channel A and B concentration data to the nearest minute, removing data points missing a $PM_{2.5}$ reading in one of the two channels, and excluding data based on abnormal temperature and RH readings (see Table 1, Step 3 for the thresholds) (Barkjohn et al., 2021). The EPA analysis used PurpleAir [cf_1] data (one of two concentration parameters provided by the sensors, which are based on differing particle density assumptions) to develop their final correction factor; see the EPA study for additional details (Barkjohn et al., 2021). In this study, EPA's data processing techniques as seen in Table 1 (Steps 1-3) were followed and data were also excluded based on the magnitude of differences in concentrations between the two channels in each sensor, as recommended in the PurpleAir manufacturer's (Plantower) manual (see Table 1, Step 4a) (Yong and Haoxin, 2016). EPA's equivalent of this procedure (Step 4b) was included as a reference. The manufacturer's criteria were used for this step because the EPA standard was only tested for outdoor sensors. Overall, the resulting hourly data completeness are the same for both indoor and outdoor sensors using Step 4a versus Step 4b, though there is some by-sensor variation (Appendix Table A.1); this choice is not expected to significantly impact the analysis.

As evidenced from the first quality control measure in Tables 1, 38% of the outdoor sensor data and 14% of the indoor sensor data were missing (Step 1); several factors can contribute to missing data, including wireless internet connectivity issues and other logistical issues, such as outlet failure. After all the quality control measures, 60% of the outdoor sensor data and 39% of the indoor sensor data were removed, including the missing data mentioned previously.

After following the processes outlined in Table 1, each remaining raw [cf_1] measurement was averaged between the two channels (as was done by the EPA) and corrected using the EPA's correction factor.[1] The [cf_1] concentrations mentioned previously were used since that is what EPA used to develop their correction factor, and the factor was applied to both indoor and outdoor sensor data. Though the EPA correction factor was developed using only outdoor sensor data, the dataset for this study contained very few values outside of the range of concentrations included in the development of the correction factor, so it was applied to indoor concentrations here as well (Barkjohn et al., 2021). These data were then aggregated into hourly averages and hourly data completeness was quantified for all sensors by calculating the ratio between the number of available hourly observations (averages) and the total number of hours that each sensor was assumed to be operating. The missing hours occur when all data for that specific hour were removed during the previously discussed data QA/QC processes. Then, the analysis proceeded, using data from 7 outdoor sensors and 17 indoor sensors based on a threshold of 50% hourly data completeness (see Tables A.2 and A.3, as discussed in more detail in Section 3.1).

For participants with sensors inside their residences, activity data were collected using an activity log. During the first month of the campaign, each recruited apartment was asked to complete a one-week activity log to record their indoor activities on an hourly basis. Information on events such as indoor cooking, window opening, and using an air purifier was requested. Completed questionnaires from 9 recruited residents for seven days each were received. Therefore, approximately 1500 hourly records were used to develop sampling logs.

Finally, additional data from two external sources were extracted for use in the outdoor sensor analysis: (1) traffic flow data (vehicles per

[1] The analysis for this study used the first version of the correction factors released in December 2020 (Barkjohn et al., 2020), which were recently updated in the final version of the EPA team's publication in June 2021 (Barkjohn et al., 2021); the revised correction factors slightly change the corrected $PM_{2.5}$ values by less than ±2%, which did not impact the analysis results for either the indoor or outdoor sensors.

hour) from the CalTrans Portable Emission Measurement System (PeMS) vehicle detector station (VDS)-718,297 located on the I-405 freeway adjacent to the study site, and (2) nitrogen dioxide (NO_2, an indicator of traffic pollution) concentration data from the EPA West Los Angeles monitor site, which is located 2 miles north of the study site. The programming language R version 4.0.3 was used for all data cleaning and analyses.

2.3. Data analysis

Before assessing indoor and outdoor sensor performance separately, the geometric mean (GM) of hourly indoor and outdoor $PM_{2.5}$ concentrations were calculated and paired *t*-tests were used to statistically evaluate the difference between the two sets of concentrations. Each pair included one indoor sensor and the nearest outdoor sensor. Seasonal averages in $PM_{2.5}$ concentrations were also calculated to compare with expected seasonal trends.

2.3.1. Outdoor sensor application and performance

The variability between sensors deployed throughout the study site (all within a 500-600-meter range) was investigated. Based on the results of a normality test (Kolmogorov-Smirnov test, 95% confidence level), non-parametric statistical methods were used to assess inter-sensor variability in this study.

Spearman coefficients were calculated to evaluate temporal variability in $PM_{2.5}$ values between all combinations (pairs) of outdoor PA-II sensors (located 500-600 m apart) – i.e., to determine if the monitoring values vary in a similar pattern over time (see Table A.4). Pearson correlations were also calculated as a form of sensitivity analysis and results were similar, providing evidence of the robust nature of the analysis.

To assess spatial variability between the various sensors, coefficients of divergence (CoD) were calculated between each pair of outdoor sensors, a statistical method that can be used to evaluate the degree of uniformity of a pollutant measured concurrently at two sites (see Table A.5) (Feinberg et al., 2019; Y. Liu et al., 2017; Pakbin et al., 2010; Wongphatarakul et al., 1998). CoD is defined using Eq. (1), as follows:

$$\boldsymbol{CoD_{jk}} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}} \sum_{i=1}^{n} \left(\frac{\boldsymbol{X_{ij}} - \boldsymbol{X_{ik}}}{\boldsymbol{X_{ij}} + \boldsymbol{X_{ik}}} \right)^{2}} \tag{1}$$

where n is the number of observations, j and k represent the two paired sites, and X_{ij} and X_{ik} represent the i-th concentration measured at site j and site k. CoD values less than 0.2 between two sites are typically seen as spatially homogenous, while a CoD greater than 0.2 shows spatial heterogeneity (Feinberg et al., 2019; Y. Liu et al., 2017; Pakbin et al., 2010; Wongphatarakul et al., 1998).

The freeway adjacent to the study site (I-405) is a major north-south auxiliary Interstate Highway in Southern California with high traffic flow, and both exhaust and non-exhaust (e.g. brake and tire wear) emissions (Pant and Harrison, 2013) are known to contribute substantially to ambient $PM_{2.5}$ in urban areas. Therefore, whether the PA-II sensors could identify the impact of traffic emissions on $PM_{2.5}$ was evaluated through temporal and spatial lenses. $PN_{0.3}$ was also included in this analysis, to compare results of the analysis for mass concentration and number concentration.

To evaluate the capacity of the PA-II sensors to monitor temporal changes in traffic emissions, hourly averages of both $PM_{2.5}$ and $PN_{0.3}$ were compared and visually analyzed alongside hourly PeMS traffic flow data and EPA NO_2 measurements from the West Los Angeles monitor site. The NO_2 measurements were included here as another reference point since NO_2 is a well-established traffic pollutant. This analysis was conducted separately for weekdays (Monday-Friday) and weekends (Saturday and Sunday).

To investigate whether the PA-II sensors are able to detect spatial trends in $PM_{2.5}$ and $PN_{0.3}$ from I-405 traffic emissions, polar plots were used to compare the hourly differences (delta, Δ) of sensor data between the west and east side of I-405 with wind speed and direction. Depending on wind directions, either side could be upwind or downwind of I-405 (see Fig. A.2 for seasonal variations in wind direction and speed at the study site). Polar plots were also developed for pairwise sensors to perform a closer examination of the trends, again using the difference (Δ) between west and east sensor measurements.

Finally, supplemental analyses comparing sensor measurements to EPA FEM measurements were conducted; those results are included in Appendix B (PA-II and EPA $PM_{2.5}$ Comparison).

2.3.2. Indoor sensor application and performance

For the indoor sensor analysis, hourly indoor activity sampling logs were used to assess the ability of indoor sensors to detect indoor emissions. $PM_{2.5}$ indoor/outdoor (I/O) ratios were calculated, which were used to compare indoor air quality with ambient air quality at a given location (Deng et al., 2015). I/O ratios were calculated by dividing indoor $PM_{2.5}$ concentration levels for each indoor sensor by outdoor $PM_{2.5}$ concentration levels recorded at the nearest outdoor sensor (the maximum distance between the paired sensors – each indoor sensor and the nearest outdoor sensor – is 200 m).

The behaviors and household characteristics reported in the residential surveys were used to examine the indoor sensors' ability to detect the effects of indoor activities on I/O ratios, comparing the ratios before and during three activities: cooking, opening a window, and using an air purifier. The statistical significance of differences in I/O ratios before and during activities were tested using Welch's two-sample *t*-tests assuming unequal variances.

The sensors' ability to detect a rapid reduction in $PM_{2.5}$ concentrations resulting from opening windows (a natural ventilation process) directly following cooking hours was also evaluated. The $PM_{2.5}$ concentrations for the open and closed window scenarios were normalized to an equivalent background level and the length of time it took for concentrations to return to background in both scenarios were calculated and compared.

To further evaluate the performance of low-cost air sensors on assessing impacts of various indoor factors and ambient air quality on indoor $PM_{2.5}$ levels, infiltration factors (F_{inf}, the fraction of ambient $PM_{2.5}$ that travels indoors and contributes to indoor concentrations) were estimated and compared to existing literature. To calculate F_{inf}, data from time periods with no indoor sources (i.e., the middle of the night - 11 pm to 5 am) were used (Bi et al., 2021).

Finally, a linear mixed-effects regression model utilizing questionnaire responses and observation data was developed. The outcome (dependent) variable was set as hourly indoor $PM_{2.5}$ concentrations. To meet linearity assumptions, the model used the natural log of measured $PM_{2.5}$ concentrations.

The model covariates are listed in Eq. (2) and include the concurrent ambient $PM_{2.5}$ concentrations from the closest outdoor sensor, three indoor activity terms, and microclimatic controls (temperature and RH). Since indoor air pollutants accumulate in indoor spaces and then continue to affect indoor air quality, indoor $PM_{2.5}$ concentrations in the previous hour were added into the model to improve the prediction of current indoor $PM_{2.5}$ concentrations (Lim et al., 2012). The three indoor activity terms were selected based on findings from the previously described I/O ratio analysis, and were coded as binary indicators of whether the activity occurred during each particular hour (i.e., cooking, opening at least one window, or using at least one air purifier in the residence), or did not occur (i.e., not cooking, closed windows, no air purifier used). To optimize the model, an interaction effect between opening a window and the ambient $PM_{2.5}$ concentrations in the final model (Eq. (2)) was also included. To account for unobserved heterogeneity between monitoring devices, building structures, residents' characteristics, and residents' daily activities, a random effects term to represent variations by sampling site was included. The lme4 package in R was used for this analysis.

The final indoor $PM_{2.5}$ prediction model equation is as follows:

$$\begin{aligned} LnCin_{ij} = \beta_0 + \beta_1 LnCin_{i-1,j} + \beta_2 LnCambient_{ij} + \beta_3 Cooking_{ij} \\ +\beta_4 Window_{ij} + \beta_5 Purifier_{ij} + \beta_6 T_{ij} + \beta_7 R.H._{ij} \\ +\beta_8 Window_{ij} * LnCambient_{ij} + u_j + \varepsilon_{ij} \end{aligned} \quad (2)$$

where i represents the hour and j represents each indoor PA-II sampler. $Cin_{i-1,j}$ represents the previous hour's indoor $PM_{2.5}$ concentration, $Cambient_{ij}$ represents the outdoor air concentration, $Cooking_{ij}$ represents cooking, $Window_{ij}$ represents window opening, $Purifier_{ij}$ represents use of an air purifier, T_{ij} represents temperature, and $R.H._{ij}$ represents RH. U_j and ε_{ij} account for random effects and error. Each β value represents the change in the dependent variable, indoor $PM_{2.5}$ concentration, when the value of the associated independent variable, or covariate, changes. For example, β_2 represents the change in indoor $PM_{2.5}$ concentration resulting from one unit of change in ambient $PM_{2.5}$ concentration (both transformed to natural log) while keeping other independent variables constant. The statistical significance of the random effects was assessed using a likelihood ratio test.

3. Results and discussion

3.1. Sensor data quality

The hourly data completeness of the sensors varied between different field locations, as shown in Fig. 1, which contains monthly averages of the hourly $PM_{2.5}$ data (see Tables A.2 and A.3 for an overall by-sensor breakdown of completeness). A red box for a particular month represents a monitoring month without any available data from that sensor; the months that do not have a red box may be missing some data, but not all data for that given month. Outdoor sensors had lower data completeness than indoor sensors (54% versus 73%). Outdoor Sensor 2 had the lowest value of data completeness throughout the entire study (4%); this sensor broke twice during the sampling period for unknown reasons. It appears that conditions around the monitoring site (e.g., outlet failure) contributed to the malfunction of monitors. However, the main reason for missing data was the instability (loss) of wireless internet connection. Similar challenges were noted in a 2017 air sensor network validation study in the Imperial Valley, which utilized a different type of sensor (Carvlin et al., 2017).

Apart from one sensor (Sensor 22), all indoor sensors had greater than 50% data completeness during the sampling period, and 12 out of the remaining 17 sensors had greater than 70% completeness (Table A.3). Incomplete indoor data mostly stemmed from the loss of stable wireless internet when residents went on vacation.

As stated in Section 2.2, sensors with hourly data completeness of less than 50% from were excluded from the analysis. This included five outdoor sensors (1, 2, 4, 10, and 11), and one indoor sensor (22). This left sufficient data to proceed with the analysis, which continued using the complete data from 7 outdoor sensors and 17 indoor sensors.

During the sampling period, the GM of hourly indoor $PM_{2.5}$ concentrations for all 17 sensors was 3.4 $\mu g/m^3$ (interquartile range [IQR]: 1.3–11 $\mu g/m^3$), compared to a GM of hourly outdoor $PM_{2.5}$ concentrations of 9.6 $\mu g/m^3$ (IQR: 5.3–21 $\mu g/m^3$) across 7 sensors (see Tables A.2 and A.3, and Fig. A.3). Both values are below annual California ambient air quality standards (12 $\mu g/m^3$) (California Air Resources Board, 2016) and ambient concentrations are consistent with reported annual averages from Los Angeles regulatory monitors (California Air Resources Board, 2019).

Based on the paired *t*-test results, mean indoor $PM_{2.5}$ concentrations were significantly lower than the mean outdoor $PM_{2.5}$ concentrations reported by the nearest sensor (difference = 6.6 $\mu g/m^3$, $p < 0.001$), confirming a protective role of buildings in the reduction of air pollution (Chen and Zhao, 2011; Snider et al., 2018). This effect was more extreme in the winter, when ambient $PM_{2.5}$ concentrations were higher (Fig. A.3). In contrast, most of the maximum hourly $PM_{2.5}$ levels reported by a single indoor sensor were much higher than outdoor $PM_{2.5}$ concentrations, and the highest hourly $PM_{2.5}$ concentration was reported by an indoor sensor (105 $\mu g/m^3$). These high concentrations were likely a result of indoor activities such as cooking events, where pollutant concentrations may increase substantially, depending on the cooking technique and type of food cooked (Amouei Torkmahalleh et al., 2017; Buonanno et al., 2009; Zhang et al., 2010).

In terms of seasonal trends, the highest outdoor $PM_{2.5}$ concentrations were observed in the winter (14 ± 12 $\mu g/m^3$), followed by fall (12 ± 10 $\mu g/m^3$), summer (10 ± 5.5 $\mu g/m^3$) and spring (7.5 ± 6.0 $\mu g/m^3$)

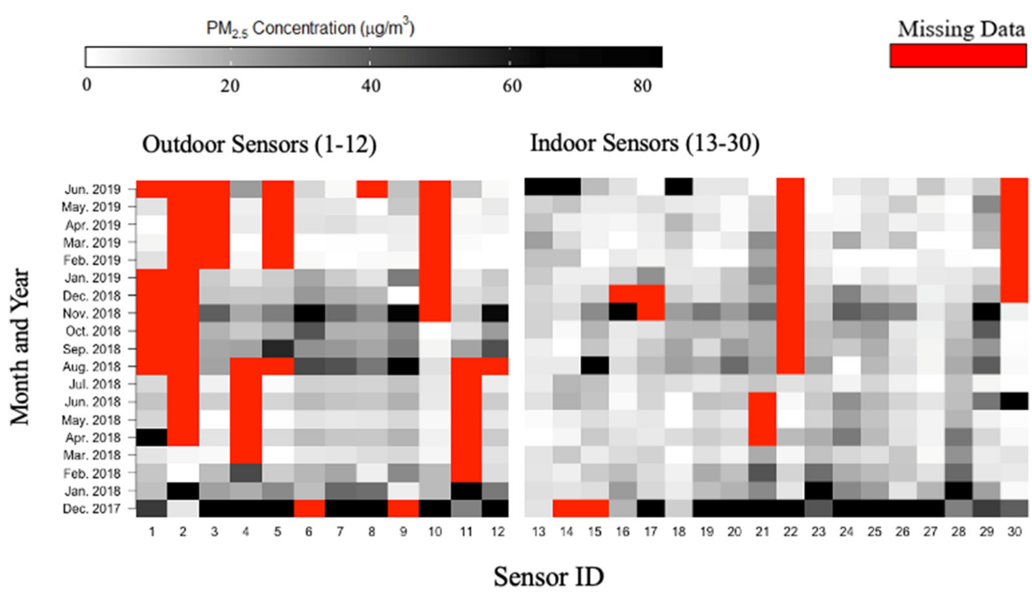


Fig. 1. Data collected by the sensor network. The white to black range represents the average monthly $PM_{2.5}$ concentration ($\mu g/m^3$). The red boxes represent a monitoring month without any available data from a sensor. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Table A.6). This indicates that the $PM_{2.5}$ pollution levels varied seasonally, which aligns with findings from existing literature (Y. Liu et al., 2005; Zhao et al., 2018), though seasonal variations in concentrations are not substantial in Los Angeles due to fairly consistent meteorological conditions (Hasheminassab et al., 2014).

Overall, we find that the major data quality issues are associated with missing data, particularly for outdoor sensors. Apart from this, the actual measurements follow expected trends and provide confidence in sensor accuracy.

3.2. Outdoor sensor application and performance

3.2.1. Inter-sensor variability

The Spearman correlation coefficients among pairwise sensors (each combination of outdoor sensors) were high, ranging from 0.98–1.0 (Table A.4). This suggests that concentrations between each pair of sensors rose and fell together as ambient conditions changed, suggesting high temporal correlation.

The CoD ranged from 0.02 to 0.06 which indicates a strong spatial homogeneity among the sensors, meaning that the concentrations between any two sensors at any given time matched very closely (Table A.5). We would not expect them to vary significantly due to their close proximity to each other, but this evidence confirms that the sensors are operating as expected.

Inter-sensor variability has been used as a metric of sensor reliability in recent studies (H.-Y. Liu et al., 2019; X. Liu et al., 2020), and our estimated PA-II inter-sensor consistency provides further evidence of outdoor sensor measurement reliability (see Fig. A.4 for the range of $PM_{2.5}$ measurements among sensors).

3.2.2. Temporal and spatial traffic impacts

To assess whether the PA-II sensors successfully detect temporal trends in traffic emissions, Fig. 2 illustrates the temporal variability of hourly traffic flow, $PM_{2.5}$, $PN_{0.3}$ and EPA NO_2 measurements, averaged over the study period (for weekdays and weekends). As shown in Fig. 2, the traffic flow on I-405 peaks (approximately 6000 vehicles per hour) once in the late mornings and again (5000 vehicles per hour) during weekday and weekend evenings. It is important to note that traffic flow is not as high as would be expected for a central portion of the I-405 (California Department of Transportation, 2021) since the PeMS sensor closest to the community is at an intersection of two freeways where traffic consistently slows (see Fig. A.1). In terms of the pollution measurements, the reference NO_2 concentration peaked shortly after the rise of morning traffic flow, soon followed by PA-II $PM_{2.5}$ and $PN_{0.3}$. The morning peaks of $PM_{2.5}$ and $PN_{0.3}$ lagged slightly behind the morning NO_2 peak, providing evidence of secondary $PM_{2.5}$ formation (particularly, the elevated midday concentrations are a likely result of secondary formation under strong solar intensity (Fine et al., 2008)) and other contributing $PM_{2.5}$ sources. Overall, PA-II measurements temporally aligned with both the traffic flow and reference NO_2 concentrations indicating that the sensors were able to detect trends in elevated concentrations of $PM_{2.5}$ and $PN_{0.3}$ in the community associated with freeway traffic emissions.

Regardless of traffic, the hourly pollutant trends are consistent with existing literature as well. NO_2, $PM_{2.5}$ and $PN_{0.3}$ all reached a minimum in the late afternoon, as expected considering well-mixed atmospheric conditions resulting in dilution (Kendrick et al., 2015; Manning et al., 2018). In the evenings, there is another rise and drop of traffic flow, and simultaneously, NO_2, $PM_{2.5}$ and $PN_{0.3}$ concentrations began to rise and continue on late into the evening, regardless of the drop in traffic flow. This aligns with existing evidence that NO_2 concentrations are highly dependent on traffic in the mornings, but traffic volumes are not a significant determinant of NO_2 concentrations in the evenings (Kendrick et al., 2015).

To assess spatially-resolved traffic impacts, polar plots (Fig. 3) of the sensor averages for $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ were developed, between the east and west sides of the freeway under high traffic flow conditions (>5000 vehicles/h). Positive differences would indicate higher

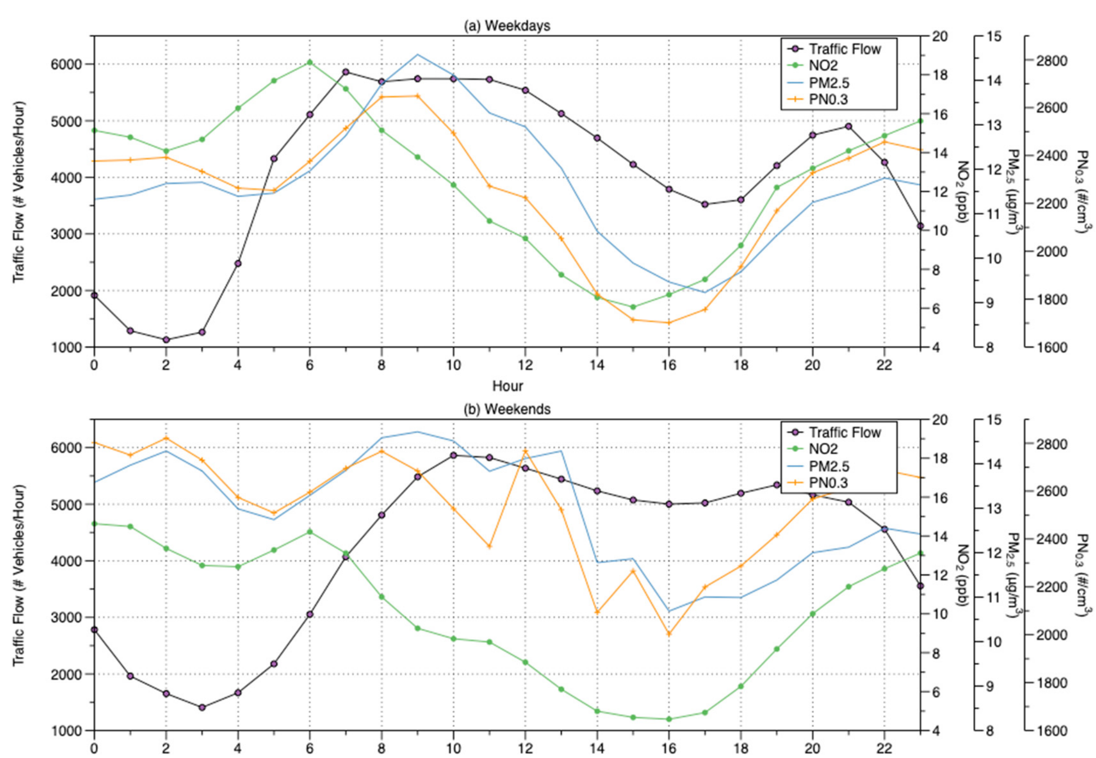


Fig. 2. Hourly variation of traffic flow (left vertical axis), NO_2, $PM_{2.5}$, and $PN_{0.3}$ (right vertical axis), during (a) weekdays and (b) weekends. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

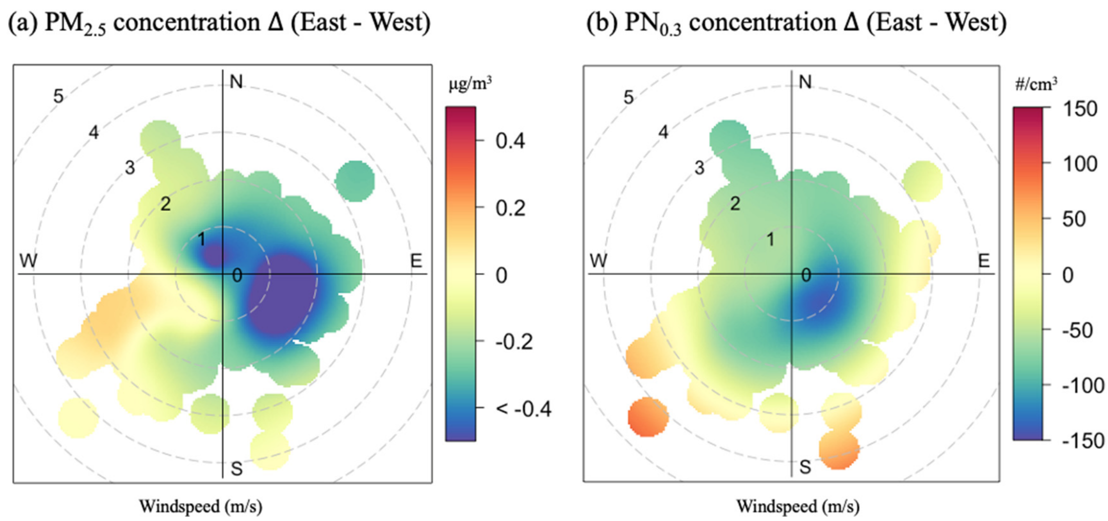


Fig. 3. Polar plots of the difference (Δ) in concentration between the east and west sides of I-405 for (a) $PM_{2.5}$ (μg/m^3) (b) $PN_{0.3}$ (#/cm^3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pollutant concentrations on the east side, while negative differences would indicate higher pollutant concentrations on the west side. The $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ were higher downwind of I-405 as evidenced by negative differences (in blue) when the wind was blowing from the east of the freeway, and positive differences (in orange-red) when the wind was blowing from the west. This indicates that the sensors were detecting the traffic emissions from the freeway.

Although using the average concentrations from the west and east sensors suggests that the sensors can be used to detect traffic emissions for $PM_{2.5}$ and $PN_{0.3}$, a closer examination is shown in Figs. A.5 and A.6, which are polar plots for pairwise sensors (each west sensor in combination with each east sensor), again using the difference (Δ) between west and east sensor measurements. The positive difference in concentrations (in orange-red) is expected to be associated with wind from the west (i.e., on the left side of the plot), as discussed for Fig. 3 as well. For $PM_{2.5}$, the results are relatively similar among pairwise plots, and trend in the expected direction.

However, the results are not as consistent in $PN_{0.3}$ plots. Several of them indicate that differences between west and east were higher when wind is blowing from directions other than the east. This is unexpected (though it is important to consider that PA-II sensors only have 50% collection efficiency for $PN_{0.3}$) (Yong and Haoxin, 2016). Previous studies have found that number concentrations of smaller particles declined more quickly than larger particle mass (Karner et al., 2010; Zhu et al., 2002). Specifically, Karner et al. observed that while peak edge-of-road number concentrations of ultrafine particles declined by 80-90% by 300-400 m away from the road, $PM_{2.5}$ has a less rapid decay, and $PN_{0.3}$ had no concentration decay trends as a response to distance to the edge-of-road (Karner et al., 2010). A similar pattern was found in a 2002 study (also on the I-405 in Los Angeles), demonstrating that smaller particles (6–25 nm) decay rapidly by 100 m and larger particles (100–220 nm, slightly less than 0.3 μm) have no trend in regard to the distance to the edge-of-road (Zhu et al., 2002). Therefore, in a spatial decay context, the extent to which PA-II $PN_{0.3}$ is an effective tracer of traffic emissions warrants further study, particularly with consideration to the contribution of smaller particles to the composition of $PN_{0.3}$.

Based on these findings, we recommend further investigation to determine whether the sensors can be used to detect the impact of traffic emissions on $PN_{0.3}$ with precision. While the sensors were able to characterize the relationships between $PM_{2.5}$, $PN_{0.3}$, NO_2, and traffic trends, for conditions in the current study, $PM_{2.5}$ might be a more reliable parameter than $PN_{0.3}$ to track traffic emissions.

3.3. Indoor sensor application and performance

3.3.1. Factors influencing indoor $PM_{2.5}$ concentration and I/O ratio

This study explored several indoor activities reported by residents that could be related to $PM_{2.5}$ emissions or mitigation, which include cooking, opening a window, and using an air purifier. The associated I/O ratios are shown in Fig. 4.

For the 75 cooking hours with available air quality data, there was a statistically significant difference between the I/O ratios during cooking hours (GM: 0.9, IQR: 0.4–2.1) and non-cooking hours (GM: 0.4, IQR: 0.1–0.9), as seen in Fig. 4a. This is evidence of a significant increase in the amount of $PM_{2.5}$ generated indoors rather than primarily infiltrating from the outdoor environment. Additionally, 37% of the cooking hours had $PM_{2.5}$ I/O ratios greater than 1.2, meaning there were higher indoor concentrations than outdoor concentrations. For 10% of the cooking hours, $PM_{2.5}$ hourly averages were higher than the 24-h national ambient air quality standard of 35 μg/m^3, which indicates that cooking can result in indoor $PM_{2.5}$ concentrations exceeding designated acute ambient air quality standards (California Air Resources Board, 2016). These findings are all in accordance with existing literature on cooking exposures, which have found elevated particulate emissions from cooking with various food and oil types (See and Balasubramanian, 2008; Wan et al., 2011; Zhang et al., 2010).

Though we did find a significant difference between the I/O ratios for cooking and non-cooking hours, it is important to note that for some apartments, the sensor did not detect a noticeable increase of indoor $PM_{2.5}$ levels during reported cooking events. This may be a result of the varied type and scale of cooking activities, distance from the cooking appliances to the sensor, or implementation of good ventilation and mitigation measurements such as opening a window or using a range hood vent during a cooking activity. Overall, the sensors were effective for measuring indoor $PM_{2.5}$ concentrations to identify potential acute exposure due to cooking. Additionally, when community residents noticed particularly high indoor concentrations, they were able to choose to implement mitigation measures known to decrease indoor $PM_{2.5}$ levels, such as the use of air purifiers, range hoods, natural ventilation or even adjusting cooking methods (Amouei Torkmahalleh et al., 2017; Kang et al., 2019; O'Leary et al., 2019; Sharma and Balasubramanian, 2020).

We also found a statistically significant difference in I/O ratios between resident-reported open window (GM: 0.9, IQR: 0.5–1.2) and closed window (GM: 0.2, IQR: 0.1–0.9) conditions (Fig. 4b). This indicates that the apartments were effectively ventilated by opening the

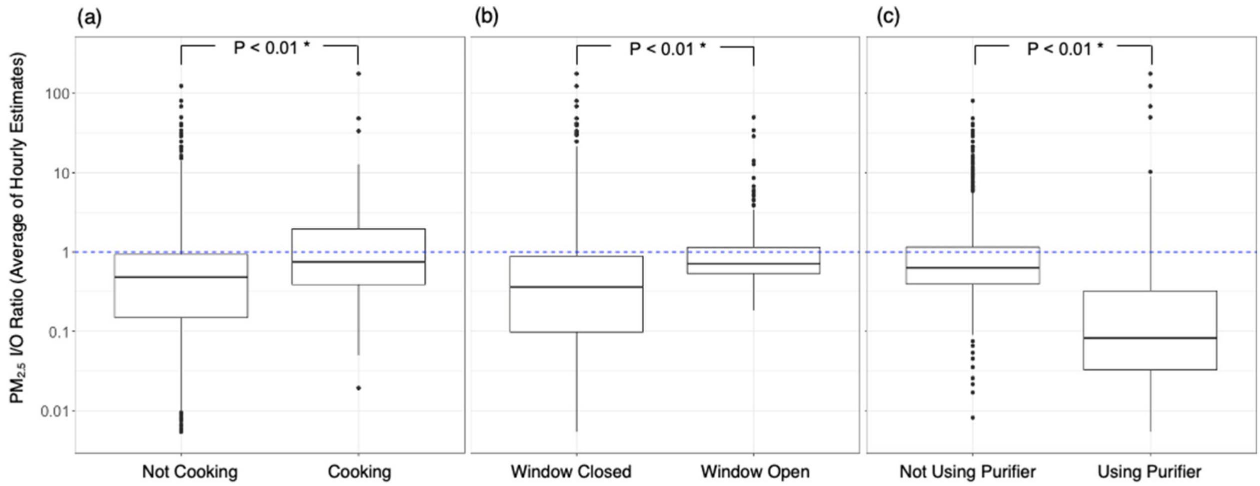


Fig. 4. Log-scale $PM_{2.5}$ I/O ratios during various indoor scenarios: (a) cooking, (b) window being open, and (c) using an air purifier. The solid horizontal line represents the median. The box represents the 25th to 75th percentiles, and the whiskers represent the outliers. The blue dashed line indicates I/O ratio = 1.
*Statistically significant difference at the $p < 0.01$ level.

window(s), as expected based on existing literature on determinants of I/O ratio values (Chen and Zhao, 2011).

The last indoor activity assessed in this study was the use of air purifiers. Residences had statistically significantly lower I/O ratios during hours when they used an air purifier (GM: 0.1, IQR: 0.0–0.3) compared to hours they did not (GM: 0.7, IQR: 0.4–1.2), indicating that using an air purifier could decrease the indoor $PM_{2.5}$ levels (Fig. 4c). This is again consistent with existing literature; studies have reported significant reductions in indoor $PM_{2.5}$ through the use of air purifiers (Batterman et al., 2012; Butz et al., 2011; H. K. Park et al., 2017; Polidori et al., 2013), as well as presented evidence of respiratory health improvements when purifiers are implemented (Butz et al., 2011; H. K. Park et al., 2017).

Furthermore, we found an accelerated reduction in indoor $PM_{2.5}$ levels when opening windows (natural ventilation) after cooking activities (Fig. A.7). $PM_{2.5}$ concentrations for both groups peaked during the cooking hour and gradually decreased to the background level; however, the GM of concentrations for the window-open group returned to background level after two hours, and the GM of concentrations for the window-closed group remained slightly higher than the background level even after 8 h. This suggests that window opening significantly accelerates the drop in indoor $PM_{2.5}$ concentrations to the background level after an indoor cooking activity, which is an effective ventilation measure to mitigate cooking derived $PM_{2.5}$. This is consistent with results from Kang et al., which evaluated the efficacy of various ventilation types in removing cooking particles and found natural ventilation to contribute to rapid particle removal (Kang et al., 2019). The anticipated effect of this natural ventilation measure on indoor $PM_{2.5}$ levels was successfully detected by the sensors.

3.3.2. Mixed-effects regression model

To further validate sensor performance before incorporating the data into the regression model, infiltration factors were estimated. The average F_{inf} is 0.57 ± 0.23, with a range of 0.11 - 0.90, which is consistent with existing literature (Hänninen et al., 2011; Shi et al., 2017).

The results of the fitted linear mixed-effects model assessing the impacts of various indoor factors and ambient air quality on indoor $PM_{2.5}$ levels are shown in Table 2. A diagnostic assessment of the fitted regression model verified assumptions of normality, linearity, and homoscedasticity (Fig. A.8). The conditional and marginal R^2 (0.86 and 0.85, respectively) of the fitted model reveal that this mixed-effects model explains 86% of the variations in the indoor $PM_{2.5}$ concentrations, with 85% of the variation explained by the fixed effects (see Fig. A.9 for a graph of the fitted versus observed values). Controlling for previous indoor $PM_{2.5}$ levels significantly improved the fit of the model (Table A.7).

Indoor $PM_{2.5}$ concentrations were positively associated with the previous hour's indoor $PM_{2.5}$ concentrations ($p < 0.001$), current ambient $PM_{2.5}$ concentrations ($p < 0.001$), indoor cooking activities ($p < 0.001$), and the interaction between opening a window and ambient $PM_{2.5}$ ($p = 0.002$). Window opening ($p = 0.001$) and the use of air purifiers ($p = 0.003$), two established household air pollution mitigation measures (Deng et al., 2015; H. K. Park et al., 2017; Sharma and Balasubramanian, 2020; Tong et al., 2020), were both significantly negatively associated with indoor $PM_{2.5}$ concentrations.

It is worth noting that the window position has two effects, as represented within the model. First, the coefficient for window opening is negative. The interpretation of this open window indicator is that the

Table 2
Linear Mixed-effects regression model results: determinants of indoor $PM_{2.5}$ concentrations.

Determinant	Symbol	Coefficient	Standard error	*p*-Value
Previous hour's concentration of indoor $PM_{2.5}$	$LnCin_{i-1,j}$	0.816	0.015	**<0.001***
Ambient $PM_{2.5}$ concentration	$LnCambient_{ij}$	0.111	0.021	**<0.001***
Cooking indicator	$Cooking_{ij}$	0.832	0.089	**<0.001***
Open window indicator	$Window_{ij}$	−0.391	0.114	**0.001***
Air purifier use indicator	$Purifier_{ij}$	−0.300	0.080	**0.003***
Temperature	T_{ij}	0.006	0.013	0.643
Relative humidity	$R.H._{ij}$	−0.008	0.005	0.154
Interaction effect of open window and ambient $PM_{2.5}$	$Window_{ij} * LnCambient_{ij}$	0.124	0.039	**0.002***

Note: conditional $R^2 = 0.86$, marginal $R^2 = 0.85$.
* Statistically significant difference at the $p < 0.05$ level.

windows being open will result in $PM_{2.5}$ from indoor generated sources (e.g., cooking) traveling outside, resulting in a lower indoor concentration (see Fig. A.7). The second effect of the window position on indoor air quality is the significant positive interaction between window opening and ambient $PM_{2.5}$; when windows are open, the effect of ambient $PM_{2.5}$ concentrations on indoor $PM_{2.5}$ concentrations significantly increases. Indoor concentrations will change more substantially along with those ambient concentrations when the window is open (see Fig. A.10, which depicts larger infiltration factors when the window is open versus closed). This demonstrates that when ambient $PM_{2.5}$ levels are elevated, closing windows can reduce indoor $PM_{2.5}$ levels, and when indoor $PM_{2.5}$ emissions occur, opening windows can effectively help dilute indoor $PM_{2.5}$ (Chen and Zhao, 2011; Kang et al., 2019), as discussed previously.

The overall impact of the window term in the regression depends on the ambient $PM_{2.5}$ for each given hour. Based on the regression coefficients presented in Table 2, when the ambient $PM_{2.5}$ is higher than ~24 μg/m^3 and the window is open, the interaction effect dominates, leading to increased indoor $PM_{2.5}$ levels. When ambient $PM_{2.5}$ is lower than ~23 μg/m^3, the window term has a larger effect than the interaction, resulting in a decrease of the indoor concentration if the window is open.

Unmeasured factors also contributed to differences in $PM_{2.5}$ levels between sites. As shown in Fig. A.11, intercepts for the $PM_{2.5}$ prediction model varied by sampling site or monitoring sensor, and the likelihood ratio test comparing models with and without the random effect term demonstrated that each sampling site or sensor was a significant random effect ($p = 0.03$), suggesting unobserved heterogeneity across residences and/or sensors deployed. Since all the low-cost sensors used in the present study were deployed in the field without laboratory evaluation, there may be undetected differences in factory calibration. Differences between sites might also be attributable to microclimatic factors, as well as other residence characteristics (e.g., unrecorded activities of residents, building structure characteristics, the number of residents living in an apartment) that varied between sampling sites.

Overall, this model performed well with the data monitored by PA-II sensors, yielding reliable and reasonable predictions of indoor $PM_{2.5}$ levels. The results of this regression analysis can increase confidence in the capacity of the indoor sensors to react to changes in indoor $PM_{2.5}$ concentrations caused by residential activities and external events. The community activity logs were an important component for improving the fit of the model, which highlights a key contribution from the community residents. This consideration is relevant for future, similar studies, or other community applications.

3.4. Implications

This is the first study to assess long-term, real-world PA-II performance and applications in a residential community setting. It is particularly innovative with respect to community participation in research, as residents were engaged in each step of sensor deployment and maintained their respective PA-II sensors independently. Therefore, we present added perspectives on strengths and challenges associated with community involvement in a low-cost sensor-deployment research study, in addition to general reporting on PA-II sensor application and performance.

The indoor sensors demonstrated substantial long-term stability in data collection, even though sensors were primarily maintained by residents instead of researchers. However, the outdoor sensors did not perform nearly as well, and we lost a significant portion of the data over the study period, with some sensors missing months of data at a time; this was the greatest challenge we faced throughout the study. The data loss was a result of several factors, but primarily inadequacy in the wireless network connection and unexpected logistical issues. Future researchers and communities developing sensor networks using PA-II devices should prepare for a multitude of challenges with the upkeep of outdoor sensors. To improve outcomes in future similar applications, research teams and community residents should either plan for a long enough study period to compensate for the loss of data or be prepared to actively maintain outdoor sensors on a regular basis to avoid the occurrence. It is important to note that a newer version of the PA-II sensor includes a data storage (Secure Digital, or SD) card, which could be used to supplement the data available on the network and reduce these concerns. However, in a project involving community members, this would present an additional challenge, considering the data would not be visible to the community in real-time if the wireless connectivity issues occur, and research teams would need to have direct contact with the community members to access the data.

Apart from data completeness concerns, the low-cost PA-II sensors performed reliably in this study setting. The outdoor measurements were temporally and spatially consistent between sensors, and the sensors were able to detect trends associated with emissions from freeway traffic. Similarly, we provide evidence that the sensors effectively monitored indoor $PM_{2.5}$ concentrations and detected the impacts of indoor activities on indoor air quality.

Our findings are generalizable to similar community settings with an installed PA-II sensor network. However, there are several limitations associated with the study design, presenting various implications. First, the study was conducted at a single university-based community with a small sample size, where the community residents have high education levels and may not represent a typical community. Second, we focus primarily on $PM_{2.5}$, so more analysis would be required to determine if our results on sensor performance are readily applicable to other particle sizes. In fact, other studies and evaluations have noted limitations associated with the PurpleAir PM_{10} measurements (H.-S. Park et al., 2020; South Coast Air Quality Management District, 2021; Wallace et al., 2021). Third, the activity logs were based on self-reporting on an hourly basis, and therefore our analyses were not able to incorporate specific timeframes within each hour that an activity occurred. Lastly, the indoor sensor analysis investigated three indoor activities and the model had limited control variables, while there are other indoor activities (e.g., burning candles and vacuuming) and other factors (e.g., room volume, ventilation system, and distance between the sensor and cooking appliances) influencing indoor $PM_{2.5}$ concentrations as well.

Given the inexpensive cost of the sensors and our findings on sensor performance and applications, we find that the PA-II sensor provides a cost-effective way to monitor real-time indoor and outdoor air quality in residential settings with active community participation. Despite certain challenges, sensor networks such as the one used in this study can successfully facilitate the development of accurate, high-resolution indoor and outdoor $PM_{2.5}$ data, which can be used by researchers, community members, and other stakeholders alike.

CRediT authorship contribution statement

Rachel E. Connolly: Conceptualization, Writing – original draft, Writing – review & editing. **Qiao Yu:** Software, Formal analysis, Visualization. **Zemin Wang:** Methodology, Writing – original draft. **Yu-Han Chen:** Methodology, Writing – original draft. **Jonathan Z. Liu:** Formal analysis, Data curation. **Ashley Collier-Oxandale:** Project administration, Funding acquisition, Writing – review & editing. **Vasileios Papapostolou:** Project administration, Funding acquisition, Writing – review & editing. **Andrea Polidori:** Project administration, Funding acquisition, Writing – review & editing. **Yifang Zhu:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Acknowledgement

This work was supported by the U.S. EPA STAR Grant program administrated through the South Coast AQMD (Contract No. 172033, Grant No. R836184).

Supplementary Information

Additional information about the study site, data processing and completeness, summary statistics, and the statistical analysis (Appendix A), as well as a supplemental analysis comparing PA-II $PM_{2.5}$ concentrations with EPA FEM $PM_{2.5}$ (Appendix B). Supplementary data to this article can be found online at doi:https://doi.org/10.1016/j.scitotenv.2021.150797

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