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Cooking emission control with IoT sensors and connected air quality interventions for smart and healthy homes: Evaluation of effectiveness and energy consumption

Jovan Pantelic [a,*], Young Joo Son [a], Brant Staven [a], Qingyang Liu [a,b]

[a] Well Living Lab, Rochester, MN 55902, USA
[b] PAXAFE, 55 Monument Circle 900A, Indianapolis, IN 46204, USA

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ABSTRACT

This is the first study demonstrating how an ecosystem of Internet of Things or IoT-enabled devices and sensors can effectively control cooking-emitted air pollution energy-efficiently. The study was conducted in the simulated fully furnished residential modules in the Well Living Lab in Rochester, MN. IoT sensor consisted of particulate matter ($PM_{2.5}$) sensors and a circuit monitor for tracking the stove on/off status. In this study, we developed and tested seven air pollution control algorithms and benchmarked them against the residential temperature setpoint-controlled constant air volume (CAV) air supply. Results show that, compared to the air temperature setpoint controlled CAV air supply, the ecosystem of IoT sensors and IoT-enabled stove hood, portable air cleaners (PAC), and bathroom exhaust operated by air pollution control algorithms produce significant improvement in indoor air quality during cooking. Reduction of integrated $PM_{2.5}$ concentration ranged from 81% to 94% compared to the CAV air supply. Cooking-emitted pollution was effectively controlled by activating a stove hood or a combination of stove hood and other interventions, producing a $PM_{2.5}$ integrated concentration reduction of ~90% compared to the CAV baseline. On an annual level, the electrical energy consumed to mitigate cooking emitted particles ranges from 39.4 kWh to 265 kWh translating to an additional cost of $5.6 to $42.5. From the energy standpoint, PM-activated PACs are the most efficient, producing a $PM_{2.5}$ integrated concentration reduction of ~80% compared to the CAV baseline. When considering exposure reduction and electrical energy consumption, PM-activated Stove Hood is the most effective intervention consuming an additional 86.9 kWh of electrical energy annually, costing $12.2. Sensors for PM monitoring must be mounted on the stove hood to produce timely control action. Using circuit monitors for intervention activation did not significantly improve the exposure.

1. Introduction

People spend over 90% of their time indoors [1]. In particular international survey found that 60–70% of the time we spend at home indoors [2]. Indoor air contains both pollutants from outdoor origins (e.g., transportation, power generation, industrial activities, and wildfires) [3] and pollutants that originate indoors (e.g., combustion from cooking stoves, emissions from building materials, paints, and furniture). [4]. Cooking, especially at high temperatures, can emit 0.2 mg/min to 2.2 mg/min of particles [5–9]. High cooking emission rates can increase indoor concentration up to 100 times compared to outdoor levels [7]. This suggests that cooking is one of the most significant contributors to indoor pollution. Exposures to indoor air pollution contribute to increased risks of cancer [10], premature mortality [11], and asthma [12].

Strategies for mitigation of cooking emissions include stove hoods [5,13,14], PACs [5,6], increased air supply, exhaust or extraction ventilation, or a combination of several [5]. Stove hood capture efficiency is between 3% and 98% depending on the position of the cooking burner relative to the stove hood and the stove hood airflow field [15–18]. Besides capturing emitted particles, stove hoods also remove particles suspended in the air by exhausting them [19]. Although stove hoods have high capture effectiveness and particle removal capabilities, they have to be turned on manually, and their actual usage is about 30% of cooking events [20]. Similar trends exist for PAC [21]. PAC particle filtration efficiency varies between 20% to over 95%, mainly depending on the filter rating [22] and clean air delivery rate. A field survey of PAC use showed that 81.4% of the surveyed homes that had PAC did not use them [21]. Assessment of motives for PAC use showed that relief of ther-

* Corresponding author at: 221 First Avenue SW, Rochester, MN 55905, USA.
E-mail address: jovan.pantelic@delos.com (J. Pantelic).

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mal discomfort was the primary motive for help and not perceived air quality [23]. In a randomized cross-over study, Huang et al. [24] showed that PAC with integrated particle sensors in automatic mode reduced cooking emitted particle concentration substantially more than the manual mode operated PAC. Previous studies suggest that the manual operation of air pollution interventions is a bottleneck in mitigating indoor air pollution. A significant improvement in exposure reduction and associated health outcomes is possible by automating the operation of appliances used for air quality interventions.

ASHRAE standard 62.2 guides the ventilation design in residential environments. Initially, ASHRAE guidance was intended for constant air supply control logic. Advances in residential ventilation control were introduced with the Demand Control Ventilation (DCV) concept or residential integrated ventilation-energy controller concept [25]. DCV measures indicators of ventilation demand to control the air supply. A smart ventilation literature review by Guyot et al. [25] showed that previous DCV studies base control on relative humidity (RH), carbon dioxide (CO_2), total volatile organic compounds (TVOC), occupancy, outdoor air temperature signals, but none of the previous studies used signals from particulate matter (PM) or nitrogen dioxide (NO_2) sensors. Previously, PM concentrations were measured only with scientific-grade instruments, which did not apply to the ventilation control integration [26]. Therefore, the lack of indoor air quality monitoring equipment capable of measuring $PM_{2.5}$ [25] and communicating that information to the control system is one of the main reasons for the absence of automated strategies for control of PM in residential environments (e.g., stove hoods, PACs). Recent developments of low-cost IoT sensing platforms [27–34] have enabled measurement and communication of $PM_{2.5}$ to control systems. Besides platforms developed by research groups, many commercially available platforms (e.g., Kaiterra, Senseware, etc.) can continuously, and with high granularity, measure one or multiple air quality indicators [35]. Research on the accuracy and reliability of IoT-based air temperature and relative humidity sensors concluded that they agree well with the reference scientific-grade instruments [36]. $PM_{2.5}$ sensors have an accuracy within a factor of 2 from a reference. Thus they can be considered suitable for indoor air quality management [15,36]. This suggests that activities that emit large quantities of particles, like cooking, can be effectively monitored and controlled with low-cost IoT sensors.

There are several examples of thermal environment control with IoT sensing. Sung and Hsiao [37] implemented a continuous thermal environmental characterization to optimize the home environment for occupants. Park and Rhee [38] used characterization of the thermal environment to calculate Predicted Mean Vote (PMV) and cool or heat the environment accordingly. Control based on a multipoint real-time calculation of PMV was developed to reduce energy consumption and improve thermal satisfaction compared to the traditional hard-wired, low-granularity sensor control [39,40]. Control using a PMV calculation based on the sensor network characterization of the thermal environment, user feedback, and skin temperature was incorporated in the temperature control logic by Salamone et al. [41]. These examples show how information from IoT sensors can improve thermal comfort compared to the traditional control approach.

In the review, Van Tran et al. [42] suggested that IoT sensors can be used to control indoor air pollution and enhance conditions that support occupants' health. Kumar et al. [43] described the concept of an IoT application for indoor air quality (IAQ) and energy management. Several studies show the potential of IoT IAQ information to improve building operations. On a conceptual level, Kumar et al. Field [43] described using real-time IAQ monitoring to control household appliances. Tastan [44] showed how continuous IAQ IoT measurements could notify occupants when the air quality is unsatisfactory. Pantelic et al. [45] showed how IoT sensing could be used to understand building operations during wildfire smoke events. Luo et al. [46] showed how to improve natural ventilation utilization with IoT sensing networks. These studies demonstrate the potential that IoT sensing has for IAQ control. However, they did not implement it. Several studies have applied IoT sensing data to control IAQ. A fuzzy logic control system for exhaust fan operation based on the real-time monitoring of CO_2 and PM_{10} was developed by Pradityo and Surantha [47]. Bushang [48] developed fuzzy logic based on CO_2 IoT sensing to control the speed and the working time of room ventilation. Dhanalakshmi [49] used CO_2 IoT sensing to control the ventilation system. Control based on IoT CO_2 sensors integrated into a lamp was developed by Salamone [50] to maintain IAQ in an office. PAC controlled with integrated particle sensors showed reduced cooking-emitted particles [24]. Previous studies discuss the conceptual implementation of IoT sensors for IAQ control or demonstrate the application of developed algorithms in a limited experimental setting.

Cooking, especially frying, emits particles into the indoor environment and represents the largest source of indoor pollution in residential dwellings. Although interventions like stove hoods and PACs can effectively mitigate the impact of indoor pollution sources on air quality, studies show that these devices are infrequently applied because users need to turn them on manually. When air pollution controls work only part of the time or not at all, they are not reducing exposure significantly. Automating interventions enable utilization of their ability to capture and remove particles, reducing dwellers' exposure to cooking emissions. The latest IoT sensing development enables continuous IAQ monitoring with high granularity and frequency. Signals from the IoT sensors can be used to automate the operation of IAQ interventions. The study aims to address cooking emission issues, automate air pollution control interventions, and examine the energy consumption of the interventions. The control algorithms were developed to mitigate cooking-emitted air pollution using IoT sensors (PM and circuit monitor), stove hoods, PASs, bathroom exhaust, and increase of supply air flow rate or a combination. We developed and compared the air quality improvement of several control algorithms that activated one or multiple interventions. We measured the electrical energy consumption of devices for each control algorithm and predicted annual energy consumption. The current study is the first study that demonstrated how spatially distributed IoT sensors can activate different decentralized interventions and mitigate cooking emissions across the residential space. Algorithms tested in the current study represent a step forward in developing healthy smart homes where indoor air quality information is converted into actions to produce a healthy indoor environment.

2. Methods

2.1. Experimental design

We designed experiments to evaluate the performance of several control algorithms to mitigate cooking-emitted $PM_{2.5}$. We performed experiments in the 1-bedroom apartment, with a dedicated air conditioning system following a cooking protocol. We developed and evaluated the performance of seven air pollution control algorithms. The effectiveness of air pollution control algorithms was benchmarked against the constant air volume supply performance.

2.2. Experimental facility

Experiments took place in the Well Living Lab (WLL) in Rochester, MN, with residential modules configured as 1-bedroom apartments. Each module with a floor area of 32.6 m^2 comprises a kitchen, living room, bedroom, and bathroom. The residential modules had suspended ceilings with a 2.9 m height, creating a 94.54 m^3. Windows in 1-bedroom apartments were not operable. Comfort conditions in the apartment were maintained by a constant supply of 164 m^3/h of conditioned air to maintain a setpoint air temperature of 22 °C. Airflow supplied to the space was measured with the thermal diffusion airflow meter (ELECTRA-flo 5 Series Thermal Airflow Measurement System) connected to the BMS. Air supplied to the indoor space was a mixture of outdoor and recirculated air filtered through the MERV14 filter. All experiments described in this study were performed in a cooling mode. The location of the 4-way supply diffusers and exhaust grilles are depicted in Fig. 1. We used CO_2 tracer gas decay to characterize airflow conditions deployed in this study. Results by Liu et al [5] showed that air supplied to the space produced 1.74 ACH with an average infiltration of 0.75 ACH. The experimental 1-bedroom apartment had installed a Panasonic WhisperHood IAQ stove hood that, when turned on, created 5.94 ACH [5] in the apartment. The bathroom exhaust was also installed in the experimental apartment that, when turned on, produced 2.63 ACH [5].

Airflow into and out of the space changes depending on the intervention or combination of interventions applied. We measured static pressure and Air Exchange Rate, which change depending on the intervention used. Details can be found in Liu et al. [5]. When the stove hood is used, we have measured that residential modules have lower pressure than in the corridor in front of the entrance door to the modules. When we used Air Flush and stove hood pressure difference was neglectable. When bathroom exhaust was used, we didn't measure any substantial pressure difference between the corridor and the residential module. A more detailed analysis of the flows in the space and measurement technique used can be found in Liu et al [5].

IoT PM sensors (Purple Air PA-II, PurpleAir, Draper, UT) were positioned in each room. Sense circuit monitor was connected to the stove to determine the stove's on and off status. Readings from IoT PM sensors and circuit monitor activated the stove hood (Panasonic WhisperHood IAQ™ FV-36RCQL1, Osaka, Japan), two PACs (Blueair 480i, Blueair, Stockholm, Sweden), bathroom exhaust (Panasonic FV-0511VK2, Osaka, Japan), or additional centralized air supply. A detailed description of the pollution mitigation control algorithms is in the section entitled Description of the air pollution control algorithms. For each experimental run, we set up the air pollution control algorithm. After setting the algorithm, we cooked following a cooking protocol. After finishing cooking, we left the module and monitored PM2.5 levels. The experimental run ended when the measured PM2.5 was below 6ug/m3. We repeated the experimental run multiple times for each algorithm. The number of experimental run repeats for each air pollution control algorithm is in Table 1.

2.3. The cooking protocol

The cooking protocol consisted of pan preheating for 1 min. After preheating, four slices of thick-cut bacon were placed in the pan, fried for 5 min on one side, and then rotated and fried for 5 min on the other side. The pan was placed on the larger burner in the back row of the stove. The stove burner was set to level 5 for the entire duration of cooking. After 11 min from the start, the stove was turned off, and the bacon slices were removed from the pan. The pan was cleaned for the next cooking event, which started only when the $PM_{2.5}$ concentrations decayed to the background level below 6 μg/m^3 for at least 3 consecutive readings.

2.4. Selection of sensor location

Stove hoods are designed to capture pollution at the source location. When applied in residential kitchens, one of the parameters influencing the overall capture effectiveness and removal of cooking emissions is matching periods of stove hood operation and cooking time. If the stove hood is activated significantly after cooking starts, emitted pollution will disperse into the residential environment. This can cause reduced particle capture and an increase in exposure. When the stove hood operation is automated, it is crucial to detect cooking events and turn it on as soon as cooking starts. Time delays between the actual start of cooking (start of particle emission) and detection of elevated particle levels impact the level of exposure reduced with an automated stove hood. Two

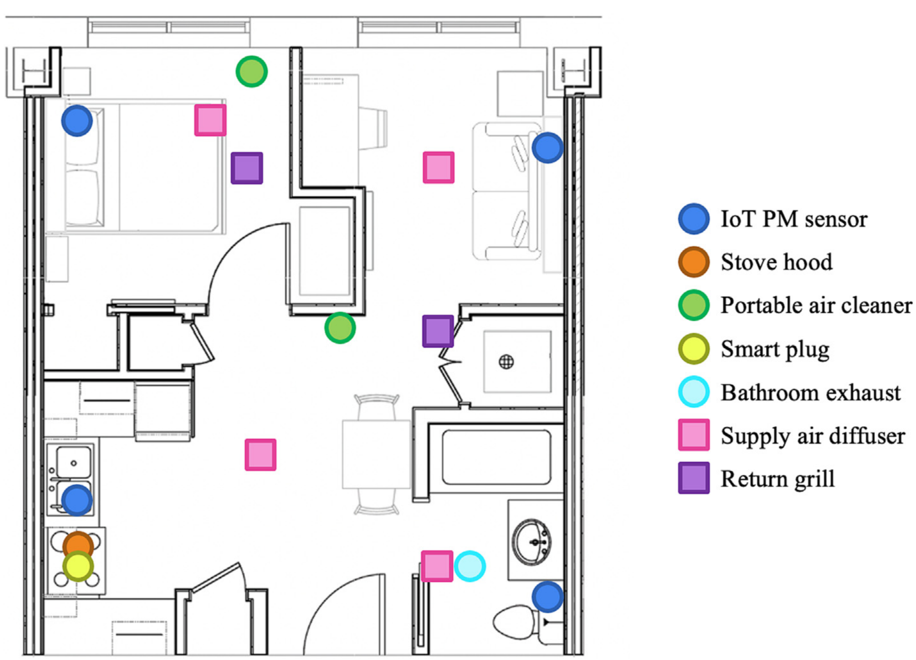

Fig. 1. Devices and sensor locations.

Table 1
Description and performance of control algorithms.

Names	Intervention(s) Activated	Intervention(s) Stop	Operational device	# completed	Integrated $PM_{2.5}$ concentration (std) [μg/m^3]	% Change	Decay Time (std) [min]	Energy per cooking event (std annual) [kWh]	Annual energy consumption [kWh] and cost	Reduction/ energy [μg/m^3/ kWh]
CAV (baseline)	Air temperature	Air temperature	–	7	23,314.8 (11,627.4)	0.000	101.43 (28.86)	–	–	–
PM-activated Stove hood	IoT PM sensor in the kitchen activating stove hood	IoT PM sensor in the kitchen	Stove hood	10	1,420.4 (527.4)	93.90	42.20 (13.70)	0.119 (0.07)	86.9 $12.2	164.62
PM-activated PACs	IoT PM sensors in the living room and bedroom activating PAC in the corresponding space	IoT PM sensors in the living room and bedroom signals turning off PAC in the corresponding space	Living room and bedroom PACs	10	4,532.1 (1,982.8)	80.56	33.50 (5.95)	0.054 (0.01)	39.42 $5.6	399.63
PM-activated ALL	IoT PM sensors in the kitchen, living room and bedroom activating stove hood and two PACs	IoT PM sensors in the kitchen, living room and bedroom turn off stove hood and two PACs	Stove hood Living room and the bedroom PACs	6	2,409.7 (1,027.3)	89.66	32.33 (4.13)	0.304 (0.06)	221.9 $31.3	98.61
Circuit monitor-activated stove hood	The stove hood is activated with the circuit monitor, and 2 PACs are activated with the IoT PM sensors	IoT PM sensors in the kitchen and bedroom for PAC and combined circuit monitor 'off' and IoT PM sensor for stove hood	2 PACs Stove hood	12	3117.3 (2219.2)	86.63	42.60 (15.09)	0.414 (0.12)	301.9 $42.5	66.01
Circuit monitor-activated stove hood and PAC	The stove circuit monitor activating stove hood and IoT PM sensor activating PAC in the living room	The stove hood turned off based on IoT PM sensor, Circuit monitor in 'off-mode' and IoT PM turning off living room PAC	bedroom PAC Stove hood living room PAC	15	1,563.9 (991.6)	93.29	31.00 (4.06)	0.322 (0.06)	235.1 $33.1	118.21
Circuit monitor-activated ALL	The stove circuit monitor signal activated stove hood, 2 PAC and bathroom exhaust	Circuit monitor in 'off-mode' and IoT PM sensors in all spaces	Stove Hood, two PACs, BE, Air Flush	15	2,773.7 (2,752)	88.10	32.46 (4.41)	0.346 (0.09)	244.9 $34.5	84.19
Circuit monitor-improved	The stove circuit monitor signal activated stove hood, 2 PAC, and bathroom exhaust.	Circuit monitor 'off' and IoT PM sensors and IoT PM sensor kitchen	Stove Hood, two PACs, BE, Air Flush	14	2,520.9 (1,966.6)	89.20	32.11 (8.131)	0.363 (0.15)	265 $37.3	80.60

types of time delays influence how quickly a cooking event is detected. The time lag is related to particle sensor measurement frequency and temporal delay associated with the distance and particle dispersion between the source point to the sensor location. Purple Air PM sensors in the current setup measure $PM_{2.5}$ concentration every 2 min.

Four IoT $PM_{2.5}$ sensors were distributed to measure particle levels (Fig. 1). Regarding the interventions, the stove hood was in the kitchen, PACs were in the living room and the bedroom, and the exhaust fan was in the bathroom. Besides $PM_{2.5}$ signals, a dedicated circuit monitor was installed to detect the stove status (on/off) and trigger devices based on the use of the stove. Turning appliances out was based on one or multiple IoT $PM_{2.5}$ sensor readings lower than 6 μg/m^3. To avoid turning devices on and off frequently, an average of 3 $PM_{2.5}$ readings (6-minute data with 2-minute frequency) had to be lower than 6 μg/m^3.

We installed several sensors in each of the spaces in the residential module (Fig. 1) to investigate if there are any delays in detecting elevated particle levels. The time delay between the start and detection of the cooking was calculated as the time difference between the start of the cooking as detected by the dedicated circuit monitor and the time when the $PM_{2.5}$ sensor detected levels above 15 μg/m^3.

2.5. Description of air pollution control algorithms

A total of eight control algorithms were examined in the study. The algorithms are described below, and the summary is provided in Table 1.

The baseline operation consisted of a CAV supply with the amount of ventilation suggested by ASHRAE 62.2–2013. Seven air pollution control algorithms were developed specifically to mitigate cooking-emitted particles. The algorithms varied in the appliances (interventions) they activate and the control signals used to turn interventions on and off (location of appliances and sensor are in Fig. 1; algorithms in Table 1). Two signals were used for device activation: IoT $PM_{2.5}$ sensors and a dedicated circuit monitor (Sense, Cambridge, MA, USA).

PM-activated stove hood algorithm automated the stove hood operation based on the $PM_{2.5}$ levels measured in the kitchen. The stove hood was turned ON when the sensor installed on the side of the stove hood measured a $PM_{2.5}$ mass concentration of 15 μg/m^3 or higher. The $PM_{2.5}$ concentration threshold of 15 μg/m^3 was chosen based on the WHO average daily exposure limit [51]. When the stove hood was ON, it continuously operated at the flow rate of 408 m^3/h. The HVAC system maintained the air supply to provide temperature setpoint conditions. The stove hood was turned off when three consecutive $PM_{2.5}$ readings in the kitchen were lower than 6 μg/m3. The 6 μg/m^3 was chosen considering sensor accuracy and reduced exposure. Our pilot measurement showed that when $PM_{2.5}$ measurement showed 6 μg/m^3 they were very quickly reduced to the level sensors could not detect with sufficient confidence.

PM-activated PACs algorithm automated PACs in the bedroom and the living room. The PACs in the living room and bedroom were turned ON or OFF based on IoT $PM_{2.5}$ sensor in the corresponding space. PACs were turned ON when the $PM_{2.5}$ concentration exceeded 15 μg/m^3 and OFF when the average of three consecutive room $PM_{2.5}$ readings was lower than 6 μg/m^3.

PM-activated ALL algorithm automated the stove hood and two PACs. Each device was turned ON or OFF using the corresponding room's IoT $PM_{2.5}$ sensor: stove hood - sensor in the kitchen on the side of the stove hood, bedroom PAC - sensor in the bedroom on the wall above the bed, living room PAC - sensor in the living room on the shelf above the couch. The device was turned ON when the corresponding sensors measured a $PM_{2.5}$ mass concentration of 15 μg/m^3 or higher. The device was turned OFF when the average of three consecutive $PM_{2.5}$ readings in the corresponding room was lower than 6 μg/m^3. When any of the sensors recorded $PM_{2.5}$ levels exceeding 50 μg/m^3, supply airflow increased to 510 m^3/h. We call this a significant increase in the supply airflow rate Air Flush. Air Flush stopped when the $PM_{2.5}$ mass concentration in each room went below 45 μg/m^3.

The circuit monitor-activated stove hood algorithm used a stove circuit monitor to turn ON the stove hood, and two PACs were turned ON based on $PM_{2.5}$ readings. When the circuit monitor detected that stove was ON, the algorithm turned ON the stove hood with a flow rate of 408 m^3/hour. Two PACs were turned on based on the corresponding $PM_{2.5}$ sensors in the living room and bedroom. PACs were ON when the corresponding sensor measured a $PM_{2.5}$ mass concentration of 15 μg/m^3 or higher. Once three consecutive $PM_{2.5}$ mass concentration readings were lower than 6 μg/m^3, the PACs were turned OFF. The control algorithm turned OFF the stove hood when the circuit monitor detected that cooking was completed (no electrical current) and the kitchen $PM_{2.5}$ mass concentration was below 6 μg/m^3. We used both circuit monitor status and $PM_{2.5}$ signals to turn OFF the stove hood. This control logic was designed to prevent the stove hood being OFF while the $PM_{2.5}$ mass concentration in the kitchen was still high. The Air Flush was on when any $PM_{2.5}$ sensor recorded 50 μg/m^3 or higher. The Air Flush was off when every $PM_{2.5}$ sensor recorded particle levels lower than 45 μg/m^3.

The circuit monitor-activated stove hood and PAC algorithm used the stove circuit monitor to turn ON the stove hood and the PAC in the living room. The idea behind this air pollution control logic was to capture emissions with a stove hood and immediately remove with PAC those that escaped the stove hood. Bedroom PAC was turned ON when the bedroom sensor measured a $PM_{2.5}$ mass concentration of 15 μg/m^3 or higher and was turned OFF when the bedroom sensor measured three consecutive $PM_{2.5}$ mass concentration readings lower than 6 μg/m^3. Three consecutive IoT $PM_{2.5}$ sensor readings lower than 6 μg/m^3 and the stove circuit monitor detecting stove status OFF represent two criteria necessary to turn OFF the stove hood and living room PAC. The Air Flush operated the same as previously explained.

The circuit monitor-activated ALL algorithm turned ON all devices based on a stove circuit monitor signal. The stove hood, two PACs, and bathroom exhaust were turned ON when the stove was on. The stop signal for each device was the combination of the circuit monitor status oOFF and the corresponding IoT $PM_{2.5}$ sensor with three consecutive readings below 6 μg/m^3. The corresponding sensors for each device were in the kitchen on the side of the stove hood for the stove hood, in the living room and bedroom for the PACs, and in the bathroom for the bathroom exhaust. The Air Flush operated the same as explained above.

The circuit monitor-improved control algorithm was designed to turn OFF interventions differently than the previous algorithm. All devices, including the stove hood, two PACs, and bathroom exhaust, were turned ON by the stove circuit monitor when the stove was on. The stop signal in this algorithm was the combination of circuit monitor status OFF, IoT $PM_{2.5}$ sensor reading in the corresponding room below 6 μg/m^3, and the kitchen IoT $PM_{2.5}$ sensor reading below 6 μg/m^3. The additional kitchen reading in the stop signal was designed to help keep the devices ON when the $PM_{2.5}$ level has not yet been transported into adjacent rooms. The Air Flush kept the same as explained above.

2.6. HVAC system

An HVAC system was operated for both modules to provide the required cooling, heating, and ventilation. Supply air diffusers were located in each room; return grilles were located in the living room and bedroom; an exhaust grill was located in the bathroom. A central air handling unit supplied air to both modules. Supply air consisted of a mixture of return and outdoor air. After outdoor and return air was mixed, the mixture passed through the MERV14 filter and entered the residential modules. Under the baseline scenario, the HVAC system was operated as CAV, where conditioned air was supplied through the diffusers with a total air flow rate of 204 m^3/hour for each module. The supply flow rate was measured with the airflow meter installed in the system (ELECTRA-flo 5 Series Thermal Airflow Measurement System). Under automated scenarios, the central air supply was operated as the Variable Air Volume system that maintained temperature setpoints by modulating the supply air flow rate. When Air Flush mode was activated, the air supply was 510 m^3/hour measured with the same thermal diffusion airflow meter.

2.7. IoT $PM_{2.5}$ sensors

Each module was equipped with the same set of instruments for home automation. IoT PM sensors measured $PM_{2.5}$ concentrations with consideration of six bins (0.3, 0.5, 1, 2.5, 5, and 10 μm), sampling air of 0.1L every 2 min. The measurement range was from 0 to 1000 μg/$m^{3.}$ and the measurement errors were ± 10% at 100 to 500 μg/m^3 and 10 μg/m^3 at 0 to 100 μg/m^3. Before the experiment, all sensors were collocated with a research-grade PM monitor (Teledyne T640, Teledyne Technologies, Thousand Oaks, CA, USA) and were calibrated at four different levels: background level (approximately 4 μg/m^3), approximately 150, 400, and 900 μg/m^3. A zero-intercept linear regression model was fit to the readings and the regression coefficients were applied to the raw data for the analysis. The calibration showed that the R^2 was greater than 0.9 for all the IoT $PM_{2.5}$ sensors.

2.8. Dedicated circuit monitor

The stove was plugged into a Sense (Sense Labs Inc., Cambridge, MA) circuit monitor that monitored the stove ON and OFF and the electrical energy consumption in the simulated apartment. The monitor reads the electrical current over 1 million times each second, while the machine learning model outputs on and off device status.

2.9. Stove hood

The outside-ducted, wall-mounted stove hood was installed 68 cm from the stove (bottom of the stove hood to the stovetop). In a similar laboratory setup, when the stove hood was operated at the airflow rate of 408 m^3/hour, the average measured capture efficiency was 86.3 %. The operational flow rate was measured in the sheet metal duct using a thermal dispersion airflow meter (ELECTRA-flo 5 Series Thermal Airflow Measurement System) with an accuracy of 2%. According to manufacturer data, these characteristics represent the middle operational level ranging from 221 to 663 m^3/hour (according to manufacturer data). Based on the measured electrical energy consumption stove hood, on average, consumed 255 W of electrical power.

2.10. Portable air cleaner

The PAC with HEPA filter operated at 595 m^3/hour (as per manufacturers' information), the highest speed among the three fan speed levels available (204, 340, and 595 m^3/h). A clean air delivery rate was between 476 and 510 m^3/h (according to manufacturers' information). Based on the measurements of electrical energy consumption using the Kasa Smart WiFi Plug Slim with Energy Monitoring, PAC, on average, consumed 90.05 W of electrical power.

2.11. Bathroom exhaust fan

The bathroom exhaust with a DC motor operated at 109 m^3/hour as measured in the duct with ELECTRA-flo 5 Series Thermal Airflow Measurement System. Measurements using a dedicated circuit monitor showed that bathroom exhaust consumed, on average, 5.15 W of electrical power.

2.12. IT architecture of control algorithms

The control algorithm architecture was based on a complex network of sensors, actuators, gateways, and products and services from Microsoft Azure (Microsoft, Redmond, WA, USA) (Fig. 2). The components used in our advanced automation are described below and depicted in Fig. 2.

Purple Air PM2.5 sensors monitored environmental conditions. These data observations were sent to a cloud ingestion point (IoT Hub) by a gateway or 3rd party cloud platform (Fig. 2). In addition to environmental observations, the situational context was also considered, such as the status of the stove, stove hood, bathroom exhaust fan, airflow from the HVAC system, and PACs.

A building automation system (Crestron Electronics, Rockleigh, NJ, USA) monitored and sent control signals to the HVAC system. Schneider Electric provided the building operation platform for the HVAC system. It ran on StruxureWare software (Schneider Electric, Rueil-Malmaison, France) and communicated over the BACnet protocol.

The Sense dedicated circuit monitoring measured electrical current flow. As typical with electric surface burners, they cycled on and off to control temperature. We smoothed out the data with system configuration to prevent unwanted status changes by setting a minimum on/off duration. The device needed to be on or off longer than this time before Sense indicated a status change.

We used Sense's web socket-based API for communication. A web socket is a protocol that provides bi-directional communication over a TCP connection. Data signals were sent every second and informed us of events like a stove on and off.

The field gateways were nodes that acted as entry and exit points for traffic between the local network and the internet. It was responsible for translating different communication protocols, such as BACnet, and exchanging data to and from the cloud over HTTPS.

We leveraged an IoT Hub, a cloud-based message hub for communication between an IoT application and on-site devices and gateways. It received device-to-cloud telemetry and sent request-reply methods to control local devices.

We used Stream Analytics, an event-processing engine, to route inbound data from IoT Hub to various output types. In addition to routing, it analyzed and enriched real-time telemetry streams using a SQL-like query language. Here are the types of actions used in our control algorithms:

- Sent data to Time Series Insights via an Event Hub data stream
- Enriched telemetry with slow-changing reference data, such as location, device descriptions, etc., by joining to SQL database table.
- Evaluated events, such as "stove-on," and triggered an Azure Function to take immediate action to actuate ventilation
- Transformed data by calibrating sensor values with slope and intercept
- Invoked custom, user-defined JavaScript functions to generate actuation messages and calculate calibration equations

We used Time Series Insights to collect data for context-based exploration. It stored our recent IoT data. It provided query capa-

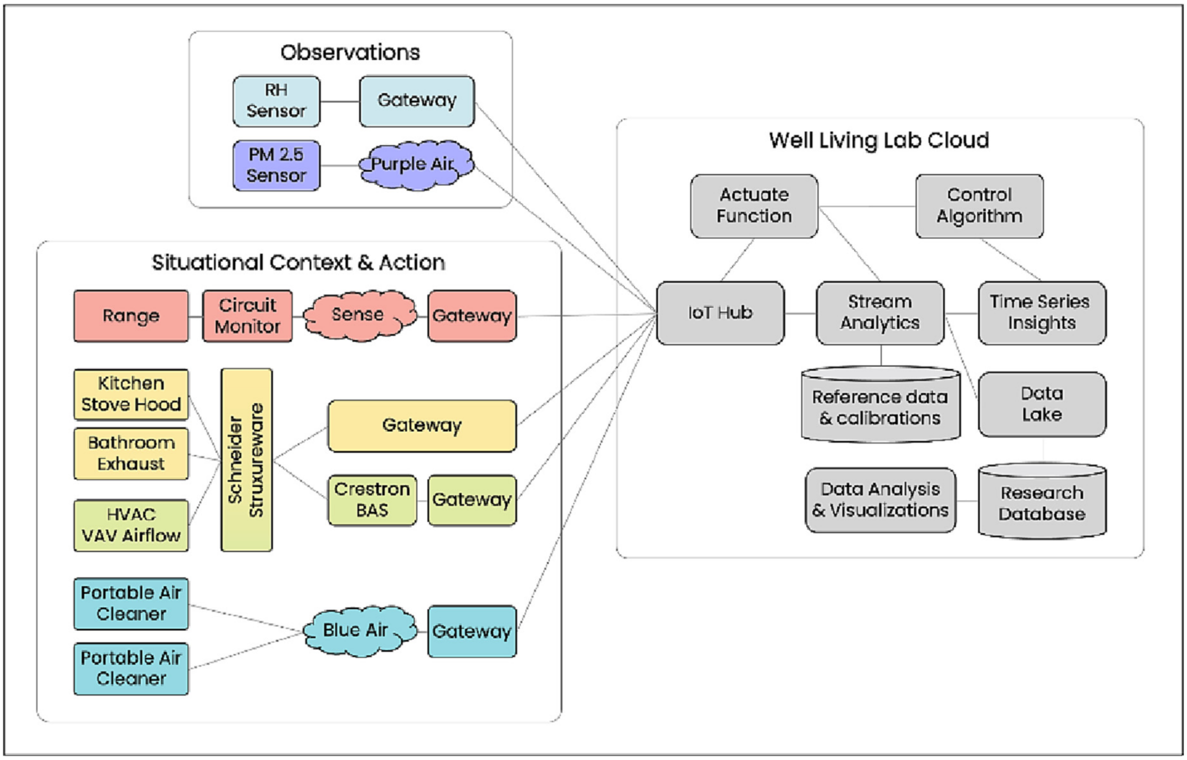

Fig. 2. IT Architecture of the control algorithm.

bility to pull relevant data to make an informed decision about air supply and activation of different interventions.

The control algorithm was configured based on the experimental design. For the residential module, we needed to make decisions in the kitchen, bathroom, bedroom, living room, and overall Air Flush. The decisions were either isolated or dependent on cross-room information. We looked at the environmental data to see if $PM_{2.5}$ levels crossed an upper threshold (described in the control narrative section). We looked at the situational context, like if the stove, stove hood, bathroom exhaust, PAC, or Air Flush was currently on or off. Once we determined that there was a need for the devices to be turned on or turned off, we acted. This involved actuating four different device types via other mechanisms and communication protocols.

- PAC (Blue Air) - Cloud
- Bathroom exhaust - Struxureware
- Stove hood – Struxureware
- Air flush – Crestron

IoT Hub sent the appropriate command to the gateway or cloud interface, resulting in a ventilation response.

2.13. Data analysis

2.13.1. Statistical analysis

Statistical testing was performed to examine and compare the impact of different air pollution control algorithms on the removal of cooking-emitted particles in the entire residential module. Skewness was tested first to evaluate whether the skew of data groups was different from the normal distribution before the paired comparison. Kruskal-Walli H-test was used for non-normal distributed data comparisons, and the T-test was used for normally distributed data. The code for processing and analyzing data was written in Python 3.7. Scipy 1.4.1 was used for statistical analysis.

2.13.2. Integrated $PM_{2.5}$ concentration

To compare the ability to remove cooking emitted particles effectively among different control algorithms, integrated $PM_{2.5}$ concentration was computed with the data from IoT $PM_{2.5}$ sensors using the Equation (1) below:

$$\sum_{i=0}^{t} C_{PM_{2.5}}(i) \tag{1}$$

The starting point of calculation was the cooking start time and the endpoint was when $PM_{2.5}$ concentration in all spaces decayed to the background level. The integrated $PM_{2.5}$ concentration was first calculated for each room then aggregated together as the volume-weighted average for the entire module.

2.13.3. Signal delay and decay time

The signal delay was calculated as a difference between the start of cooking and the time when the Purple Air sensor detected $PM_{2.5}$ levels above 15 $\mu g/m^3$.

Decay time was calculated as the time that elapsed between peak $PM_{2.5}$ concentration and the return of particles to the background level.

2.14. Energy consumption

Energy consumption per cooking event is calculated using the time of operation for each intervention, measured electrical energy consumption, or based on the information provided by manufacturers for the set conditions used in the experiments. The time of operation per cooking event (from the time of activation of the intervention until the intervention was turned off) was collected using an IoT ecosystem developed in the Well Living Lab that recorded the start and end of operation time. When we considered additional energy consumption, we calculated Air Flush consumption based on increased airflow rate compared to the residential HVAC operation. Based on the US Energy Information Administration, the average U.S. household consumes about 11,000 kWh of electrical energy per year [52]. 17% of annual energy is consumed for air conditioning, and 15 % is used for space heating [52]. In 2021 the USA had 1490 cooling degree days [53] and 3936 heating degree days [54]. Considering the US Energy Information Administration data on the energy necessary for heating, cooling, and conditioned air delivery, Air Flush, which supplies three times more air than standard ventilation conditions, would, in the USA, on average, consume 1718.2 W of electrical power. Annual energy consumption was modeled considering 2 cooking events per day for 7 days a week or 730 cooking events annually. The current study occurred in Rochester, MN, and the annual operating cost was calculated based on the cost of electrical energy at 14.09¢/kWh for Minnesota in 2021 [55].

3. Results

3.1. Selection of sensor location

We investigated temporal delays in detecting elevated particle levels caused by cooking emissions when sensors are placed in different locations (e.g., sensors are in the kitchen, next to the stove hood, on the side wall, and on the wall opposite to the stove). The time difference is calculated as the time between the start of the cooking and the time when $PM_{2.5}$ readings exceeded 15 μg/m^3. Time delays for different sensor locations are in Table 2.

$PM_{2.5}$ sensors positioned across the residential module (Fig. 1) show that elevated cooking-emitted particle levels were first detected by sensor position on the side of the stove hood with a delay of 7.5 min after cooking started. The $PM_{2.5}$ sensor in the kitchen on the dining table detected elevated particle levels after ~ 12.5 min, the same as the kitchen sensor on the cupboard. Results point out that the location of the sensors is of critical importance from the stove hood's control perspective that captures and exhausts cooking-emitted particles. Cooking in the current study lasted for 10 min, and a sensor placed on the side of the stove hood detected elevated particle levels in 7.5 min. If the other two sensors were used, the stove hood would be activated after cooking. This would be detrimental to the performance since the stove hood would not be able to perform timely particle capture.

After being emitted, particles dispersed through the residential module and after *11.15 to 11.9* min were detected by the three sensors in the living room (above the sofa and on the table, Fig. 1). This suggests that the location of the sensors in the living room is not critical since the detection delay is less than one min. Similar to the living room, two of the sensors in the bedroom detect cooking emissions within one min, suggesting that a specific location in the bedroom is not critical.

Table 2
The delay between the start of cooking and the detection of elevated $PM_{2.5}$ levels.

Location	Signal delay (min) mean (std)
Bathroom	14.56 (1.63)
Bedroom	12.55 (1.84)
Bedroom Shelf (right)	13.23 (1.81)
Kitchen (stove hood)	7.53 (2.80)
Kitchen (dining table)	12.48 (1.71)
Kitchen (cupboard)	12.57 (2.06)
Living Room Shelf	11.15 (2.86)
Living Room desk	11.80 (1.66)
Living Room	11.89 (1.83)

Delays of emission detection reveal a dispersion pattern of particles through the residential module. Particles emitted in the kitchen are detected above the stove and then in the living room. Shortly after being detected in the living room, particles were detected in the kitchen with the sensors on the dining table and the cupboard (Fig. 1). The most probable explanation is that a hot plume with emitted particles raised to the ceiling, attached to the ceiling (Coanda effect), and moved across the kitchen ceiling to the living room, and then from the living room dispersed into other parts of the kitchen opposite to the stove. Particles were detected in the bedroom after they were detected with the sensors on the dining table and the cupboard in the kitchen. The bathroom was the last place where particles were detected.

3.2. Comparison of air pollution control algorithms

Integrated $PM_{2.5}$ concentration was calculated for each air pollution control algorithm and presented in Fig. 3. We also calculated the percentage of integrated concentration reduction between the CAV baseline operation and each of the evaluated automation algorithms. Results are presented in Table 1. Statistical analysis shows that there is a statistically significant difference between baseline operation and every control algorithm developed and tested. Results in Fig. 3 show that all seven algorithms designed for air pollution control significantly reduced (>80%) integrated $PM_{2.5}$ concentration when compared to the ASHRAE 62.2 prescribed ventilation supply controlled with CAV maintain a setpoint temperature (baseline; mean: 23,314 μg/m^3, $p < 0.05$).

The measurement uncertainty of the Purple Air IoT $PM_{2.5}$ sensor is 10%. When considering measurement uncertainty, developed algorithms can be divided into two groups. One group that reduces integrated concentration by ~80% consists of the operation of PM-activated PACs. The second group reduces integrated concentration for ~90%. This second group consists of the remaining six developed algorithms that use stove hood or a combination of stove hood and other interventions. Statistical analysis shows that the performance of these six algorithms are statistically not significantly different. Since these six air pollution control algorithms in the second group each include stove hood alone or in combination with other interventions, results indicate that automated stove hood and the capture of emitted cooking particles has the most important role in control of the integrated $PM_{2.5}$ concentration. This finding is in line with results from previous studies that experimentally examined performance of stove hoods [5,17].

Control algorithms that activate only one intervention, PM-activated stove hood and PM-activated PACs, produce 94% and 80.6% change in the integrated concentration compared to the baseline respectively (Fig. 3, Table 1). Results show that when properly sized automated single intervention produces a significant improvement of integrated $PM_{2.5}$ concentration.

When performance of PM-activated stove hood and PM-activated ALL are compared to the PM-activated PAC's, algorithms that use stove hood showed improvement in reducing integrated $PM_{2.5}$ concentration ($p < 0.05$) larger than measurement uncertainty (Fig. 3). This indicates that source control with a stove hood is more effective than removing particles suspended in the air through PACs.

Circuit monitor-activated stove hood, circuit monitor-activated stove hood and PAC, circuit monitor-activated ALL had the same performance as PM activated stove hood and PM activated ALL (Fig. 3). For control algorithms that activate interventions with circuit monitor response time is ~1 min (Table 3). PM activated stove hood and PM activated ALL had response time of ~6 min. Considering total cooking time of 10 min circuit monitor activated interventions has much faster response time then PM activated interventions, but with this faster response integrated $PM_{2.5}$ con-

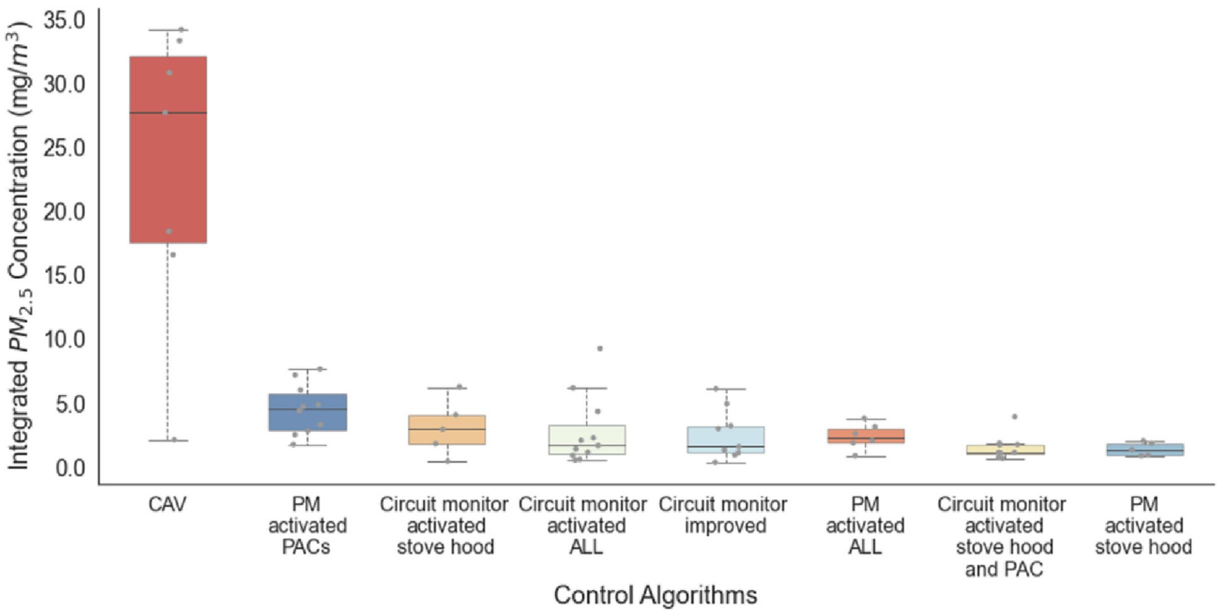

Fig. 3. Integrated PM2.5 concentration in the residential module.

Table 3
Response time in minutes (std).

Air pollution control algorithms	Bathroom exhaust	Bedroom PAC	Kitchen stove hood	Living Room PAC	Air Flush (All spaces)
PM-activated ALL	–	17.48 (1.15)	6.22 (0.58)	18.25 (2.15)	13.00 (3.69)
Circuit monitor-activated stove hood	–	12.91 (1.46)	0.61 (0.17)	13.42 (1.19)	13.87 (1.39)
Circuit monitor-activated stove hood and PAC	–	16.50 (1.35)	0.70 (0.297)	0.59 (0.29)	15.57 (2.029)
Circuit monitor-activated ALL	1.19 (0.81)	1.06 (0.80)	1.18 (0.79)	1.04 (0.79)	14.11 (2.76)
Circuit monitor-improved	0.82 (0.29)	0.69 (0.31)	0.81 (0.28)	0.65 (0.30)	14.38 (1.14)
PM-activated Stove hood	–	–	7.57 (1.08)	–	–
PM-activated PACs	–	14.20 (3.00)	–	13.19 (2.14)	–

centration was not reduced. This was unexpected result since capture of emitted particles and their removal started earlier. The reason might be associated with the temporal rate of emission $PM_{2.5}$ changes during cooking which is probably related to the changes in the temperature of the cooked ingredients. Most probably emission increased with the increase in temperature.

3.3. Response time for different control algorithms

Results in Table 3 represent response time of each of the control algorithms to cooking emissions. We use the term response time to depict time that passed from the beginning of cooking until control action was taken. Algorithms developed to activate interventions based on the circuit monitor signal (circuit monitor-activated stove hood, circuit monitor-activated stove hood and PAC, circuit monitor-activated ALL, and circuit monitor-improved) have a response time of ~ 1 min after cooking started. When PM sensors installed on the side of the stove hood activate operation of the stove hood results in Table 3 shows that response time was ~ 6 min. When particle sensors were used in other spaces in the residential module to activate intervention, response time was between 12 min and 17 min.

Considering that cooking in our experiment lasted 10 min, using a circuit monitor to activate the stove hood in ~1 min compared to ~6 min (considering 2 min measurement frequency) with a PM sensor (Table 3) shows circuit monitor's significant improvement in response time. From the integrated $PM_{2.5}$ concentration perspective this shorter response time did not result in important indoor concentration reduction. The reason is probably associated with the changes in the rate of emission of $PM_{2.5}$ during cooking as a function of cooking temperature.

Response time (Table 3) and integrated $PM_{2.5}$ concentration results combined suggest that circuit monitor or $PM_{2.5}$ measurements on the side of the stove hood can be both successfully used to control stove hood operation and reduce exposure of occupants. If the $PM_{2.5}$ sensor is used for the control where it is located is still a factor that plays a role and should be evaluated.

Using circuit monitors for activation of interventions away from the source did not lead to significant improvement in the exposure, although it led to increased energy consumption by activating intervention faster compared to signals from PM sensors. Considering integrated $PM_{2.5}$ concentration, energy consumption and response time, the control of intervention's operation can be achieved with $PM_{2.5}$ signals.

3.4. Energy consumption analysis

The PM-activated stove hood algorithm's median operation duration was 28 min (Fig. 4). Per cooking event, this consumed 0.119 kWh of electrical energy during the operation alongside the energy consumed by the HVAC system maintaining the temperature in the space. On an annual basis, the PM-activated stove

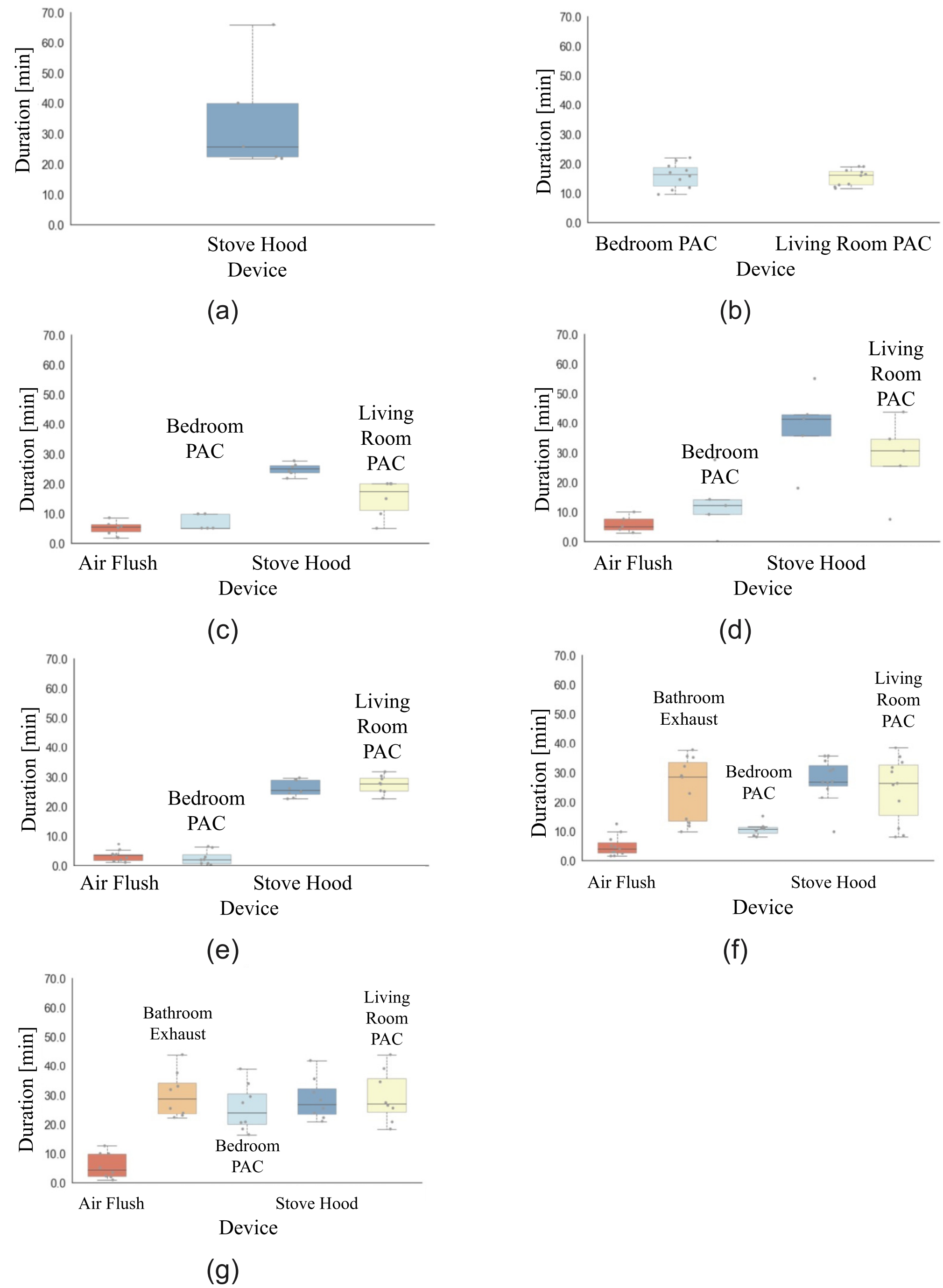

Fig. 4. Average operation times for interventions under (a) PM-activated stove hood, (b) PM-activated PACs, (c) PM-activated ALL; (d) Circuit monitor-activated stove hood; (e) Circuit monitor-activated stove hood and PAC; (f) Circuit monitor-activated ALL; (g) Circuit monitor-improved.

hood algorithm for mitigating cooking emissions would consume 86.9 kWh of electrical energy.

For the PM-activated PACs algorithm, each PAC worked for 18 min (Fig. 4), making the total working period 36 min and total electrical energy consuming 0.054 kWh per cooking event or 39.42 kWh annually.

For the PM-activated ALL algorithm, PAC in the living room worked for 20 min, PAC in the bedroom worked for 8 min, stove hood worked for 28 min in the kitchen, and Air Flush worked for 5 min (Fig. 4). This is in a total working period of 61 min in all spaces. When we compare operation time with PM-activated stove hood, PM-activated PACs and PM-activated ALL, results show that corresponding devices (stove hood or PACs) are active for a shorter period. Still, the total period of operation is longer. Total electrical energy consumption per cooking event was 0.304 kWh or 221.9 kWh annually.

For the circuit monitor-activated stove hood algorithm, PAC in the living room worked for 35 min while PAC in the bedroom worked for 15 min, jointly consuming 0.075 kWh of electrical energy. The stove hood worked for 46 min, consuming 0.1955 kWh of electrical energy. Air Flushed worked for 5 min, consuming 0.143 kWh (Fig. 4). This is, in total, 101 min of operation and 0.4135 kWh of electrical energy consumption per cooking event or 301.9 kWh annually. Total operation time was increased when circuit monitor signals activated the stove hood. This led to an increase in electrical energy consumption.

For the circuit monitor-activated stove hood and PAC, results in Fig. 4 show that PAC in the living room worked for 30 min, and PAC in the bedroom worked for 5 min, consuming 0.052 kWh of electrical energy. The stove hood works for 30 min and, during that time, consumes 0.127 kWh. Air Flush operated for 5 min consuming 0.143 kWh (Fig. 4). This control algorithm employed interventions for 70 min, consuming 0.322 kWh of electrical energy per cooking event or 235.1 kWh annually.

For the circuit monitor-activated ALL, the stove hood operates for 30 min and, during that time, consumes 0.127 kWh of electrical energy per cooking event. The PAC in the living room operates for 30 min, and the PAC in the bedroom works for 12 min, consuming a total of 0.063 kWh per cooking event. The bathroom exhaust worked for 30 min, consuming 0.0025 kWh per cooking event. Air Flush worked for 5 min (Fig. 4), consuming 0.143 kWh of electrical energy per cooking event. The total operation time of this algorithm is 107 min, and it consumes 0.3355 kWh of electrical energy per cooking event, or 244.9 kWh annually.

For the circuit monitor-improved algorithm, each intervention worked for 30 min (Fig. 4). The total operation time for this algorithm is 120 min, and the electrical energy consumption is 0.363 kWh of electrical energy per cooking event or 265 kWh. When results for this algorithm are compared to the circuit monitor-activated ALL algorithm, we can see that the improved off switch resulted in longer operation time overall but smaller electrical energy consumption.

The stove hood operated for the most prolonged period in all developed control algorithms. PAC in the living room worked for the second most extended period among all interventions. This is the expected result because operation time is correlated to the proximity to the emission source. When the control algorithm activated all interventions based on the circuit monitor signal and used a modified off procedure, all interventions worked for $\sim$30 min. This pattern is different from other control algorithms where operation time was correlated to the proximity to the source of particles.

If we compare control algorithms from the total energy consumption perspective, using two PACs consumes the least amount of electrical energy (39.42 kWh annually) (Table 1). If we evaluate the PM-activated PACs algorithm from the air pollution reduction vs. energy used perspective using the ratio between integrated $PM_{2.5}$ concentration and electrical energy consumed, it shows the best result (398.15 $\mu g/m^3/kWh$) (Table 1). PM-activated stove hood algorithm reduces integrated $PM_{2.5}$ concentration the most and consumes the second lowest amount of electrical energy (Table 1). This algorithm is also the second most energy efficient because it consumes 164.45 $\mu g/m^3/kWh$ (Table 1). The algorithm that activates stove hood and PACs with the signal from the circuit monitor consumes the most electrical energy, 265 kWh annually (Table 1), and is the most energy inefficient with the mass concentration reduction to energy consumption ratio of 51.028 $\mu g/m^3/kWh$.

4. Discussion

Additional electricity consumption and associated air pollution control costs are important considerations when implementing energy efficiency paradigms in residential dwellings. Xiang et al. [56] studied energy consumption and estimated that $\sim$5 kWh monthly or 60 kWh annually of electrical energy is needed to operate a PAC in a continuous mode (automation based on the signals from the integrated particle sensor). An additional annual cost of electricity to operate PAC is $5.55. Lugue and Singer [57], in the study on stove hood energy use, suggested that the average USA household would spend less than an additional $15 annually on electrical energy for manually operated stove hoods to control cooking emissions. In the current study, the algorithm most comparable to the Lugue and Singer [57] study is the PM-activated Stove Hood which would create an additional cost of $12.2, or on the opposite end, the most energy-intensive control algorithm is the circuit monitor-activated stove hood, which would cost an additional $42.5 annually. Additional annual energy costs are negligible for PM-activated PACs, and they can be considered insignificant for other algorithms considering the reduction or removal of odor, the reduction of exposure, and potential health impacts.

An ecosystem consisting of IoT environmental sensors and IoT-enabled devices for air pollution control decouples thermal from air quality control. In a decoupled system, each of the setpoints can be achieved independently. This gives significant flexibility in operation that coupled systems don't have. If equivalent air pollution control can only be achieved by increasing the air supply, then air pollution control can lead to substantial energy savings. This is especially important in very humid climate zones or climate zones with very cold winters. For example, if the air is filtered locally, that does not impact the thermal environment, and there is no need to compensate with another control action. Another significant advantage from the system perspective is scalability and the ability to easily retrofit existing homes and enable the decoupling of thermal and air quality control. Only a supply of electrical energy is required to operate a standalone PAC. With a PAC cost between $200 and $900 per device [58], additional PACs can be considered a significant low-cost retrofit. The ducted stove hood costs between $200 and $400, with installation estimated at $100 to $1000 [59], totaling from $300 to $1400. Although it's more expensive and labor-intensive, it still falls within low-cost retrofits. IoT sensors for environmental monitoring cost $200 - $500 annually and require minimal installation, similar to PACs. As a system, PACs and stove hoods can be considered scalable, low-cost interventions.

Operational cost represents the last component of the total cost. IoT sensors need re-calibration; yearly sensor replacement is usually included in the annual package. PAC requires filter replacement. The yearly filter replacement cost is between $90 and $175 [58]. The stove hood filter needs replacement every 1–3 months [60] with the price between $11 to $35 per filter [61]. Considering the first cost, installation cost, operating and additional energy cost compared to the effectiveness in reducing exposure to $PM_{2.5}$, an ecosystem of IoT environmental sensors and IoT-enabled air quality interventions should be part of every smart, healthy home.

Although the current study focuses on mitigating cooking-emitted particles, the principles depicted here can be used for other pollutant sources. For example, PACs are effective Field [44], and automated operating PACs can keep indoor air clean in extreme pollution events such as the spread of wildfire smoke. Most residential dwellings have operable windows. Windows with linear actuators can be automated and play a role in diluting cooking emissions. We did not study the impact on operable windows, which is one of the strategies we should consider in the follow-up study.

The control algorithms we developed detect an increase of particle concentration beyond the specified threshold and activated stove hood (exhaust flow), PAC (supply clean air delivery), bathroom exhaust (exhaust flow), and increasing centralized HVAC system air supply. All interventions were operated only at one setpoint condition. Further refinement of cooking-emitted air pollution control should include modulation of operation intensity as a function of the pollution level in the space. This will be a subsequent phase of the control algorithm development alongside considering only stove hood and PAC for decoupled indoor air quality control.

Technology developed in this study with some modifications can be applied in commercial kitchens. Instead of open loop control, close loop control can be used, and extraction rates of the stove hoods can be modulated based on PM2.5 levels measured in commercial kitchens. This would be an effective protection for cooks in commercial kitchens. Besides advanced control of stove hoods, supplemental activation of portable air filters would reduce the exposure of workers who are not directly involved with cooking.

The current study aimed to minimize particle exposure to occupants with energy consumption as a secondary aspect. Lawrence Berkeley National Laboratory, for example, developed the Residential Integrated Ventilation-Energy Controller [62], designed to save energy while maintaining the same levels of exposure as a constant air supply. These are two different concepts, and while energy consumption reduction has obvious benefits starting from a lowering of the operational cost to reducing the carbon footprint, reduction of exposure still needs further research to understand to what degree acute and chronic exposure needs to be reduced to improve health outcomes.

5. Limitations

The pollution reduction examination took place in the 1-bedroom residential module with a floor area of 36.2 m^2. This space is small, and to have exposure reduction estimation for a more comprehensive set of floor plans, we will have to repeat our study in different apartment configurations and sizes.

In the current study, our cooking protocol consisted only of bacon frying. We chose this cooking protocol because it emits many particles. We are currently conducting experiments in which we cook multiple dishes so we can examine system operation for different emission levels.

The doors of all the spaces were open during the experiments. When control algorithms developed in the current study are applied in the occupied environment configuration of the space might change. Work by Liu et al. [5] shows the variation of integrated concentration as a function of space configuration, which might influence pollution control's effectiveness.

Developed control operated based on the arbitrarily chosen concentration values that trigger and turn off interventions. To avoid turning the interventions off and then being caused by the delay in particle dispersion, three consecutive values had to be below the threshold to turn interventions off. This approach worked well in the small apartment but might need further refinement for a more robust response.

Since this is the first study that develops and assesses the effectiveness of IoT automated air pollution control ecosystem, we focused only on open loop control and adopted one $PM_{2.5}$ threshold for activating all the air quality interventions we used. One of the study's objectives was to compare the performance of one vs. complete ecosystem of interventions and different methods of intervention activation. In the future, we plan to develop a more sophisticated air quality closed-loop control algorithm that considers a threshold and a slope of the $PM_{2.5}$ change.

The IoT network worked without disruptions during our experiments, and our evaluation reflects that. IoT networks usually encounter disruptions, and since this is an episodic effect, some of the events may be missed in the filed application. We will explore this aspect in a follow-up study.

6. Conclusion

This is the first study that demonstrates how an ecosystem of IoT-enabled devices and sensors can be effectively used to control air pollution emitted during cooking at a negligible additional energy expense. IoT sensor consisted of $PM_{2.5}$ sensors and a circuit monitor for tracking the stove's on/off status. Control algorithms operate a single or a system of air pollution interventions developed to reduce exposure to cooking-generated particles. We designed and tested seven algorithms in this study and benchmarked them against the temperature setpoint-controlled CAV air supply. By using this approach, we decoupled thermal and air pollution control. Decoupled thermal and indoor air quality control provide additional flexibility in residential settings.

Based on the results presented in the study, we can derive the following conclusions:

- Compared to the air temperature setpoint-controlled CAV air supply, the ecosystem of IoT sensors and IoT-enabled stove hood, PAC, and bathroom exhaust operated by air pollution control algorithms produce significant improvements in indoor air quality during cooking. Reduction of integrated $PM_{2.5}$ concentration ranged from 81% to 94% compared to air temperature setpoint-controlled CAV air supply.
- Cooking-emitted pollution was effectively controlled by activating a stove hood or a combination of stove hood and other interventions, producing a $PM_{2.5}$-integrated concentration reduction of ~90% compared to the CAV baseline. From the electrical energy consumption standpoint, additional electrical energy necessary to reduce exposure to cooking emitted particles ranges from 221.9 kWh to 265 kWh annually. From the exposure reduction standpoint, $PM_{2.5}$, automated stove hood is the second-best control algorithm consuming an additional 221.9 kWh of electrical energy annually. Combinations of stove hood and other interventions were also effective but did not produce statistically significant integrated $PM_{2.5}$ concentration reduction compared to stove hood alone.
- Sensors for PM monitoring must be mounted on the stove hood to produce effective operation. If sensors for stove hood activation are in some other locations within the kitchen, they will lead to a delayed activation, potentially reducing particle capture. The results of different spaces in the WLL residential unit show that location is less critical.
- From the energy standpoint, PM-activated PACs are the most efficient consuming an additional 39.42 kWh of electrical energy annually, with an annual cost of $5.55. Although PACs are not the most effective from the exposure reduction perspective in addition to energy efficiency, PACs are stand-alone and scalable so that they can be implemented as a straightforward retrofit in residential buildings.
- Using a circuit monitor for air pollution intervention activation did not significantly improve the exposure. However, it increased energy consumption by activating intervention faster than particle sensor signals. Considering integrated $PM_{2.5}$ concentration, energy consumption, and how quickly interventions are started, results show that particle sensor signals can control all interventions.

A demonstrated ecosystem of IoT sensors and IoT-enabled devices should be a feature in every home to make it smart and healthy at a small additional energy cost.

Data availability

Data will be made available on request.

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.

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