Indoor Household Particulate Matter Measurements Using a Network of Low-cost Sensors

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ABSTRACT

The World Health Organization estimates that 4.3 million deaths globally in 2012 were attributable to household air pollution, of which particulate matter (PM) with a diameter of 2.5 µm or less ($PM_{2.5}$) is a significant contributor. When integrated with a wireless network, low-cost PM measurements potentially provide personalized information on indoor concentrations in real time so that individuals can take action. The objectives of this study were to (1) deploy a network of research-grade instruments and low-cost sensors in a home environment and evaluate the performance, (2) characterize activities and conditions that increase PM concentrations, and (3) identify how these activities affect the PM levels in different rooms of a home. The wireless sensor network included low-cost PM sensors, a gateway, and a database for storing data. Based on the commercially available Dylos DC1100 Pro (Utah Modified Dylos Sensor) and Plantower PMS sensor (AirU), the low-cost sensors were compared to three research-grade instruments—the GRIMM, DustTrak, and MiniVol—in two households in Salt Lake City during summer and winter, with the results suggesting that the low-cost sensors agreed well with the DustTrak. Of the activities, frying food and spraying aerosol products generated the largest increase in PM, both in the room of the activity (the kitchen and bedroom, respectively) and the adjacent rooms. High outdoor PM concentrations during a cold air pool episode also caused indoor levels to rise. In addition, different PM sources triggered different sensor responses. Consequently, obtaining accurate estimates of the mass concentration in an indoor environment, with its wide variety of PM sources, is challenging. However, low-cost PM sensors can be incorporated into an indoor air-quality measurement network to help individuals manage their personal exposure.

Keywords: Indoor air; Particulate matter; Sensor network; Low-cost particulate matter sensor; Cold air pool.

INTRODUCTION

The World Health Organization (WHO) estimates that 4.3 million people die annually from household air pollutant exposure (World Health Organization, 2014), and particulate matter (PM) is one key driver of air pollution's adverse health effects. Particles with an aerodynamic diameter of 2.5 µm or smaller ($PM_{2.5}$) are a particular concern because these particles can penetrate deeply into the lungs and can cause serious health effects, including cardiac arrhythmia, coronary heart disease and premature death (Sorensen *et al.*, 2003; Brook *et al.*, 2010; Anderson *et al.*, 2012). Consequently, the WHO and government organizations have set ambient air quality standards for $PM_{2.5}$. For example, the U.S. National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$ are 35 µg m^{-3} (24 hour) and 12 µg m^{-3} (annual average) (U.S. Environmental Protection Agency, 2014). The WHO $PM_{2.5}$ standards are 25 µg m^{-3} (24-hour mean) and 10 µg m^{-3} (annual average) (World Health Organization, 2006). Indoor levels of PM are significant contributors to an individual's exposure because people typically spend up to 90% of their time indoors (Spengler and Sexton, 1983; Zhang and Smith, 2003; Zhu *et al.*, 2015), and PM concentrations indoors can surpass outdoor levels (Klepeis *et al.*, 2001). In addition, individuals with chronic health conditions often spend a greater portion of their time indoors and are more vulnerable to the adverse impacts of indoor PM exposure. Sources of indoor PM include aerosol sprays, cooking, burning candles or heating/cooking with solid fuel, inadequately tuned gas stoves and furnaces, pets, dust mites, cleaning and tobacco smoking. In addition, indoor air is also affected by infiltration of outdoor air (Goyal and Kumar, 2013). Indoor

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PM concentrations can be affected by infiltration of outdoor air. Depending on the outdoor PM levels, this infiltration can result in increasing or decreasing indoor PM levels (Morawska *et al.*, 2001; Kumar and Morawska, 2013).

Numerous studies have measured PM concentration indoors by pulling air through a size-selective inlet and collecting PM on a substrate/filter that is subsequently weighed (Braniš *et al.*, 2005; Fromme *et al.*, 2007; Hering *et al.*, 2007; Fromme *et al.*, 2008; Braniš *et al.*, 2009) or have used passive samplers that rely on particle settling onto a substrate that is subsequently weighed (Amaral *et al.*, 2015; Bo *et al.*, 2017). However, these methods suffer from limitations. First, the substrate/filter measurements are integrated over time (from several hours to several days) and do not capture temporal variations in particle concentration. Second, they are time-consuming to collect and analyze, and results may not be available for several days after sampling is complete (Amaral *et al.*, 2015; Kumar *et al.*, 2016). Third, many of these samplers require a pump, and are bulky and noisy for indoor use. For passive samples that require long sampling times, there is a risk of loss of sampled material (Kumar *et al.*, 2016). Research-grade instruments based on optical detection methods have also been used to measure indoor PM levels (Amaral *et al.*, 2015). They can provide accurate, time-resolved, rapid PM measurements, but the cost for these ranges from $5,000 to $20,000, making them too expensive to deploy many instruments in multiple indoor environments or for use in population-based studies.

Commercially available low-cost PM sensors are becoming more widely available, and with their rapid response they offer the potential for gathering large quantities of high-resolution spatio-temporal air-quality information in indoor and outdoor environments (Kumar *et al.*, 2016). They typically use light scattering to estimate PM concentrations, and light scattering is a common measurement strategy for research-grade PM monitors. The cheapest PM sensors cost less than $20. Examples include the Shinyei PPD42NS Dust Sensor (Shinyei Corp.), Sharp GP2Y1010 (Sharp Corp.), Plantower PMS series (Plantower Technology), and Honeywell HPM series particle sensor (Honeywell Inc.). These sensors require an interface with an external microprocessor and either a display or a way to transmit data to the user. Adding these features can significantly increase the price, above $100 (e.g., Alphasense OPC from Alphasense). However, once integrated with a microcontroller, these types of sensors are well suited for deployment in a sensor network. Slightly more expensive sensors, costing between $200 and $500, push their data to the cloud for viewing through a user interface (e.g., Air Quality Egg from Wicked Device, LLC) or an on-screen display (e.g., Dylos monitors from Dylos Corporation or Speck from CREATE Lab, Carnegie Mellon University) (Jovašević-Stojanović *et al.*, 2015). These more expensive sensors may require modifications to allow integration with a sensor network.

However, low-cost PM sensors have their drawbacks. They are not as accurate as gravimetric sampling methods (Dacunto *et al.*, 2013) or reference PM instruments (Manikonda *et al.*, 2016). These sensors can also be affected by humidity (Wang *et al.*, 2015), temperature (Gao *et al.*, 2015) and the same set of sensors can perform inconsistently (Gao *et al.*, 2015; Zikova *et al.*, 2017). In addition, most sensors lack guidance on deployment and calibration data under different conditions. Furthermore, light-scattering PM measurements require regular calibration and an appropriate correction factor (CF) for the aerosol types (Dacunto *et al.*, 2015) and environmental conditions under which the sensors are operating (Kelly *et al.*, 2017; Sayahi *et al.*, 2019). Low-cost PM sensors may be more sensitive to particle properties than research-grade monitors (Kelly *et al.*, 2017). Also, laboratory performance observed by these sensors are often not reproducible under field conditions, where they exhibit lower correlations with reference instrumentation (Castell *et al.*, 2017). In spite of these limitations, the sensors can provide valuable information on relative levels of PM, aid in estimating personal exposure and help identify strategies for reducing these exposure levels. For example, real-time monitoring can aid health researchers in determining which measures, e.g., maximum 10-minute concentration, are most relevant to health outcomes. They are also valuable for development of intervention measures and for meaningful public health metrics, which are accessible to the general public.

Several studies have evaluated the performance of low-cost optical PM sensors in laboratory settings and found moderate to strong correlations with reference instruments, which include Dylos vs. TSI DustTrak ($R^2 > 0.81$; Northcross *et al.*, 2013), Dylos vs. GRIMM ($R^2 > 0.86$; Vercellino *et al.*, 2018), and Shinyei PPD42NS vs. TSI Aerodynamic Particle Sizer Spectrometer ($R^2 > 0.66$; Austin *et al.*, 2015). Wang *et al.* (2015) used the TSI SidePak AM510 and a TSI Scanning Mobility Particle Sizer to evaluate sensor performance and found $R^2 > 0.78$ for the Shinyei PPD42NS, Samyoung DSM501A, and Sharp GP2Y1010AU0F. Manikonda *et al.* (2016) evaluated the performance of four low-cost PM monitors (Speck, Dylos, TSI AirAssure, and UB AirSense) against co-located reference instruments (Grimm 1.109, TSI APS 3321 and TSI Fast Mobility Particle Sizer 3091) in a laboratory chamber and found $R^2 > 0.85$ between the four monitors and APS 3321.

Outdoor studies have also found moderate to strong correlations. For example, Holstius *et al.* (2014) compared Shinyei performance with a Federal Equivalent Method (FEM) beta-attenuation monitor (BAM) 1020, a Grimm 1.108 and a DustTrak ($R^2 > 0.6$). Gao *et al.* (2015) studied a network of Shinyei PPD42NS sensors in an urban environment and found strong correlations ($R^2 > 0.87$) between the DustTrak and Met One BAM but only a moderate correlation with mass-based measurements ($R^2 > 0.5$).

A few studies have deployed low-cost PM sensors in indoor environments, some to evaluate performance and others to understand events that affect indoor air quality. Zikova *et al.* (2017) evaluated sixty-six Speck monitors collocated with a Grimm 1.109. They found a poor correlation during indoor measurements ($R^2 = 0.2$–0.3), but when the measurements were divided into combustion and non-combustion particles, the R^2 rose to 0.5. Patel *et al.* (2017) deployed a network of five Sharp GP2Y1010AU0F sensors in two different homes to measure PM levels from solid-fuel cookstoves. They found reasonably good correlation ($R^2 = 0.713$) between the

Sharp sensors collocated with a TSI SidePak AM150. Weekly *et al.* (2013) designed a wireless PM sensor network consisting of five Samyoung DSM501A, three Shinyei PPD20V sensors and Met One GT-526S laser particle counter to infer resuspension of coarse ($\geq$ 2.5 µm) particles caused by movement of occupants. Li *et al.* (2017) used a wireless network of low-cost sensors (Sharp GP2Y1010AU0F) in a woodworking shop to develop an estimate of worker PM exposure. Jeon *et al.* (2018) proposed an IoT-based occupancy detection system in indoor environments using a low-cost PM sensor, SEN0177.

The objective of this study was to deploy a wireless PM sensor network in two home environments, evaluate sensor performance, characterize activities (i.e., cooking, spraying aerosol products, burning a candle and cleaning) that affect indoor air quality by household room, identify conditions that affect PM concentrations, and identify how these activities affect different rooms in a home.

MATERIAL AND METHODS

Study Locations and Measurements

This study was performed in two homes in two different seasons, summer and winter (Fig. S1). The residents of these two homes volunteered to host the sensors, and they kept a logbook where they manually recorded activities that could generate PM (i.e., cooking, candle burning, etc.). All sensors were placed on a table approximately 0.75–0.80 m above ground and at least 0.3 m away from the wall. The first study was conducted between 19th May to 19th July 2016 in a two-story home with a finished basement in Cottonwood Heights, Utah (Home I). A finished basement has been outfitted in a manner making it suitable as a living space. In this study, the occupants were using the finished basement as a living area. The following analyses focus on one calibration week (20th–25th May) (Table S1) and one week of deployment when events are annotated, from 1st to 7th June. This home built in 2002 was located in a suburban, residential area, near the I-215 interstate (364 m away) in Utah's Wasatch Front (with a population of 2.21 million; U.S. Department of Commerce, 2010). The home was 3300 sq. ft. with 1650 sq. ft. in the basement and 1650 sq. ft. on the first floor. This home was located 16 km from the nearest state air-quality monitoring station (Hawthorne). Although some sensors were placed in the basement, there were no annotated events, and the basement was not used for this study. The study in Home II (built in 1942) occurred from 16th January to 16th February 2017 in a two-story house in an urban, residential neighborhood of Salt Lake City, Utah, with a calibration study from 15th–21st October 2016 (Table S1). The home was 1500 sq. ft. with a finished basement. The calibration in Home II was conducted in the basement, and the basement was not used for the later part of the study. This home was located 8 km from the nearest state air-quality monitoring station (Rose Park).

At each of the homes, a 1-week calibration experiment was performed to assess sensor precision and accuracy by collocating the low-cost sensors with four research-grade PM instruments (two GRIMM 1.109s from GRIMM Aerosol Technik, GmbH; one DustTrak II aerosol monitor from TSI

Inc.; and one filter-based measurement, Airmetrics MiniVol) (Table 1). In Home I, ten Utah Modified Dylos DC1100 Pro sensors (UMDSs) were placed alongside four custom AirU sensors for comparison, and in Home II, four UMDSs were deployed. The state of the doors in each home can affect PM levels and the time required for PM levels to change. During the calibration period, doors were closed, but during the remainder of the study the occupants behaved normally, with no control on the state of the door. After the calibration week, sensors were distributed throughout the home and placed outside the home (locations shown in Fig. S1). The modifications to the Dylos and the AirU sensors are described below.

The GRIMM 1.109 continuously measures particle count and mass distribution by light scattering over the size range of 0.25–32 µm in 31 class sizes. The signal from the scattered light is then classified by size and count, and these counts are converted to mass concentrations (Peters *et al.*, 2006). During this study, only the GRIMM's $PM_{2.5}$ concentrations were used. The DustTrak II Aerosol Monitor 8530 (TSI) is a light-scattering laser photometer, which measures mass concentration (PM_1, $PM_{2.5}$ or PM_{10}) with a size-selective inlet (Alvarado *et al.*, 2015). During this study, the DustTrak II operated with the $PM_{2.5}$ inlet. The Airmetrics MiniVol is a portable air sampler that was equipped with a size-selective $PM_{2.5}$ inlet and a 47mm Whatman filter (pore size 0.2 µm). These filters were replaced every week during indoor testing, and the difference in weight along with the flow rate provided an integrated mass concentration and allowed for mass adjustment of the GRIMM and DustTrak concentrations.

Sensor and Network Description

The AirU, developed at the University of Utah, consists of a small custom printed circuit board with a Plantower PMS3003 particle sensor, Bosch BMP180 (temperature, pressure and altitude), an SGX SensorTech MiCS-4514 (CO and NO_2), an Aosong Electronics DHT22 (temperature and humidity) and an Adafruit Ultimate GPS chip all interfaced with a custom printed circuit board and a Beaglebone Black (BBB). The component costs of the AirU are approximately $175. The Plantower PMS sensor reports PM_1, $PM_{2.5}$ and PM_{10} concentrations (µg m^{-3}) every 60 seconds. This study focused on the AirU's $PM_{2.5}$ measurements. The AirU can store up to 500 MB of data to an onboard microSD card or it can send readings directly through our gateway to a database (discussed below). This Plantower PMS sensor is described in detail in Kelly *et al.* (2017), and its $PM_{2.5}$ concentration correlated well with Federal Reference Method (FRM) $PM_{2.5}$ concentrations during several winter clean air and cold air pools (CAPs; $R^2 > 0.88$) and with research-grade instruments exposed to alumina oxide particles in a wind tunnel ($R^2 > 0.83$). The Plantower PMS sensors were also evaluated by the South Coast Air Quality Management District (SCAQMD) and correlated well with an FEM ($R^2 > 0.93$).

Each UMDS includes a Dylos DC1100 Pro Air Quality Monitor (Dylos Inc., Riverside, California, USA). The UMDS detects PM concentrations in two size ranges: small (2.5 µm and less) and large (10 µm and greater) particles. This study estimated $PM_{2.5}$ counts as the UMDS small count

Table 1. Summary of the PM measurement instruments used in the study.

	GRIMM 1.109	TSI DustTrak II	AirU	UMDS	AirMetrics MiniVol
Type	Research, light-scattering	Research, light-scattering	Low-cost, light-scattering	Low-cost (commercial), light-scattering	Research, filter based collection
Dimensions (cm)	24 × 12 × 6	13.5 × 21.6 × 22.4	8.4 × 4.9 × 2.5	18 × 12 × 8	30 × 26 × 18
PM sensor/laser wavelength (nm)	655	780	PMS3003/laser[a] 650 ± 10	650	NA
Measurement	PM_1, $PM_{2.5}$ and PM_{10}, particle size distribution from 0.25 to 0.32 µm	$PM_{2.5}$ (PM_1 or PM_{10} options)	PM_1, $PM_{2.5}$ and PM_{10}, temperature, humidity	PM count-small and large, temperature, humidity	$PM_{2.5}$ mass concentration integrated over a week
Sampling interval	1 minute	1 minute	1 minute	1 minute	1 week
How many used?	2	1	4 in Home I	10 in Home I 4 in Home II	1
Power (W)	13.5	60	2	NA	NA
Cost[b] (\$)	12,000	5,000	200	366	3,650
Limit of detection (µg m^{-3})	0.1[c]	1	2.62–11.5[d]	1[e]	NA

[a] Measured by Kelly *et al.* (2017).
[b] Parts only, excludes labor.
[c] GRIMM (2010).
[d] Ambient conditions (Sayahi *et al.*, 2019).
[e] Laboratory condition (Northcross *et al.*, 2013).

minus the large count. The Dylos sensor was modified to allow networking capabilities. This modification included adding a BBB microprocessor unit with a Wi-Fi module, a compact USB Wi-Fi Adapter with 4″ Antenna (UWN200), an SHT21 relative humidity and temperature sensor and an RGB LCD display. The BBB collects all sensor data, displays information (temperature, humidity, small and large particle count) to the RGB LCD display, and transmits data to the cloud server via our gateway. Data from the sensors are also stored on a microSD card so that no data is lost if power is lost to the sensor.

Our in-home sensor network architecture consists of three components—the sensors, a gateway, and database. The data from all low-cost sensors were collected using a gateway, which can support various wireless protocols like BLE (Bluetooth Low Energy), Wi-Fi, and ZWave. The gateway runs on a Raspberry Pi 3 and is connected through Ethernet to a home's wireless router. A custom component was written that automatically discovers and pulls data from the UMDS and AirU sensors. CoAP (Constraint Application Protocol) was used as the communication protocol between the sensors and gateway. CoAP is a UDP (User Datagram Protocol)-based protocol with similar semantics to HTTP. In our architecture, the AirU and UMDS sensors act as CoAP servers, and the gateway acts as a CoAP client. Periodically, the gateway will send a discovery message (a GET request to CoAP's specified multicast address) looking for new sensors. When a sensor receives this message, it responds back with information about itself, such as its type (AirU or UMDS) and ID. Once a sensor has been discovered, the gateway periodically pulls data from it. After the gateway receives data from a sensor, it tags the data with a unique ID for that gateway, and it uploads data to a central database. The gateway is the central hub of communication for our architecture. The gateway and sensors are co-located in the home, and the database (InfluxDB) is in the cloud.

Data Analysis

The data analysis focused on the following four components: calibration measurements, the distributed deployment, detection limits, and air exchange rates (AERs). The calibration measurements included evaluations of the time-series $PM_{2.5}$ concentrations/counts and linear-regression modeling for each AirU and UMDS versus the mass-adjusted DustTrak $PM_{2.5}$ concentrations (described below) for different types of aerosols. This enabled each sensor to be bias corrected. In addition, the GRIMM $PM_{2.5}$ concentrations were included in the time-series evaluations, and the average of all AirUs and the average of all UMDSs were fit with a linear model versus the mass-adjusted GRIMM $PM_{2.5}$ mass concentrations. During the calibration period in Home I, one of the GRIMMs lost data for 1 day, and the other GRIMM registered an unknown peak not identified by the other two research-grade instruments or any of the fourteen low-cost sensors. Consequently, the majority of this evaluation focused on the low-cost sensors and the DustTrak $PM_{2.5}$ measurements.

The raw mass concentrations from the GRIMM and DustTrak were multiplied by a mass-adjustment factor (MAF) to provide the mass-adjusted DustTrak or GRIMM

measurements:

$$MAF = \frac{MV\_PM_{2.5,avg}}{LS\_PM_{2.5,avg}} \qquad (1)$$

where MAF = mass adjustment factor (unitless), $MV\_PM_{2.5,avg}$ = MiniVol mass concentration during the calibration period ($\mu g\ m^{-3}$), and $LS\_PM_{2.5,avg}$ = light-scattering instrument's (DustTrak or GRIMM) average concentration during the calibration period ($\mu g\ m^{-3}$).

The MiniVol flow rate was confirmed using a Bios Defender 520 AirFlow Calibrator. The filters from the MiniVol were conditioned for 24 hours at 20°C and 20–30% relative humidity before and after sampling, and all samples were weighed in triplicate using a Mettler AE160 balance.

During the distributed study, each individual AirU and Dylos $PM_{2.5}$ concentration/count was bias corrected, as described in the previous paragraph, and then an aerosol-specific CF was applied to obtain the best estimate of actual $PM_{2.5}$ mass concentration. Only the DustTrak was used to develop the CFs, and CFs were generated for PM from candle burning, cooking, CAPs (outdoors with the UMDS) and general/unidentified PM events (Table S4). The CFs for candle burning and cooking were developed by collocating the DustTrak and MiniVol next to the PM generation source. The filter collection and weighing procedure are described in the previous paragraph. The candle burning was performed in a 0.3 m high, 0.3 m diameter cylindrical chamber and included burning/extinguishing six unscented tealight candles during a 4-hour period. For cooking, the DustTrak and MiniVol were collocated next to an outdoor gas grill, where vegetables and meat were grilled for 2 hours. The CF for the AirU and UMDS for candle burning and cooking were obtained by multiplying the AirU or UMDS by its corresponding MAF (bias correction) and then by the DustTrak/MiniVol (aerosol-specific CF). It was not possible to obtain filter measurements and CFs for Febreze™ and hairspray due to the volatile nature of Febreze™ and stickiness of the hairspray. Consequently, the CF for each individual AirU or UMDS obtained from the entire calibration week was used for the Febreze™, hairspray and other unidentified activities. In addition, two of the UMDSs were collocated with the Utah Division of Air Quality's Thermo Scientific 1405-F Tapered Element Oscillating Microbalance (TEOM) during an 8-day period at the Hawthorne monitoring site to develop a factor for converting the UMDS small minus large particle count to $PM_{2.5}$ mass concentration during CAPs (factor in Table S4). During this outdoor CAP calibration period, the $PM_{2.5}$ levels ranged from 0 to 59.5 $\mu g\ m^{-3}$ with a mean of 26.8 $\mu g\ m^{-3}$.

Limited data is available regarding the limit of detection (LOD) for the PMS and Dylos sensors. Sayahi *et al.* (2019) reported that the PMS sensors had a LOD ranging from 2.62 to 11.5 $\mu g\ m^{-3}$ (field evaluation), and Northcross *et al.* (2013) reported that the Dylos had a LOD of 1 $\mu g\ m^{-3}$ (laboratory evaluation). An estimated LOD of 5 $\mu g\ m^{-3}$ for the PMS sensor was selected from the reported range. The fraction of AirU measurements below 5 $\mu g\ m^{-3}$ and UMDS measurements below 1 $\mu g\ m^{-3}$ were considered in the discussion of the

measurements. The effect of measurements below the estimated LODs on the fit coefficients from the linear regression were also considered. However, none of the data (whether below the reported LODs or not) were excluded from the evaluation.

The AERs were estimated for the different rooms in each home (Table S6) based on four PM spikes, using the method described by Burgess *et al.* (2004) and the time required for the $PM_{2.5}$ concentration to decline by 90% from its peak value after the PM generation ceased:

$$AER = -\ln\left(\frac{C_{max}}{C_{min}}\right) \times \frac{1}{t} \qquad (2)$$

where C_{max} and C_{min} = maximum and minimum $PM_{2.5}$ concentration ($\mu g\ m^{-3}$) and $C_{max}/C_{min} = 10$, t = time (h) required to reduce the concentration from C_{max} to C_{min}, and AER = number of air changes per hour (h^{-1}) and is a function of ventilation rate that has been normalized by the room volume.

The estimated AERs assume that the air is well mixed and that the concentration of $PM_{2.5}$ in the incoming air is small compared to C_{max} and C_{min}. It is important to note that the AER measurements during this study are representative of the AER at the time of the annotated activity and that at other times of the day, AER can vary significantly from the ones calculated.

RESULTS AND DISCUSSION

Calibration of Sensors
Fig. 1 shows how PM concentrations from the low-cost and research-grade sensors respond to a variety of household events during calibration week in Home I (Table S1) although some activities that increased PM levels were not annotated. $PM_{2.5}$ concentrations increased rapidly when cooking and heating oil in the kitchen, which is close to the bedroom (Fig. S1), when spraying Febreze™ and using the humidifier in the bedroom (Table S1). Cooking activity in the kitchen (Table S1) caused smaller spikes in PM levels in the bedroom compared to candle burning activities, which occurred in the bedroom.

Fig. 2 compares the responses of the average of four AirUs and ten UMDSs with the DustTrak to a variety of household activities during the 6-day calibration period in Home I (Table S1). The different activities from the calibration period resulted in a scatter plot with distinct strips, and these strips corresponded to $PM_{2.5}$ from different sources. Light-scattering-based measurements depend on aerosol optical properties (size, density and refractive index) (Jiang, 2010; TSI Inc., 2012), and for accurate mass concentration estimates from different aerosols, appropriate CFs are required (Jiang *et al.*, 2011). Several researchers have found different CFs for different sources. For example, Jiang *et al.* (2011) found CFs for secondhand smoke (SHS), incense and toast that differed by more than a factor of 2 (TSI SidePak). Dacunto *et al.* (2013) estimated CFs for common indoor PM sources including cigarettes, candles, cooking and incense using a TSI SidePak. These also varied

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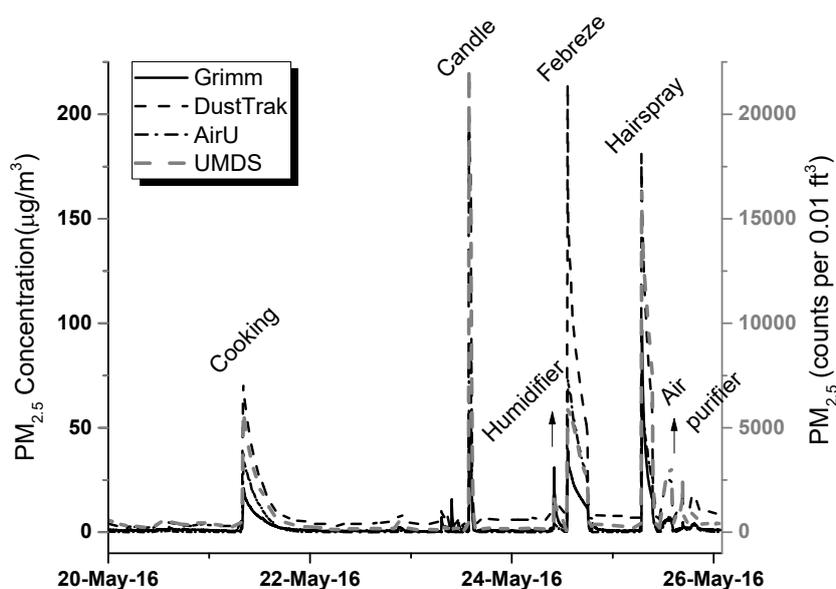
Fig. 1. Comparison of co-located 5-minute rolling average of PM$_{2.5}$ concentrations (µg m^{-3}) measured by a Grimm, DustTrak, average of 4 AirUs and average of 10 UMDSs (PM$_{2.5}$ count, small minus large bins, per 0.01 ft^3) for the calibration period of 20th–25th May 2016 (Home I). The concentrations measured by all sensors were uncorrected raw data.
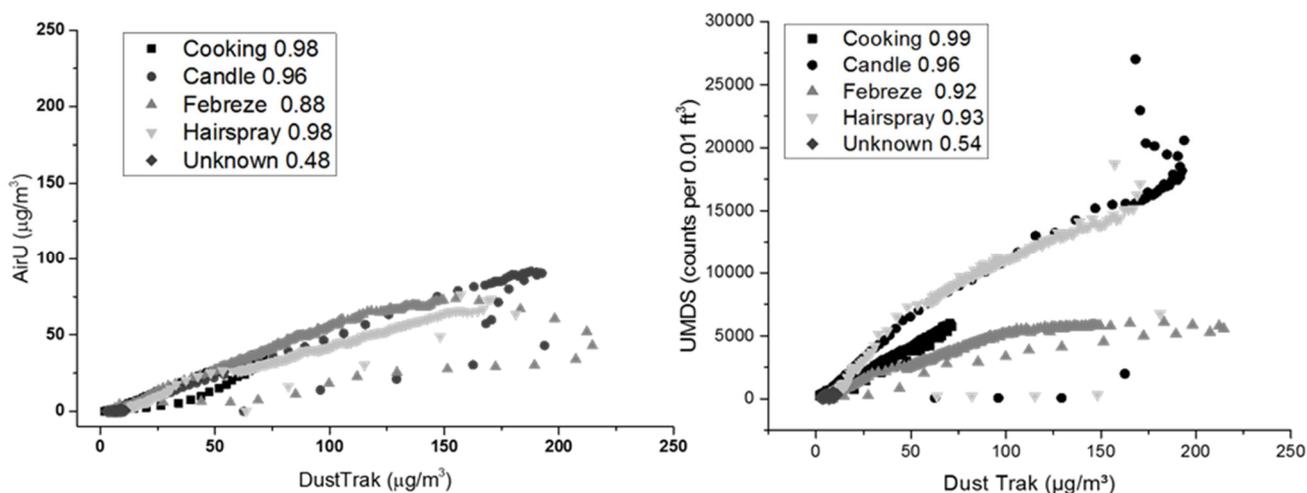
Fig. 2. Scatter plots and coefficients of determination (R^2) of the linear model (low-cost sensor and DustTrak) for 5-minute rolling average of PM$_{2.5}$ concentrations (µg m^{-3}) for several types of aerosols measured with a DustTrak (uncorrected), average of 4 AirUs (uncorrected) and average of 10 UMDSs, uncorrected (PM$_{2.5}$ count, small minus large bins, per 0.01 ft^3) during 20th–25th May 2016 (Home I).

by a factor of 2 depending on the source. The CFs in this study for cooking and candle burning differ by more than a factor of 2.5 (Table S4(c)). The slopes of the linear regression for different activities (aerosols) can be found in Table S2. Fig. S2 compares the response of the AirU and the UMDS with the GRIMM. Note that one GRIMM detected a PM event (not annotated) not detected by the two reference instruments or any of the fourteen low-cost sensors. Consequently, the comparisons with the GRIMM are presented only in the supplementary material.

Aerosol optical properties depend on their composition and size, and common indoor aerosols exhibit a variety of optical properties. For example, the main ingredient in Febreze™ is

a water-alcohol mixture, with a refractive index (RI) of 1.33 (water)–1.36 (ethanol) (Andher *et al.*, 2015). Hair-care products, like hairspray, contain mixtures of polymers in a glycol-water solvent, and glycol-water mixtures (10–80% ethylene glycol) have a RI in the range of 1.39–1.42 (Sun *et al.*, 2005). Cooking emissions from oils contain particles with RI of 1.46–1.47 (Lide, 2005). Candle burning results in fine carbon particles with a diverse range of RI (1.75–1.95) and adsorbed hydrocarbons (Poudel *et al.*, 2017).

The four AirUs correlated well with each other (R^2 = 0.907–0.985), as did the ten UMDSs (R^2 = 0.952–0.997) (Figs. S3 and S4). However, for these intra-sensor comparisons, the slopes of the linear regressions were not always equal to

1. For example, comparing the AirU sensors showed that slopes of the linear regressions for two of the sensors agreed within 5%, for three sensors agreed within 10% and for all of the sensors agreed within 25%. All of the slopes of the linear regressions for the UMDS sensors in Home I agreed within 40%, while the slopes for five of the sensors agreed within 10%. Intra-sensor variability has been previously reported for both the PMS and the Dylos sensors (Collingwood et al., 2019; Sayahi et al., 2019).

The correlations between the UMDS and the DustTrak are in the range reported in laboratory (R^2 = 0.81; Northcross et al., 2013) and in ambient studies (R^2 = 0.78; Holstius et al., 2014). In addition, Semple et al. (2013) (Dylos vs. TSI SidePak AM510: R^2 = 0.86) and Klepeis et al. (2013) (Dylos vs. DustTrak: $R^2 > 0.98$) determined the relationship between $PM_{2.5}$ mass concentration and Dylos response for SHS from tobacco. Although these studies did not investigate how the Dylos responded to other common indoor PM sources, they found that the Dylos sensors responded adequately to changes in PM levels caused by SHS. In a laboratory evaluation of the Dylos, the SCAQMD observed that the Dylos showed good correlation ($R^2 > 0.89$) with reference monitors, but it overestimated the $PM_{2.5}$ concentrations as measured by the GRIMM (SCAQMD, 2017). Han et al. (2016) made a similar observation. Kelly et al. (2017) evaluated the Plantower PMS sensor (used in the AirU) during a winter period with several CAPs and found an $R^2 > 0.88$ with Federal Reference Methods, but the PMS sensors overestimated $PM_{2.5}$ concentrations when $PM_{2.5}$ levels exceed 10 μg m^{-3} (Kelly et al., 2017). As Fig. 1 illustrates, both the AirU and the UMDS track indoor activities that caused significant changes in PM levels. The calibration results for Home II can be found in the supplemental data (Figs. S5–S8 and Table S3). The correlations between the UMDS and the GRIMM (Fig. S2) are in the same range as those reported in different settings: ambient (Williams et al., 2014: R^2 = 0.533; Han et al., 2016: R^2 = 0.778; Holstius et al., 2014: R^2 = 0.99) and indoor (Taylor et al., 2016: R^2 = 0.74).

Effect of Household Activities on Indoor $PM_{2.5}$ Levels

During the distributed deployment, the sensors in different rooms (Fig. S1) responded to typical activities that occurred in the room where the sensor was located as well as activities that occurred in adjoining rooms. The home occupants periodically noted activities by manually recording the events. Tables 2 and 3 summarize the average and maximum concentration (obtained by applying the average CF from calibration week) during this part of the study for Home I and II, respectively. On average, the $PM_{2.5}$ levels in Home I (summer) were well below the EPA and WHO 24-hour and annual standards. Home II $PM_{2.5}$ levels were much closer to the EPA and WHO annual standards. The differences between homes may be due to seasonal differences in outdoor PM levels or differences in the homes and the associated HVAC systems. Specifically, Home I was built in 2002 and Home II in 1942. Apart from the high PM levels caused by fireworks (4th of July), the winter CAP events caused higher average outdoor levels than those observed in summer.

The average $PM_{2.5}$ concentrations in Home I (Table 2) are below the AirU's LOD of 5 μg m^{-3} (field evaluation; Sayahi et al., 2019) and are close to the UMDS's LOD of 1 μg m^{-3} (laboratory evaluation; Northcross et al., 2013). During the calibration week, less than 15% of the AirU measurements were below the LOD of 5 μg m^{-3}, whereas, less than 6% of

Table 2. $PM_{2.5}$ concentrations during the summer sampling period (1st–10th June 2016) in Home I.[a]

Room	Sensors	Average (μg m^{-3})	Maximum (μg m^{-3})	S.D.[b] (μg m^{-3})	% of data below LOD
Outside	AirU 3	5.70	33.0	2.31	11.6
	UMDS 110	3.10	54.4	12.8	13.8
Living Room	AirU 8	1.82	18.0	1.98	57.6
	UMDS 115	4.15	90.8	6.89	0
Kitchen	AirU 2	2.57	89.0	4.54	53.1
	UMDS 124	3.45	113	7.12	0
Bedroom	AirU 6	5.62	642.0	27.84	58.9
	UMDS 13	6.71	233.0	17.89	10.3

[a] $PM_{2.5}$ concentrations corrected using an individual bias correction for each sensor based on the calibration week.
[b] S.D.: Standard deviation.

Table 3. $PM_{2.5}$ concentrations during the winter sampling period (31st January–9th February 2017) in Home II.[a]

Room	Sensors	Average (μg m^{-3})	Maximum (μg m^{-3})	S.D.[c] (μg m^{-3})	% of data below LOD
Outside	UMDS 124	12.0	44.5	14.3	0
Living Room [b]	UMDS 116	22.0	345	32.8	0
Front Door	UMDS 121	20.4	258	26.0	0
Bathroom	UMDS 114	17.8	471	24.8	0
Bedroom	UMDS 117	20.0	227	21.2	0

[a] $PM_{2.5}$ concentrations corrected using an individual bias correction for each sensor based on the calibration week.
[b] The living room in Home II represents a combined kitchen/living area. The cooking events occurred in the kitchen which is very close to the living area.
[c] S.D.: Standard deviation.

the UMDS measurements were below the LOD of 1 μg m^{-3} in Home I. In Home II, less than 1% of the UMDS measurements were below the LOD. Removing measurements below the estimated LOD resulted in a 6% maximum change in slope of the AirU vs. DustTrak. Tables 2 and 3 show the percent of measurements below the reported LODs in each room in Home I and II, respectively. Although the AirUs and the UMDSs have similar laser wavelengths, differences in their internal configurations and flow patterns may also lead to differences in sensitivities related to particle size. Particles entering the PMS sensor (AirU) must make three 90° turns before reaching the laser, and larger particles do not reach the photodetector as efficiently as smaller particles (Kelly *et al.*, 2017). In the UMDS, particles make one long, sweeping turn before they can reach the laser/photodetector. Kelly *et al.* (2017) also found that the PMS sensors tend to overestimate PM mass concentration for small particles and underestimate it for large particles. Consequently, the average and maximum concentrations exhibit somewhat unexpected trends. For example, in Home I (Table 2), the UMDS maximum concentration outside is 40% more than AirU, while in the living room, the UMDS maximum concentration is 80% more than the AirU concentration.

The room-to-room comparison showed good correlations in Home II, with $R^2 > 0.72$ between all the UMDSs, while the sensors in Home I showed poor to no correlation between UMDSs ($R^2 > 0.02$). The AirU sensors in Home I also showed low room-to-room correlations ($R^2 > 0.01$) except between the sensors in living room and bedroom ($R^2 = 0.92$) (Table S5). The size of the home and the proximity of the sensors to cooking and heating/burning sources appear to be important factors in how well the sensors in different rooms correlate with each other.

Identification of PM sources (or source categories) would be needed to select an appropriate CF to convert each low-cost PM measurement to an improved estimate of PM mass concentration. Research is underway to address these challenges by annotation and automatic source categorization.

Tolmie *et al.* (2016) highlight the importance of annotation in networked sensing systems in order to contextualize the data and reduce incorrect data interpretation. Fang *et al.* (2016) developed an indoor air-quality sensing system that is able to automatically detect and identify up to three sources of indoor pollution events. Moore *et al.* (2018) developed a system that allows *in situ* annotation and real-time interactive visualization from air-quality data collected by a network of Dylos monitors. Furthermore, even if the source category is known, CFs can vary within that category. For example the CF for cooking would depend on variables such as type of food, method of cooking and temperature (Dacunto *et al.*, 2013). However, focusing on relative differences may be valuable for individuals trying to minimize their PM exposure.

The highest indoor PM levels occurred in the kitchen and bedroom, where the bulk of the annotated events occurred (Fig. S1). In addition, Home II was smaller, making the rooms with sensors closer to the rooms with the highest PM concentrations. In general, cooking that involved frying caused some of the highest levels in the kitchen and also affected nearby rooms. Use of candles and aerosol products, like Febreze™, were the main causes of the high levels of PM in the bedrooms. The effect of these events on the PM$_{2.5}$ levels in the rooms and their effects in adjacent rooms are illustrated in Fig. 3, Fig. 4 and the supplemental data (Fig. S9). It should also be noted that room AERs can also influence maximum PM$_{2.5}$ concentrations and decay times for an emission source (Ni *et al.*, 2018; Singer and Delp, 2018). The time required for an aerosol to be removed from a room depends on the AER, type of emission source (i.e., cooking, cleaning, candle burning etc.) and characteristics of the aerosol particles (i.e., density, size, shape). The AER ranges observed in both homes (Home I: 0.27–1.96; Home II: 0.51–2.66) (Table S6) are in the ranges reported by Rosofsky *et al.* (2019) (0.36–0.74) and Yamamoto *et al.* (2010) (0.37–1.13) for U.S. residences.

Bekö *et al.* (2013) report candle burning as a significant contributor to high indoor particulate levels. Our study supports
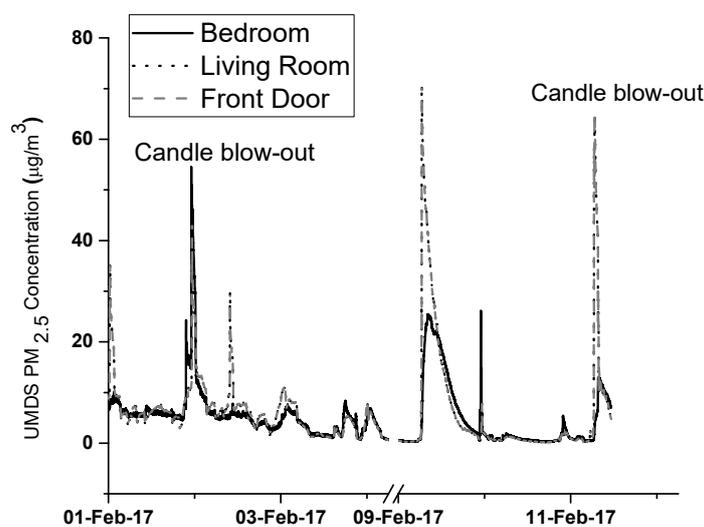
Fig. 3. Change in PM$_{2.5}$ levels in other rooms when blowing out a candle (Home II). PM$_{2.5}$ measurements from the UMDS (bedroom, living room, front door) were individually bias corrected with a CF for candle smoke (Table S4).
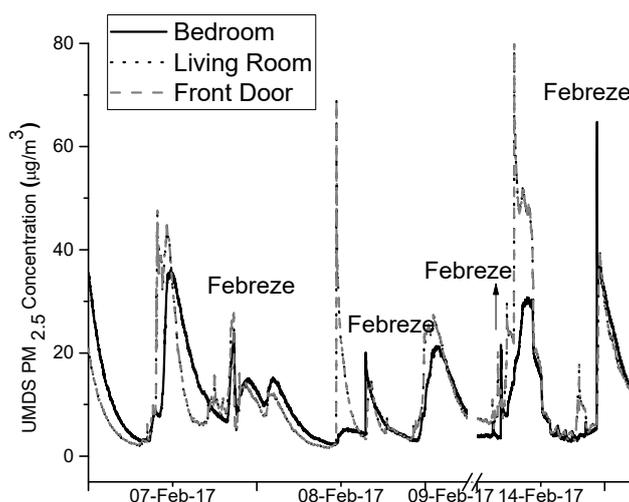
Fig. 4. Increase in PM$_{2.5}$ levels in the room of activity and adjacent rooms when spraying Febreze™ (Home II). PM$_{2.5}$ measurements from the UMDS (bedroom, living room, front door) were individually bias corrected with a CF for the calibration week (Table S4).

this (Fig. 3). Initially, lighting the candle in the bedroom generated a spike, but the largest spike (5-fold increase in PM levels) came from extinguishing the candle, as reported by Afshari *et al.* (2005) and Hussein *et al.* (2006). Dacunto *et al.* (2013) also found that the vast majority of PM$_{2.5}$ measured by a Dylos was emitted while candles were being extinguished. In this study, the increased PM$_{2.5}$ levels from candle extinguishing lasted between 3 and 5 hours. Blowing out a candle also affected PM levels in adjacent rooms, causing a spike 3 to 4 times the background PM level in that room.

The use of aerosol products like Febreze™ air freshener (Fig. 4) and hairspray (Fig. S9) caused a sharp transient spike in PM levels with a long decay time, which was also observed during the calibration week. For example, spraying Febreze™ (bedroom) showed an initial sharp spike, with PM$_{2.5}$ levels above 75 µg m^{-3} for up to 20 minutes, and PM levels required up to 6 hours to decay to background levels. PM$_{2.5}$ levels for hairspray showed a similar trend with PM$_{2.5}$ levels increasing above 200 µg m^{-3} and decay time of up to 2 hours. Hairspray used in the bathroom did not appear to affect PM$_{2.5}$ levels in other rooms, perhaps because the door was closed. Isaxon *et al.* (2015) also observed hairspray to cause an increase in PM$_1$ levels, with levels close to 100 µg m^{-3}.

In the kitchen, cooking (frying) activities increased PM$_{2.5}$ levels up to 150 µg m^{-3} (Fig. 5). Both homes had 4-burner electric stoves. Home I had an over-the-range microwave fan filtered the cooking emissions, while Home II did not have any hood or venting system. Dacunto *et al.* (2013) and Jiang *et al.* (2011) found that cooking generally did not generate very high PM levels unless it involved frying or burning of food. Dacunto *et al.* (2013) reported that frying, particularly frying meat in oil tended to produce greater PM emissions than burning candles or incense. Loo *et al.* (2014) developed a wireless network that included a PMS Lasair II-110 and a TSI AeroTrak optical particle counter that measured a 10-fold increase in PM levels from cooking. A particularly interesting event occurred in Home II when cooking steak,

which showed that the indoor levels rose above outdoor PM levels, even during a winter CAP when PM$_{2.5}$ levels were high. The sensor host did not annotate other cooking activities during the calibration or the distributed deployment.

PM levels during other common household activities like cleaning depended on the type of activity, the duration of the activity and its intensity. For example, making a bed generated a smaller spike, of a 2-fold increase, and vacuuming generated larger spikes, between 2- and 3-fold increases, where particles lingered for about 60 minutes (Fig. S10). Indoor PM levels in Home II on a winter day displayed a sawtooth pattern, which appeared to be caused by the furnace turning on and off (Fig. S11). The furnace caused PM level to vary from 20–42% over background levels. These regular increases may be caused by resuspension of particles in the heating ducts.

Outdoor PM$_{2.5}$ and its Effect on Indoor Levels

Ambient sources of PM are an important contributor to indoor PM levels (Qing *et al.*, 2005; Wheeler *et al.*, 2011; Goyal and Kumar, 2013). In this study, we identified one case where elevated PM levels outdoor had a significant effect on indoor air and one where it did not. In Home II, the PM levels outside were consistently high (between 30 to 40 µg m^{-3}; corrected UMDS) and opening a window (31st Jan) for a mere 5 minutes raised PM levels inside the house in all three rooms for up to 50 minutes. Jin *et al.* (2015) also found that opening a window for an hour caused PM$_{2.5}$ levels indoors to increase (by 9% when outdoor levels were 100 µg m^{-3} and by 20% when outdoor levels were 300 µg m^{-3}). Rodes *et al.* (2001) found that indoor PM$_{2.5}$ concentrations, on average, were only 45% of outdoor concentrations, but reached 80% when homes were ventilated through open windows (April–May). In addition, the baseline PM$_{2.5}$ concentrations slowly increased over the course of the CAP (Fig. 6). During a week-long CAP period when outdoor PM$_{2.5}$ levels were close to 35 µg m^{-3}, PM levels indoors began to increase from a background level of 5 µg m^{-3} (25th Jan) to 10 µg m^{-3}
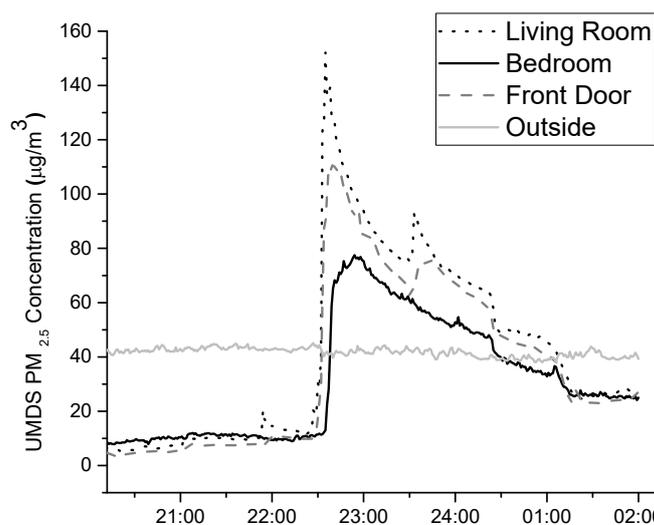
Fig. 5. High PM$_{2.5}$ levels in Home II caused by cooking steak in the kitchen/living room (31st January 2017). PM$_{2.5}$ measurements from the UMDS (bedroom, living room, front door) were individually bias corrected with a CF for cooking (Table S4). PM$_{2.5}$ measurements from the Outside UMDS was corrected with the CF for the CAP (Table S4).

(29th Jan) (Fig. 6). In two studies made in different climate zones by Kulmala and Vesala (1991) and Morawska *et al.* (2001), indoor concentrations followed the outdoor concentration changes in a smoothed and delayed pattern.

In contrast to the CAP event, on the 4th of July holiday, the AirU sensor showed high outdoor PM levels beginning around 9 PM associated with the fireworks display (Fig. S12). These high outdoor levels caused by fireworks were consistent with previous studies that found large increases in PM levels associated with fireworks (Lin, 2016: 9-fold during fireworks in Western countries; Seidel and Birnbaum, 2015: 42% increase in the U.S.). However, the elevated levels of PM$_{2.5}$ were not seen inside the home, which had windows closed.

Effect of Humidity on Light-scattering Measurements

During this study, outdoor humidity levels outside Home I appear to follow a similar pattern to outdoor PM$_{2.5}$ levels (Fig. S13). This diurnal humidity pattern is typical of RH during summer in Salt Lake City. Both the AirU and the UMDS use light scattering to estimate PM$_{2.5}$ concentrations/particle count. A variety of factors affect particle light scattering, including particle size, shape, composition and relative humidity (RH) (Johnson *et al.*, 2016). Since many aerosols are hygroscopic, changes in humidity can affect particle size and consequently particle mass estimated by light scattering. Both the UMDS and AirU contained sensors for measuring humidity. The UMDS had an SHT21 Sensirion humidity sensor, while the AirU had an Aosong Electronics DHT22 humidity sensor. Although the RH levels from the two different RH sensors are offset, the trends are consistent with each other and with high-quality RH measurements in the vicinity (MesoWest, 2018; Weather Underground, 2018). During the time period illustrated in Fig. S13, RH varied from less than 10 to 75%, and both the lower RH and the upper RH levels can affect light-scattering PM measurements. Chakrabarti *et al.* (2004) and Soneja *et al.* (2014) found that

at RH of less than 20 or 30%, respectively. Several studies have reported that light-scattering instruments substantially and nonlinearly overestimated mass concentrations at RH levels higher than 70% (Sioutas *et al.*, 2000; Chakrabarti *et al.*, 2004; Wu *et al.*, 2005). Other researchers found that when RH increased above 50% (Day and Malm, 2001) to 75% (Chakrabarti *et al.*, 2004; Soneja *et al.*, 2014) a humidity correction was needed for nephelometers. Our results suggest that the effect of RH on these low-cost PM sensor measurements requires further evaluation.

CONCLUSIONS

This study demonstrated that two low-cost PM sensors, the AirU and the UMDS, accurately tracked indoor and outdoor variations in PM concentrations (compared to research-grade instruments) and also exhibited good intra-sensor agreement, indicating that they provide reliable relative measurements of the concentration, e.g., if the measured concentration doubles, it reflects an actual doubling of the real concentration. Sharp increases in the PM$_{2.5}$ levels were produced by several indoor activities, including frying food, burning candles, and spraying aerosol products, in the rooms where they occurred as well as in adjacent rooms. In both homes, the highest PM$_{2.5}$ concentrations were measured in the kitchen and the bedroom. Elevated outdoor PM$_{2.5}$ levels during a CAP event also caused indoor levels to rise over both the short and the long term. Finally, the sensors responded differently to different PM sources due to the latter's varying optical properties. Consequently, obtaining accurate estimates of the mass concentration in an indoor environment is challenging because it requires a specific CF for each sensor and source type, which in turn requires a strategy to identify each source. However, low-cost PM sensors can be incorporated into an indoor air-quality measurement network to help individuals manage their personal exposure.
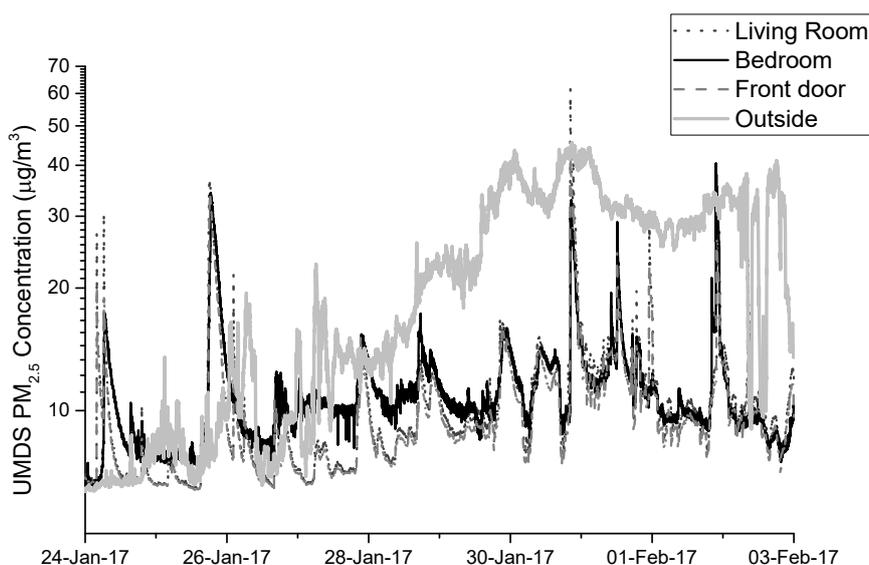
Fig. 6. PM$_{2.5}$ levels during a winter CAP from 24th January to 3rd February 2017 (Home II). PM$_{2.5}$ measurements from the UMDS (bedroom, living room, front door) were individually bias corrected with a CF for the calibration week. PM$_{2.5}$ measurements from the outside UMDS was corrected with the CF for the CAP (Table S4).

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CONFLICT OF INTEREST

Dr. Kerry Kelly, co-author on this paper, has a financial interest in the company Tetrad: Sensor Network Solutions, LCC, which commercializes solutions for environmental monitoring.

SUPPLEMENTARY MATERIAL

Supplementary data associated with this article can be found in the online version at http://www.aaqr.org.

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