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Air-19: Reliable monitoring of air quality and microorganisms in postpandemic municipality building

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Abstract Nowadays, the link between air pollution and covid-19 is proven beyond doubt in the literature with key pollutants being particulate matter and CO_2. Our team has been involved in the development of reliable air quality sensing devices using low-cost sensors measuring particulate matter, differential pressure, humidity, and temperature. We have developed a new measuring device, that detects with high reliability CO, CO_2, humidity, and temperature but also viruses in ambient air. The new architecture consumes less power and supports the integration of industrial CO_2 sensors operating at 12 to 24 volts and using the industrial 4-20mA protocol. Furthermore, five novel near-real-time indices were developed to model risks that endanger public health indoors: a) risk of infection, b) ventilation efficiency, c) aggregated exposure d) AQI and e) congestion. Real-time data streams from six devices (three PM ones and three C2O2O ones, in pairs) that were deployed at a municipality building in the center of Athens, Greece, during a 5-month-long pilot application were used for the indices calculation also generating real-time warnings. Results show that congestion exceeds the limits frequently in the cashier area on the third floor during visitor hours while outdoor pollutants penetrate indoors from a busy road.

Keywords: low-cost sensors, infection risk, aggregated exposure, ventilation efficiency, middleware

1. Introduction

Recent developments link covid-19 to poor air quality. The authors of [2] found that when the daily concentration of PM2.5 rises above 50ug/m3, the number of cases doubles while [1] reports that during long term exposure, even 1ug/m^3 raise in daily concentration of PM10 leads to an 8% increase in mortality rate with 98% confidence level. Le Quere et al. [3] mentioned that although before Covid-19 pandemic, the emissions of CO_2 were increasing by about 1% in a yearly basis [4], the day-to-day global CO_2 releases, was decreased by -17% by April 2020 (vs 2019). On the other hand, indoor emissions such as VOCs were found to have grown by 30% during the first lockdown. The above issues make reliable measurement and control of air pollution a priority in the policy making agenda.

Low-cost sensor technology[15], low-noise electronics, low-power communication, real-time processing, analytics and AI allow for the measurement of air pollution ad hoc and in great spatio-temporal resolution [5], which is required for advanced processing and analytics functions, such as the estimation of aggregated exposure.

Poorly ventilated indoor spaces pose a risk for airborne transmission of SARS-CoV-2. The work of [6] showed that improving ventilation rate to levels with CO2 <1000 ppm was independently associated with a 97% decrease in the incidence of TB among contacts while [7] measured CO2 levels in a multiple areas in an acute care hospital to assess the adequacy of ventilation and proposed a limit of 800ppm. Although CO2 concentrations have been proposed as a metric of infection risk by CDC in the USA, REHVA in Europe and EMG/SPI-B in the UK, they constitute only one strategy that should be implemented together with other CDC recommendations[8]. CO2 sensors provide absolute concentration readings in parts per million (ppm), which is indicative of the occupancy [9,10]. However, reliably correlating CO2 levels with the actual occupancy is difficult due to the high variability and second, high latency of the CO2 sensor responses while uncertainties in the estimation errors have been reported in several cases.

Historical PM2.5 exposures are positively associated with higher county-level COVID-19 mortality rates [1]. While it may be acceptable for individuals to be exposed to a higher concentration of certain pollutants for a short time, this may not be the case in the long run. Because of that pollution thresholds may vary between different time scales; Average measurement benchmarks for 1-hour, 8-hour, and 24-hour intervals provide more accurate air quality data, which in turn allows individuals and governments to make better health and safety decisions.

This work addresses the above issues by implementing an end-to-end sensor-driven air quality and infection risk estimation approach based on a) a novel reliable real-time CO2 and CO sensing device that uses low-cost sensor technology, b) novel indices that combine a ventilation strategy, an infection factor based on average daily concentration and an estimator of occupancy using a simple HMM modelling approach that also provides a theoretical bound in estimation uncertainty.

2.1. Experiment

The Liossion 22 building was built in the 70s; it is located between two very busy roads with a lot of traffic. It offers services such as council tax payment and licensing outdoor drinking and dining. Apart from its large number of employees/public servants, it accommodates on a daily basis a large number of visitors that want to use the above services. As a result, congestion is often noted especially at the beginning at the end of the month when payments are due. A wireless sensor network comprising of six air quality devices for monitoring reliably particulate matter, CO_2, CO, humidity and temperature was installed in three selected locations/spatial zones in the building for monitoring air quality. These were:

* the ground floor public entrance,

* the 2nd floor council tax service

* the 3rd floor checkout / cashier's office area.

In order for the devices to communicate with the cloud a Virtual Private Network was installed on top of a dedicated IOT Wi-Fi network. This was required as the public Wi-Fi network is targeted to visitors and only supports one-hour long sessions before disconnecting the visitor. A pair of a PM device [14] and a C2O2O device were mounted on the ceiling in each location covering both the open office space and the adjacent public visitor area.

2. Device architecture

C2O2O is a new device developed for the needs of the project that measures CO, CO_2, humidity by integrating the CO B4 sensor, the NDIR A1-IRC sensor (measures both CO_2 and temperature) and the RHI120A sensor, respectively. The range of CO_2 is 0-5000ppm while for CO it is 0-1000ppm. Both sensors have a response time <30sec from 0 to 10ppm and very low noise (ppb equivalent). Both sensors are pre-calibrated and come with a certification as well as a calibration sheet. RHI120 measures humidity in the 10-90% range with +-3% computing board connected to a low power microprocessor which is in turn connected to a 16-bit ADC. A 24V-5V Step down DC-DC converter powers all components from a 24V DC power source. Sensor boards integrate supporting circuits for the sensors. Both the motherboard and the sensor are integrated in a single printed circuit board. The device also integrates real-time embedded software that continuously collects measurements and communicates them to the cloud. First, measurements are collected from the sensor at a once per second rate (1Hz). Next, they they are calibrated by applying the corrections provided in the calibration sheets and then they are aggregated in batches of 60 by applying an average function that gets rid of peaks. Last they are communicated to a timeseries database [12] in the cloud where they are visualized in dashboards and trigger the calculation of indices and alerts.

3. Indices

Five new indices providing estimates of air quality related risk were developed: a) risk of infection, b) ventilation efficiency, c) aggregated exposure d) AQI and e) congestion. In order to cater for the large volume, velocity and variability of the measurements, a data stream approach using the InfluxDB[11] query language was used to calculate four of the indices. Each raw timeseries, was converted to a real-time data stream using a 48-hour rolling window. Then the data were grouped by a desirable interval while a (running) aggregation function was applied to the group to create an aggregated data stream. Next, in many cases, mathematical conditions linking members of the aggregated data stream to thresholds were defined along with alerts that evaluate each condition every 1 minute. If a condition is breached the alert goes into a pending state. If the alert is pending for longer than 5min it becomes a firing alert issuing visual (and email) notifications. *No-data* and *error handling* alerts were also defined. Congestion was estimated using a modeling technique based on Markov models as only estimates of the number of people present in the room during working hours was known.

3.1. risk of infection

Literature reports that whenever the PM10 daily average *exceeded the 50ug/m^{3,}* the risk of infection from covid-19 doubled [2]. Based on this, and as indoor air is between 2 and 10 times worse than outdoor air and can get up to 100 times worse, a data stream of PM daily average values for each monitored location was constructed over a 48h window:

$$SELECT\ mean\ (\text{"PM10"})\ FROM\ PMDataS\ WHERE\ time > now - 2d\ GROUP\ BY\ time(24h)\ ORDER\ BY\ time\ desc;$$

Query A: PM10 daily average data stream in InfluxQL

whenever the most recent value exceeded the 50ug/m^3 threshold a *high risk of infection alert* is triggered.

$$WHEN\ last(\,)\ OF\ Query\ A\ IS\ ABOVE\ 50$$
$$evaluate\ every\ 1m\ for\ 5m$$

Condition A: Conditions of alert rule using Query A in Grafana

3.2. ventilation efficiency

Literature reports that when *CO_2* concentration rises above 600 ppm stronger ventilation is required to mitigate the risk of infection from airborne diseases such as tuberculosis [6]. In the scope of this work, two alert levels were defined**.** A "*poor ventilation*" alert is triggered whenever *the most recent value of the CO_2 one minute average timeseries is higher than 600 ppm* while a "*critical ventilation*" alert is triggered when CO_2 exceeds 800 ppm [7].

$$SELECT\ mean\ (\text{"}CO_2\text{"})\ FROM\ CO_2Data\ WHERE\ time > now - 2d\ GROUP\ BY\ time(1m)\ ORDER\ BY\ time\ desc;$$

Query B: CO_2 1min average data stream

$$WHEN\ last(\,)\ OF\ Query\ B\ IS\ ABOVE\ 600$$
$$evaluate\ every\ 1m\ for\ 5m$$

Condition B: Conditions of alert rule using Query B

3.3. Aggregated exposure to PM2.5

Literature reports that whenever the 24h-aggregated exposure to ambient PM2.5 rises by 1% the covid-19 infection risk doubles [1]. The raw PM2.5 measurements can be summarised at the monitoring intervals, and compared in real time with desired limits to calculate the actual exposure of workers (E) in the time period (T) from the relationship:

$$E = \frac{1}{T} \sum_j \int_0^j C_j dt_j$$

Equation 1: Aggregated exposure

where C_j the time-varying concentration in the microenvironment and t_j the time spent in that microenvironment. Because public building occupants rarely exceed 8-hour-long stays, 24h, 4h and 8h exposure was calculated in order to approximate more closely visitor and employee daily occupancy, respectively. The value of exposure is equal to the area under the curve of *Equation 1*. A four-hour average of 1min averages of each pollutant was multiplied by 240 (the number of minutes in 4 hours) to approximate the 4h-exposure and similarly for the 8h and 24h ones.

```
SELECT 240 * mean("PM1.0")
into one_min_avg_1st_floor FROM PMData
WHERE time < (now − 4h) GROUP BY time(1m)
order by time desc;
SELECT mean("mean") FROM one_min_avg_1st_floor
WHERE time < (now − 4h) GROUP BY time(4h)
```

Queries C,D : 4H-exposure to PM1.0 at the 1st floor

The results were visualised in Grafana with line charts.

3.4. AQI

Government stations usually report a moving average of pollution levels from the last 24 hours. The overall air quality index for a certain timeframe is then based on the worst air quality index rating for the individual pollutants. Similarly to above, 4hAQI variants were implemented for each pollutant based on moving averages summarized over 4h intervals. The results were visualised in Grafana with gauge charts. The following alert thresholds were set based either on legislation, AQI standards[13], guidelines [8] or on the distribution of observations:

PM1.0, PM2.5: [0,12.5], (12.5, 25], (25, 50],>51.

PM10: [0 to 50], (50, 150], (150, 250],>250.

CO: [0, 5], (5,9],(9,15],(15,30], >30

T(C): [0 to 26], (26, 30], (30, 35],>35.

RH(%):[0 to 30], (30, 50], (50, 70], >70.

3.5. Congestion

To model CO_2 fluctuations over time and associate them with human occupancy information, two Markov Models were developed that consist of three states - "equal," "plus," and "minus". The “plus” state is reached when the CO_2 concentration is increased in two consecutive data points, the minus state is the opposite. For the definition of the “equal” state, first the datasets were pre-processed and summarized with respect to the variance [16] and average values. These were analyzed to determine possible CO_2 ranges in which, the change in occupancy would be considered insignificant. The first model represents a 3x3 table of transition probabilities when the office is occupied, while the second model, when it is unoccupied. The models are trained using hourly sensor data extracted from the pilot dataset, in the range 8am to 3pm EET, each corresponding to either an occupied or unoccupied space.

4. Results

The following conclusions can be drawn from the monitoring so far (mid-April 2022 - today):

Increased carbon dioxide concentration > 800 ppm during the public visiting hours in the 3rd floor. More specifically, the threshold of poor ventilation is exceeded instantaneously many times in the period from 8am to 2pm especially towards the end of the month, while at the beginning of the week it is also increased.This can be observed also from the microparticles and CO.

Sharp changes in carbon monoxide between 2 - 4 ppm (significant indication of indoor smoking, although within limits). At the tills (3rd floor) spikes often coincide with the start and end of the shift, while at the 2nd floor they also occur at other times of the day, almost every two hours.

Good pollution levels on the ground floor (an indication of good ventilation combined with the transient movement of visitors to other floors)

Rather high levels of carbon monoxide (and carbon dioxide) and particulate matter at night on both floors (a significant indication of the presence of openings that allow outdoor pollutants to penetrate the building.)

On public holidays concentrations are stable at very low levels. In August the concentrations are lower than in September. On weekends when there is no human presence both the 2nd and 3rd floor devices record the same picture.

The daily cycle of all pollutant concentrations includes an increase during the night, a reduction during the day and a subsequent increase in the afternoon.

Occupancy can be predicted with over 97% accuracy, from 9am to 2pm, and with over 95% accuracy, from 8am to 9am and from 2pm to 3pm. Furthermore, indicative graphs of the estimation error in, show that it is promising as an indicator of changes in occupancy, such as those that incur during arrival (between 8am and 9am) and departure from the workplace (between 2pm and 3pm)

5. Conclusions

The indices defined in this paper provide a good indication of both air quality and hygiene conditions in public buildings. However more attention is needed where thresholds are not defined by legislation. Furthermore, due to the real-time elements that are inherent in the monitoring process, our system can be used as a decision support system for predicting user presence with hourly granularity.

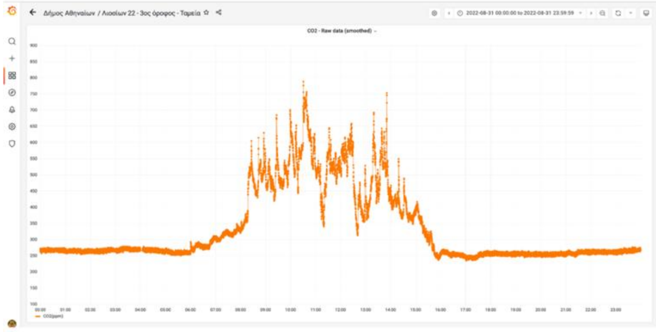

Figure 1. Critical ventilation conditions at the Cashier area during visiting hours

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