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Indoor Air Quality (IIAQ) and Infection Probability Rate (IPR): Developing better spread risk models

A practical approach to asses the risk of airborne disease with sensors

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Impact Statement

The Covid-19 pandemic has changed the perception of society about different aspects of life.

Human perception of air quality is subjective. Many gasses are odorless. We can only perceive the air quality by factors such as difficult breathing, lack of concentration or headaches.

Carbon dioxide concentrations have been pointed out as the best expression to monitor the air quality indoors.

This paper has further developed the existing infection risk models going one step beyond, taking into account the concentration of Aerosols and other relevant risk factors.

Some specific impacts from this study are:

1) Developing a new indoor specific Air Quality Index (IIAQ) using a simple multiple polynomial algorithm.
2) Developing a new airborne Infection Probability Rate index (IPR) using a modified Wells-Riley model.
3) Develop from scratch a practical sensor device that measures air variables and delivers real-time IIAQ and IPR indexes
4) Learning from air data: Analyzing the air quality in real indoor case study scenarios and generate recommendations to minimize airborne spread disease risks.
5) Using an on-the-cloud server to store data providing air quality traceability to public places.

Abstract

The development and future use of two new indexes related to the risk of airborne disease propagation are proposed in this paper: Indoor Air Quality Index (IIAQ) and Infection Probability Rate (IPR)

Research published up-to-date takes into account mainly Carbon Dioxide concentrations. The authors have implemented the IIAQ and IRP indexes taking into additional factors such as the concentration of aerosols and other environmental variables such as occupancy and voice sound pressure level in the room.

This paper is partially inspired by the recent works by Martin Z. Bazant et al, where the risks of airborne disease infection such as Covid-19 were evaluated.

That previous research was based on the CO_2 concentrations measured by an NDIR gas sensor.

Nonetheless, the authors expressed that the risks were also dependent on other factors such as the concentration of aerosols, the speech sound pressure level produced by occupants, and the occupancy rate itself. However, no device to quantify and include those variables on the risk assessment was proposed on the mentioned work.

The purpose of this paper is to follow the findings by Martin Z. Bazant et al. and develop a practical air quality monitoring device design that evaluates:

- IIAQ or Indoor Air Quality Index. A new IAQ index created by the authors
- IPR or Infection Probability Rate. A new concept derived from the Wells-Riley model

The Wells-Riley model is used by Martin Z. Bazant et al. and other previous work (Chung Min Liao et al. and Freja Nordsiek et al) The model was further developed to include additional variables beyond the CO_2 concentration.

Background

Six months after the first wave of the SARS Cov2 coronavirus that causes the disease called Covid-19, the authors started to read research articles and white papers regarding the possibility that the Covid-19 was a disease primarily spread by airborne contagion. [17]

As it happened with other imported viral outbreaks from the far east (such as H1N1 in 2009 and the Middle East Respiratory Syndrome (MERS-CoV) in 2012), the SARS Cov2 is primarily spread by airborne contagion and has been passed through different countries by passengers in public transportation such as trains and airplanes. [1],[2],[11]

The disease was also spread thereafter in Restaurants, cruise ships, and health care centers around the globe. [14]

Back in 2005 Chung-Ming Liao Chao-Fang Chang and Huan-Min Liang from the National Taiwan University in Taipei published a paper [3] " A probabilistic transmission dynamic model to assess indoor airborne infection risks" where the Wells-Riley mathematical model has used the estimate the relationship between the carbon dioxide (CO_2) concentration in a "well-mixed" indoor environment and the inhalation of airborne viral loads.

In this work, the authors established that just one SARS1 infected person will generate an average of 2.6 secondary cases by airborne transmission in indoor places where medium to high concentrations of carbon dioxide gas (CO_2) are registered.

In February 2009 Tse To and Chao, working with the Department of the Mechanical Engineering of the University of science and technology in Honk-Kong, published an interesting paper [4] "Review and comparison between the Wells-Riley and dose-response approaches to risk assessment of infectious respiratory diseases"

In this paper, the spatial distribution of airborne pathogens is discussed for the risk assessment of respiratory disease transmission. The Wells-Riley model and dose-response models are compared to get the best approach for particular conditions.

By 2020 the concerns about airborne spread disease threats to human health such as the COVID-19 triggered the publication of several important papers on the subject in Europe and the US.

In November 2020 Freja Nordisek, Eberhard Bodenschattz, and Gholamhossein Bagheri from the Max Plank Institute in Germany, The Institute of dynamics University of Gottingen, also In Germany and the Cornell University in N.Y, USA published a paper [7] "Risk assessment for airborne disease transmission by Poly-pathogen aerosols" where new approaches to the use of the Wells-Riley model where discussed taking into account new facts such as the filtering by the individuals while breathing, which may become significant in poorly ventilated indoor environments showing high occupancy.

In April 2021 Martin Z. Bazant et al. from the MIT in Cambridge, Massachusetts published a paper [1],[2] "Monitoring carbon dioxide to quantify the risk of indoor air transmission of COVID-19" where the approach of monitoring the carbon dioxide concentration in indoor spaces was taken as the main computation factor regarding the possible spread of airborne transmitted disease.

An improved mathematical model was proposed in that paper from real-time carbon dioxide (CO_2) measurements. Also other factors affecting airborne infection were suggested (such as Aerosols and optionally measuring the voice Sound Pressure Level and Room Occupancy Monitoring).

However, these new factors were not taken into account in the real-time sensor device proposed in the April 2021 paper by Bazant [2]. These new variables were only reflected in an online model calculator published as a webpage. You can check the static model published by Bazant on this link:

https://indoor-covid-safety.herokuapp.com/

Reason for further development

As mentioned, over the past decade most of the interest about the risk of air-borne infection was focused to the Far East.

MERS and H1N1 among other viral infections put the scientific community in China under the stress of developing models on how to assess the risk of infection.

Over the last two years that stress was passed to the western world. The COVID-19 pandemic has shut down the economy in many countries for months creating a huge economic loss and burden to governments, businesses and the average citizen.

There is an evident increasing interest of the western scientific community into developing models for the prevention of airborne diseases in mind. The end of the mandatory mask wearing in public places over the year 2022 in Europe and the U.S. is also of major concern without additional measures to monitor the airborne infection risk.

Definitions

Infectious dose can be defined as the amount of virus necessary to establish an infection.

Depending on the virus, people exposed to as few as ten virus particles could become infected. This happens for example with the influenza virus.

In other infections, it is necessary to inhale thousands of virus particles for a human being to become infected.

Pathogen size Coronaviruses are very small particles (about 70-100 nm), these pathogens float in the air carried by aerosols measuring between 1 and up to 400 μm and are involuntarily inhaled.

Viral load refers to the number of viral particles found in each milliliter sampled from an infected patient.

In the case of Covid-19 and as an example, when taking a sample from an infected person, the viral load is an expression of the number of viral genomes that are detected in a nasopharyngeal swab, taken from a patient.

Aggravation of risks. Another common question is whether receiving a higher dose of virus, for example through prolonged exposure to an infected person, will lead to more serious illness. There are indications that a high viral load may be an important factor. Then exposure time is also a factor considering the computation of risks. [15]

PART 1 Defining the variables and sensors available

Measuring the CO_2 and its relationship with airborne viral load

Carbon dioxide levels outdoors range from the low 400 ppm to 450 ppm. As the combustion of oxygen happens by breathing, the carbon dioxide (CO2) levels rise. That is true for any indoor environment whether is properly ventilated or not.

Lack of ventilation heavily rises the CO2 levels, so carbon dioxide concentrations are a good measure of the air renovation rate in indoor spaces.

CO2 is an odorless gas, that at medium to high rates (1200-2500 ppm and up) provides a feeling of stale air, gathering symptoms such as lack of concentration, difficult breathing, or headache. In such the CO2 and except in very high concentrations (well over 2500 ppm) it's not dangerous or life-threatening.

For those non-familiar with the subject, we want to clarify that high CO2 levels do not gather any inhalation of airborne viral loads per-se. CO2 is just a variable related to airborne infection risks. The higher the carbon dioxide ppm concentration, the poorer is the indoor air renovation.

Today is undiscussed that there is a correlation between the airborne viral load and the levels of carbon dioxide indoors. [15]

The CO2 levels will be measured using a non dispersive infrared (NDIR) transducer that is sensible to CO2 has high selectivity to other gases and VOCs.

Aerosols and its relationship with airborne viral load

Airborne spread infection happens because there are aerosols that transport viral loads. There are many case studies regarding the importance of aerosols in the COVID-19 infection spread. [7],[8],[9],[10]

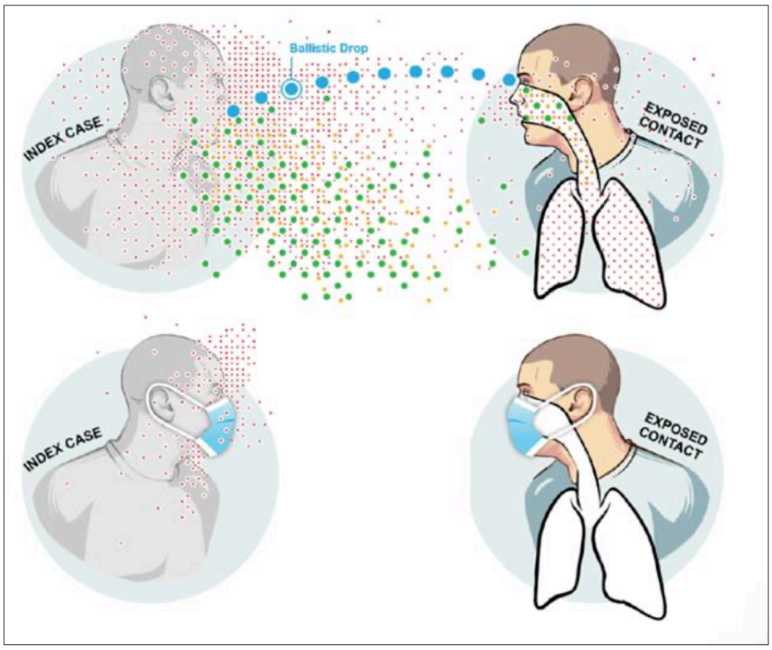
Well-known cases include the Diamond Princess cruise outbreak where thousands of passengers were infected by Covid-19 during the first wave. Many of those passengers never shared the same facilities such as restaurants, toilets, or bars. So, it was evident that the only spread possibility was the ship's HVAC, and that the infection was transmitted airborne.

Different cases were reported in China in buses, airplanes, and restaurants, where the aerosols were reported to play a dominant role in the spread of infection. [16]

The importance of aerosols in the prevention of the spread of COVID-19 is the base of the requirement for the use of face masks to confine the wet particulate aerosols created by normal breathing and talking.

When the air is not renovated, aerosols accumulate over time. As the concentration of aerosols increases, and in the presence of an infected individual; a certain viral load is built-up over time in the indoor air.

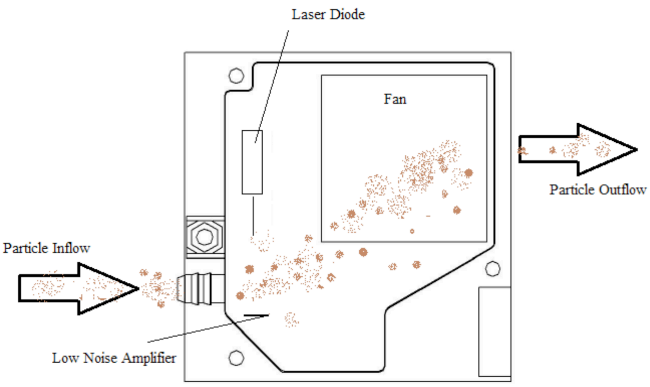
Aerosol behavior and size were studied in a paper written by Milton (Ncbi, October 2020). In this paper [5], aerosol particulate matter was measured and reported to spread in sizes between 100 μm (some drops larger) and as small as 5 μm and below.

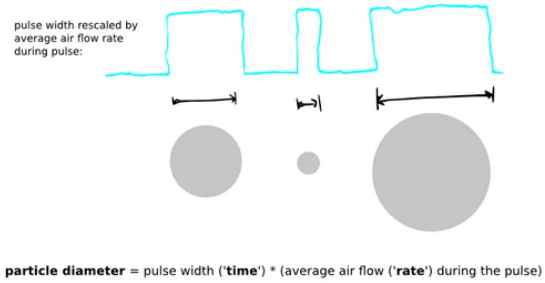


Source : Milton (Oct 2020, NCBI) A Rosetta Stone for Understanding Infectious Drops

Measuring Aerosols

A particulate matter sensor works by optically measuring the particles using a small Laser and an optical detector by measuring the reflectivity of the particles, the amount of different sizes can be easily evaluated by measuring the timing on the reflection effect as shown in the image below.





Indoor air without particulate matter is a clean air. Clean air doesn't hold any significant viral load.

SARS Cov2 coronavirus is reported to be only 70 to 100 nm in size. What we can measure is the aerosols that contain and carry the viral load.

Our research team decided on the implementation of a high-end particulate matter transducer for the sensor device project. This new sensor has to show enough sensitivity and selectivity to detect, classify and quantify particles in the air by size.

The idea was to evaluate the aerosols measured as particulate matter and include this new variable into the airborne disease risk calculations with a broader perspective.

The rationale here was that clean air with no floating aerosols means that there is low risk of infection. This happens even if the carbon dioxide concentration is high.

Clean air (Particulate free) and stale air (renovated with outdoor air) are two different concepts

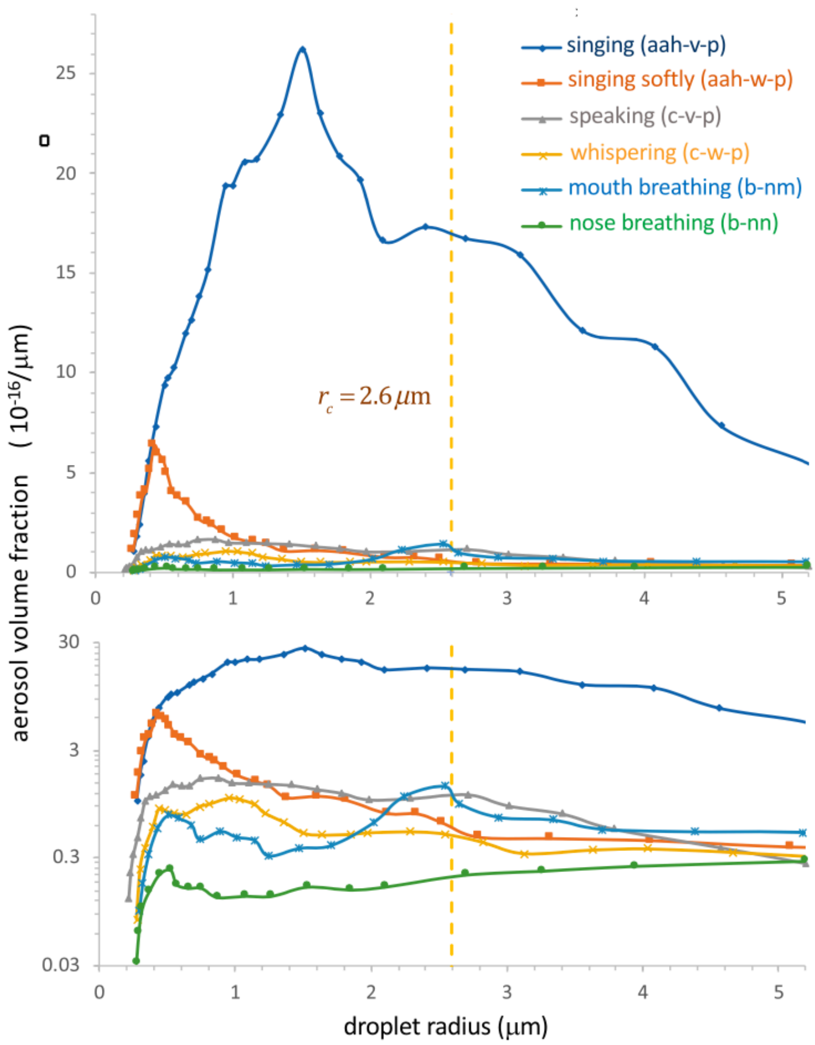
Clean air = No aerosols
Stale air = No air renovation

The idea is to separate these two different variables in the computation of IIAQ (Indoor Air Quality Index) and the IPR (infection Probability Rate).

Measuring sound pressure level

The paper [2] of Martin Z. Bazant et al, was an eye-opener to us regarding the importance of voice sound level and the airborne disease spread probability. We have learned from their work, that there is a vast difference between the number of droplets that are produced among different speech events.

Speaking softly can produce just a fraction of the droplets emitted with other events such as loud voices or singing. The graph below reproduced from his work details the average droplet size in micrometers while monitoring Sound Pressure Level (SPL) at different events.



Martin Z. Bazant et al. (DOI.org March2021) "A guideline to limit indoor airborne transmission of Covid-19"

According to Martin Z. Bazant et al [1] "*A guideline to limit indoor airborne transmission of Covid-19, April 2021"* there is a high correlation between how loud is the people in the room, and the amount of aerosols concentration while performing different activities, from singing to normal, relaxed nose breathing.

So it looks like it's not only important to measure the amount of particulate matter floating on the air as aerosols but also measuring the amount of noise created by the people while speaking, as that is a factor that aggravates the risk of airborne infection spread.

After studying the Bazant et al aerosols graph, it becomes evident that measuring with a sensor the sound pressure level of the place under monitoring makes a lot of sense.

According to the study, the infection probably rate (IPR) will be much higher in a noisy place where people are talking loud.

Another lesson from the Bazant et al graph is the high risk involved in some musical events. For example, a pop concert where people usually dance, shout, and sing. We have no doubt that music shows and mass public demonstrations produce a really bad combination of events, that multiplies the possibility of airborne disease spread.

An important fact is that the SPL sensor design will have to include some pre-processing, because background noise and other sound events such as traffic noise, construction noise, etc, will be otherwise counted as an aggravation source while they are not.

Our team has designed such a pre-processing algorithm that takes into account the voice-related signal only,

Subtracting the background and mechanical noises that are not human-produced by the articulation of voice.

The audio algorithm detects the voice levels by differentiating background noise and repetitive noise using FFT (Fast Fourier Transform).

Measuring occupancy

Occupancy is one of the airborne spread factors mentioned by Martin Z. Bazant et al in their last paper [2].

Measuring the occupancy is not difficult today, due to the availability of millimeter-wave sensors that have been developed to be used as radar for unattended vehicles.

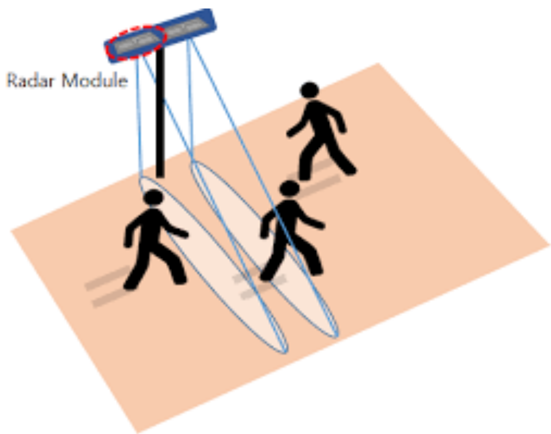
However, it was found over the research, that the occupancy could also be calculated from the carbon dioxide concentration if the conditions are known.

If the air renovation rate is known, there is a correlation between the carbon dioxide concentration and the number of people breathing in a certain place. That was proven to be a certain fact by the authors monitoring the air quality data from the cloud storage I places such as restaurants.

However, it is true that in certain circumstances when the air renovation depends on different factors, other than the HVAC (like opening doors or windows) measuring the occupancy using a millimeter-wave sensor might help to create a better model. Higher occupancies lead to a higher risk of infection.

So the final decision to include or not a radar millimeter-wave sensor to calculate the occupancy of a certain place depends on the final desired application.

It is an optional sensor that can help to improve the infection risk evaluation depending on the facilities available such as the HVAC and the architectural characteristics (window openings for natural ventilation, etc)...



PART 2 Development of the Algorithms

Air Quality Index is an outdoors figure

The Air Quality Index (AQI) is being used not only by the scientific community but also by government agencies to communicate to the public how polluted the air is.

Different countries have their own air quality indices, corresponding to different national air quality standards.

AQI	Air Pollution Level	Air Pollution Category	Health Implications
0–50	Level 1	Excellent (好极了)	No health implications.
51–100	Level 2	Good (良好)	Some pollutants may slightly affect very few hypersensitive individuals.
101–150	Level 3	Lightly Polluted (輕度污染)	Healthy people may experience slight irritations and sensitive individuals will be slightly affected to a larger extent.
151–200	Level 4	Moderately Polluted (中度污染)	Sensitive individuals will experience more serious conditions. The hearts and respiratory systems of healthy people may be affected.
201–300	Level 5	Heavily Polluted (重度污染)	Healthy people will commonly show symptoms. People with respiratory or heart diseases will be significantly affected and will experience reduced endurance in activities.
>300	Level 6	Severely Polluted (嚴重)	Healthy people will experience reduced endurance in activities and may also show noticeably strong symptoms. Other illnesses may be triggered in healthy people. Elders and the sick should remain indoors and avoid exercise. Healthy individuals should avoid outdoor activities.

The air quality index refers to the outdoors only. It takes into account the concentration of gases from combustion among other factors, that illustrates how good or bad the air is, with a single figure.

From the different AQI yardsticks available, the Chinese AQI that ranges from 0 to 500 is the most widely index used worldwide and it is now accepted in Europe and the US. It is being used in AQI sensors devices to show the Air Quality at Glance.

Development of an indoor specific Air Quality Index (IIAQ)

However, the problem indoors is quite different. The existing outdoors AQI includes into the computation of the index the presence of gases such as nitrogen oxide and sulfur dioxide.

These gases are related to the combustion in the presence of air and are also related to the cycles of Nitrogen Oxides (NOx) and the creation of Ozone (O3) through natural or human-induced combustion.

The problem that the authors were facing, was how to express the Indoor Air Quality as a separate index where the combustion gases are not relevant for computation of the index, but as a measure of the infection spread risks.

The concentration of carbon dioxide has been discussed thoroughly as the main indication of unhealthy air. Many paper research publications have put emphasis on that fact.

High concentrations of carbon dioxide are directly related to the poor renovation of air, mostly produced by the recirculation in HVAC systems to improve energy efficiency.

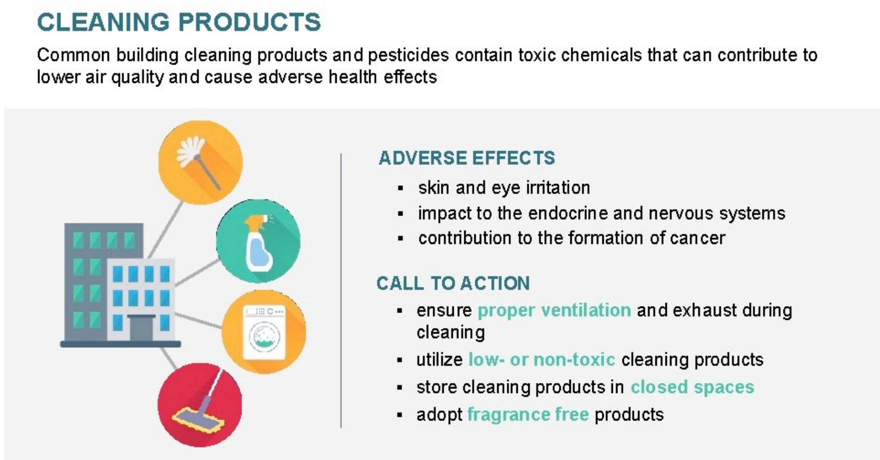
It was obvious that a new indoor AQI index definition was needed. Our newly developed IIAQ (Indoor air quality index) takes into account carbon dioxide concentration and particulate matter volumetric ratios as the two main factors to express the quality of the environment experience indoors.

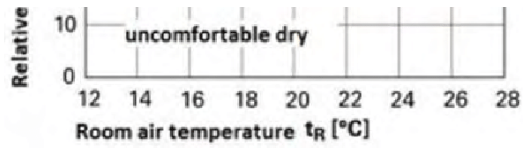
We were thinking about schools, malls, offices, public buildings, hospitals, etc.

Two months after the first tests with real data from the prototype sensors, a correction was done into the early version of the IIAQ algorithm, taking now into account (but mildly) the temperature and humidity values measured from the sensors (see graph).

Our consideration was that the feeling indoors is also mildly related to a comfort zone that is the right combination of temperature and humidity.

The last factor that was includes was the presence of solvents. To detect Total Volatile Organic Compounds (TVOC) a dedicated wide-band TVOC solid-state transducer was included in the sensor device.





TVOC transducers detect the presence of solvents (ammonia, ethanol, methanol, formaldehyde, acetone, and others) and are everywhere today in cleaning products. TVOC Emissions also come from furniture, electronics, and decoration materials such as flooring laminates.

Developing the IIAQ algorithm

As a summary four factors and different weights were considered in the computation of the new IIAQ

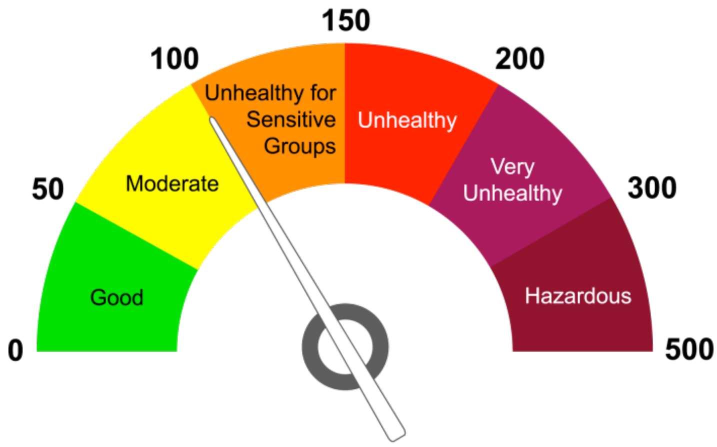
- Carbon dioxide concentration (45%)
- Particulate matter (40%),
- Temperature - humidity comfort zone (10%)
- TVOC (5%).

IIAQ was then expressed by a multiple variable (CO2, PM,T-H, TVOC) polynomial formula as follows:

IIAQ=(CO2 ppm (map 440,2500/0,100) x 0.45 + PM $\mu g/m^3$ (map 0,200/0,100) x 0.40 + TH (map 18,26/0,100) x 0.05 + (map 35,70/0,100) x 0.5) x 0.05 + TVOC (map 0,2000/0,100) x 0.05)

Where the expression map refers to a C/C++ linear mapping method between sensor variable values (V init, V final/0,100), in order to express the minimum and maximum values (from heterogeneous variables such as ppm or $\mu g/m^3$ as a 0-100 ratio.

The quality range was set from 0 to 500, similar to the Chinese outdoors model that is widely used all over the world.



An IIAQ index from 0 to 50 shows an optimum quality of indoor air where carbon dioxide concentrations are low. In this scenario also low volumetric concentrations of particulate matter (PM) are measured denoting excellent indoor air quality.

Optimal Temperature 18-25^{o}C and humidity 35-70% range, makes the environment healthy and comfortable These factors are combined as a unique figure and weighed all together, to correct the IIAQ.

A higher IIAQ measurement, from 50 to 100, expresses a higher concentration of carbon dioxide and particulate matter in the weighted proportions as computed by the algorithm. Showing less healthy indoor air.

IIAQ index over 100/150 warn that something has to be corrected.

The model created for the indoor air quality index was tested in real conditions. The Air Quality Sensor module prototypes that include the new IIAQ index were installed in schools, hospitals, restaurants, and other public places in Spain.

The algorithm was further improved by mid-2021 while at the same time we started the definition of our proposal to the INNO4COV-19 H2020 European Project to develop a more complex indoor air quality trend index called Infection Probability Rate or IPR.

Infection Probability Rate (IPR)

The development of an algorithm call Infection Probability Rate or IPR was one of the innovative proposals included in a researcher's project awarded to the authors from the INNO4COV-19 European Cascade Funding Instrument.

The Infection Probability Rate (IPR) proposal was to create a model going far beyond the indoor air quality index (IIAQ). The previously mentioned algorithm that was already working in air quality sensor prototypes and delivering relevant information to the authors and the sensor device users.

The indoor air quality index (IIAQ) described in this paper doesn't take time as a variable into consideration.

Time-lapse in an unhealthy air environment [18] is an essential variable in assessing the risk of infection.

The longer a subject spends on a confined space where indoor air quality is poor, the higher is the risk and the probability of acquiring an airborne infection, such as Covid-19. [18]

Therefore, the factors to be computed while developing an infection probability rate (IPR) index are:

- Carbon dioxide (CO_2) concentrations are expressed as a risk following the works by Martin Z. Bazant et al and others [1] [2] [7] [8] [13].
- Aerosols volume measured as Particulate Matter (PM) concentrations expressed as the increased risk triggered by the presence of droplets in sizes from 1μm to >10μm following the publication by Milton (Oct 2020, NCBI) [5]
- Human voice produced Sound Pressure Levels (SPL) expressed as the aggravation of the risk triggered by people talking loud that produce a logarithmic increase in droplet production from normal breathing following Martin Z. Bazant. [2]
- Occupancy (OCC) of the room assessed from CO_2 concentrations with an algorithm. If the room conditions are known, using a radar mm-wave sensor as an optional measure for better accuracy. [2]
- Time (Tm): Time lapsed in minutes with rising CO_2 and PM concentrations. How long has the room been with high levels of CO_2 and high volumetric concentrations of Aerosols? Are the levels rising over time without corrective action? (HVAC, natural ventilation, etc…) This variable was taken into account by numerous authors. [18]

Developing the Infection Probability Rate (IPR)

The Wells–Riley equation provides a simple and quick assessment of the infection risk of airborne transmissible diseases. For the development of the IPR algorithm we take this model as a starting point. The Wells–Riley equation can be derived as follows:

$$P_i = 1 - e^{-\frac{Ipqt}{Q}} \quad (1)$$

Where:

P_i is the probability a person becomes infected,
I is the number of infectors,
p is the breathing rate per person (m^3 / s),
q is the quantum generation rate by an infected person (quanta/s),
t is the total exposure time (s) and
Q is the ventilation rate (m^3 / s).

A quantum is defined as the number of infectious airborne particles required to infect the person, indeed not every droplet/aerosol that is inhaled will lead to an infection.

For this project, we have assumed that the exposure to one quantum of infection gives an average probability of 63% of becoming infected.

To be able to derive Equation (1) Wells and Riley made two main assumptions:

- The infectious particles are assumed to be randomly distributed throughout the air of confined spaces, thus the pathogen is distributed uniformly throughout. (Well mixed environment)

- The quantum concentration and the outdoor air supply rate (ventilation rate) remain constant with time (steady-state conditions). That assumption simplifies the model.

Using CO2, Particulate Matter (PM) concentrations, and other parameters measured by our prototype sensor allows the formulation of a mathematical model (called IPR - Infection Probability Rate) that does not require the assumption of steady-state conditions and will show dynamically and in real-time the probability of airborne spread disease.

CO2 concentrations

Rudnick and Milton [8] postulate that from the total CO_2 contained in the air indoors, a portion comes from human origin, and the rest enters the room outdoors. They formulate the the fraction of re-breathed air *f* as

$$f = \frac{C - C_0}{C_a} \quad (2)$$

where
C is the measured CO_2,
C_0 is the outdoor CO_2 levels and
C_a is the concentration of CO_2 added to exhaled breath during breathing.

Rudnick and Milton [8] also assume that the rate of breathing remains constant during short-duration exposures making C_a a constant equals 0.038.

Within most indoor spaces human breathing is the dominant rising source of CO2, so we can assume that the portion of CO_2 that enters the room from outdoors is negligible compared to the portion of CO_2 created by human breathing.

Following the assumption. We can express the fraction of rebreathed air *f* as follows

$$f = \frac{C}{C_a} = \frac{C}{0.038} \tag{3}$$

This equation provides, at any instant, a good estimate of the fraction of exhaled breath that an inhaled breath contains. For the total exposure period, the time-weighted fraction of indoor air that is exhaled breath can then be computed easily by integrating f over time
and dividing by the elapsed time.

We integrate (3) into (1) considering that the breathing rate per person (p) is as potentially harmful as the fraction of exhaled breath that its inhaled breath contains.

$$IPR = 1 - e^{-\frac{Ipfq}{Q}t} = 1 - e^{-\frac{IpCq}{0.038Q}t} \tag{4}$$

Ventilation rate

In the Wells-Riley model, the ventilation rate Q is a constant parameter used to calculate the probability of infection in a well-mixed environment and steady conditions.

Indeed if the ventilation rate is higher, more clean outdoor air enters the room and so the probability of infection decreases. The ventilation rate is the air-change rate relative to the volume of the space and is calculated as:

$$Q = \frac{air\ change\ rate \times room\ volume}{3600} \tag{5}$$

Room volume (m^3) is a known value as we know the dimensions of the room where the device is being installed. The air change rate is defined as how many times we ventilate the room in an hour. This value is not constant, some places are being ventilated 10 times per hour, others 2 times per hour.

Q is a variable in a real environment not a constant. But to simplify our model we are going to assume that each room is going to be ventilated at a constant air change rate.

The prototype sensor can detect when we start ventilating the room. Indeed, by measuring the CO2 in real-time we can immediately that the air renovation is happening

So the development of an iterative algorithm that, depending on the number of times the room has been ventilated in the previous 30 minutes dynamically predicts the value of Q during the following 30 minutes time period.

So integrating this feature to our IPR model (4) we have:

$$IPR = 1 - e^{-ICkqt} \tag{6}$$

where $k = \frac{p}{0.038Q}$, and Q is a constant calculated ad-hoc for each place where the sensor device is installed.

Sound Pressure Level

With this sensor, we want to take into consideration the impact of vocalization (articulation) intensity on the virus quantum generation rate. Following the research by Matin L. Bazant et al. and as shown by [9] and [10] the emission rate of micron-scale respiratory aerosol particles strongly correlates with the loudness of speech.

From the research of [11] we can obtain the average particle emission rate depending on vocalization intensity L_p, the fraction of time the infected individual is vocalizing (ϕ) and, the expiratory particle emission rates for breathing and vocalization ($\widehat{N_{br}}$ and $\widehat{N_{voc}}$):

$$N = (1-\phi)\widehat{N_{br}} + \phi\widehat{N_{voc}}(\frac{L_p + 25}{105})^{10.6} \tag{7}$$

The estimation presented before (7) was made for a single individual speaking. In our IPR model, we take into account the sound pressure level of a whole indoor place, not only a person speaking, so we can make the following assumptions:

- $\widehat{N_{br}} << \widehat{N_{voc}}$: the breathing parameters are going to be many orders of magnitude below the vocalization parameters
- $\phi = 1$: for our model, we can assume that at all times an individual will be vocalizing
- $\widehat{N_{voc}}$: is a constant that can be overrun as it doesn't have that much impact on the total value

With these assumptions, we can derive the average particle emission rate depending on vocalization intensity Lp as:

$$N = (\frac{L_p + 25}{105})^{10.6} \tag{8}$$

And moreover

$$N = L_p^{'} + N^{'} \tag{9}$$

where N' is the constant element from equation (8) but applied to our use case, as well as L'_p.
With this equation we can conclude that the louder the place is, the more particles are being emitted in the air. The q, that is the quantum generation rate by an infected person from equation (1) is proportional to the average particle emission rate. So we can derive the IPR model as:

$$IPR = 1 - e^{-ICkq(L+N^{'})t} \tag{10}$$

PM concentrations correcting the CO2 level calculated risk: Air cleanliness as factor

As mentioned before in this paper, clean air with no floating aerosols means that there is little risk of infection. So in a certain indoor environment even if the carbon dioxide is high due to poor air renovation, if the Particulate matter count is very low, the probability of infection is still low, and the opposite relationship is also true.

A paper proposed by the Italian Society of Environmental Medicine (SIMA) considers Particulate matter (aerosols) as an important carrier contributing to the spread of COVID-19 [12]. This paper found a direct relationship between the number of persons infected by COVID-19 and the PM_{10} concentration levels due to the PM_{10} pollution being able to serve as the carrier of viral load and other pathogens.

So it is necessary to introduce a correction factor (β) in our model:

$$IPR = 1 - e^{-ICkq(L+N^{'})\beta t} \quad (11)$$

The particulate matter sensor installed in our device detects four different particles: PM1, PM2.5, PM4 and, PM10. The correction factor (β) applied to the IPR model changes depending on the PM distribution and concentrations measured during the prototype tests.

Final IPR equation

The IPR model is finally derived as

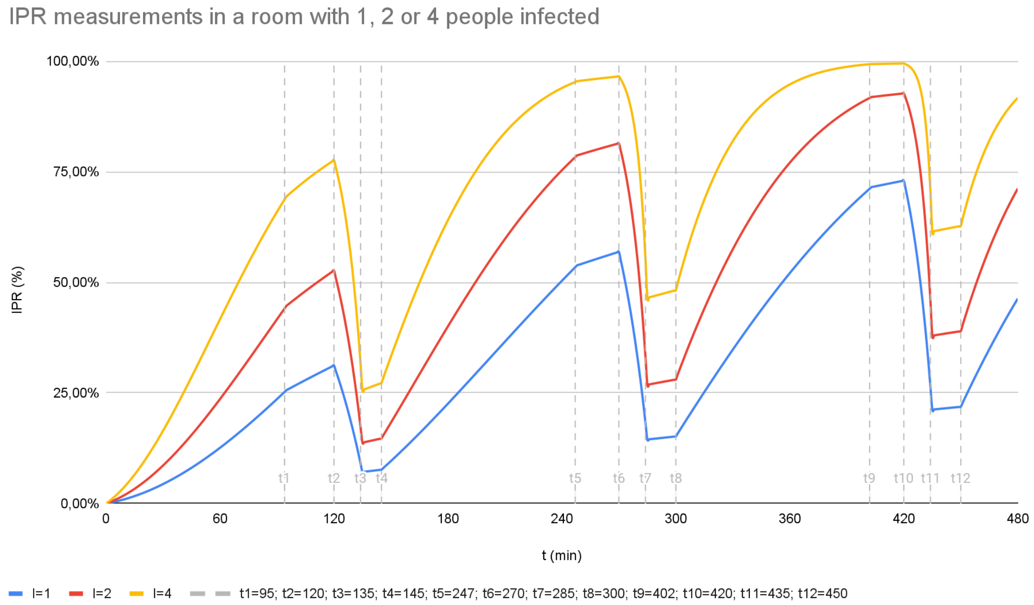
$$IPR = 1 - e^{-ICkq(L+N^{'})\beta t} \quad (12)$$

where
C is the CO_2 concentration measured by our sensor,
L is the sound pressure level measured by our sensor and
β is the correction factor applied using the PM measurements.

IPR is expressed in % from 0 to 100 where:

- 0% < IPR < 30% means low risk of infection
- 30% < IPR < 50% means moderate risk of infection
- 50% < IPR < 70% means high risk of infection
- 70% < IPR < 100% means extreme risk of infection

Below a graph with the IPR measurements for a room during an 8 hour period is shown.



GRAPHS SHOWING IPR EVOLUTION OVER TIME (SIMULATED VENTILATION ACTION)

The previous figure shows how IPR varies according to different situations that are common in indoor environments. For easy comparison, the timed events are the same, but the results are applied to 1 infected person (blue line), 2 infected people (red line), or 4 infected people (yellow line). An in-deep explanation follows:

- At t = 0 an infected person enters the room
- From t = 0 to t_1 = 95, the room is closed, no HVAC, no air renovation. The variables measured by the sensor prototype device build-up. In particular the CO2 concentration and the PM concentration. This causes the probability of infection (IPR) to also increase exponentially. This should trigger an alert to apply corrective actions!
- From t_1 = 95 and t_2= 120, the room is still closed with no ventilation. The variables measured by our device are topping up. The IPR is still rising because the exposure time-lapse is still counting, but it rises with a lower slope.
- From t_2=120 to t_3 = 135, the room is being ventilated for 15 minutes. We can see how the IPR drastically drops to even more than a half. The probability of infection doesn't reach 0 because the corrective actions (in this case ventilating) are not perfect. There is still a lot of stale air in the room.
- From t_3=135 to t_4 = 145, the room is still being ventilated. The variables measured by our sensor prototype device reach their minimum. The IPR starts to rise slowly for the same reason as between t_1 and t_2, time is increasing.
- At t_4 = 145, we stop the ventilation, we can see that the IPR starts to rise exponentially again.
- The same behavior is repeated periodically. At t_6 = 270 and t_{10} = 420 to illustrate a common HVAC cycle.

The IPR measurements shown in the graph take into account that an infected person enters at t=0 and that this is when the increase in the probability of infection begins for the rest of the people in the room. For each person that enters a room at a time t and leaves at t', his probability of infection is the time integral of the IPR:

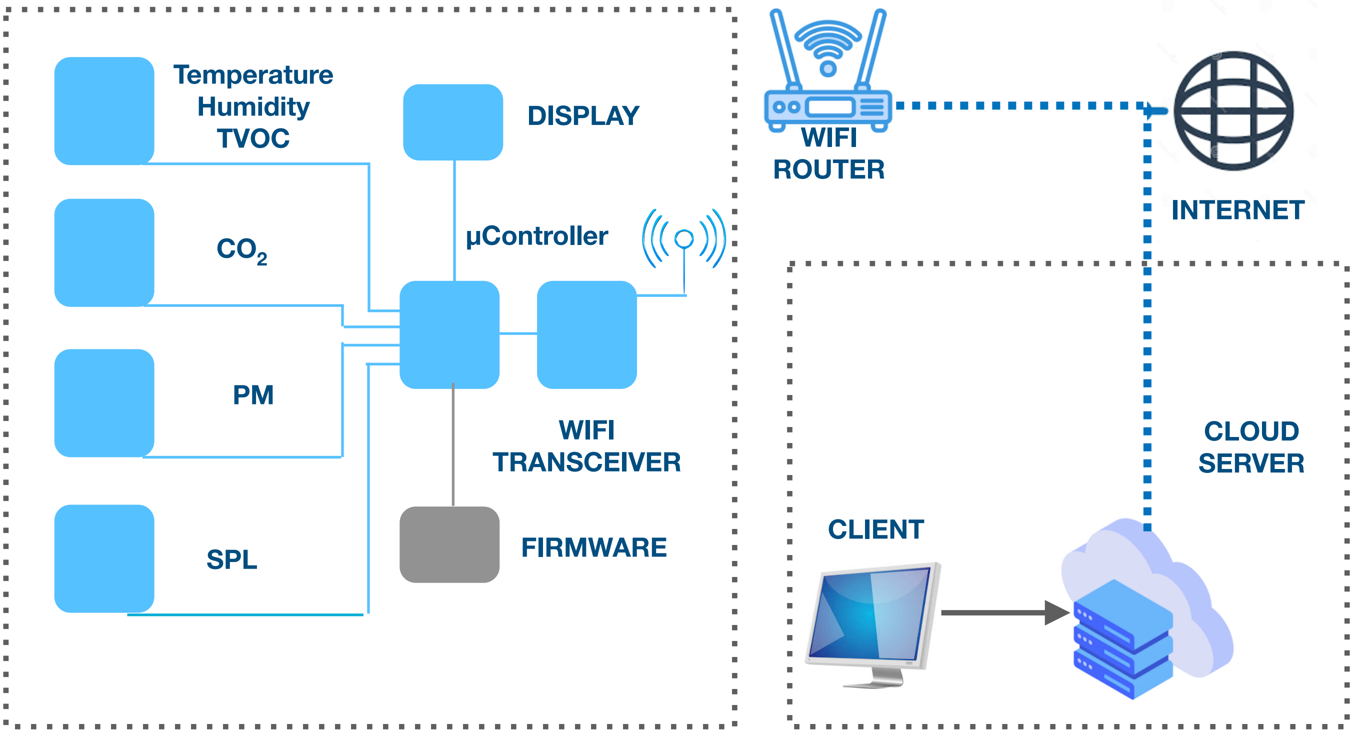
$$IPR_{person} = \int_{t_{in}}^{t_{out}} 1 - e^{-ICkq(L+N')\beta t} \delta t \qquad (13)$$

As an example, the calculation for the IPR of 2 people is shown below. Two persons enter the room at different moments, and stay in the room for a period of time. This equation is applied to Figure X.

	t_{in} (min)	**t_{out} (min)**	**IPR_{person} (%)**
Person A	240	300	41,1
Person B	285	330	21,47

Developing the sensor prototype device PM

The image is showing the general layout of the sensor design. The core of the system is a 32 bits micro-controller connected to a Wi-Fi transceiver.



SENSOR DEVICE GENERAL LAYOUT INCLUDES SERVER SIDE (RIGHT)

Hardware

Several serial ports from the micro-controller connect the transducers or sensors.

CO2, Particulate Mater, TVOC, Temperature, and Humidity sensors provide real-time data about concentration levels that are used in conjunction with algorithms to evaluate the risks related to the indoor air quality (IIAQ) and the infection probability rate (IPR)

The micro-controller polls the data each second updating the value of each air quality variable in real-time. An air pump system is included in the design. This device avoids the problems related to the stratification of gases while avoiding turbulence-free airflow to the sensors.

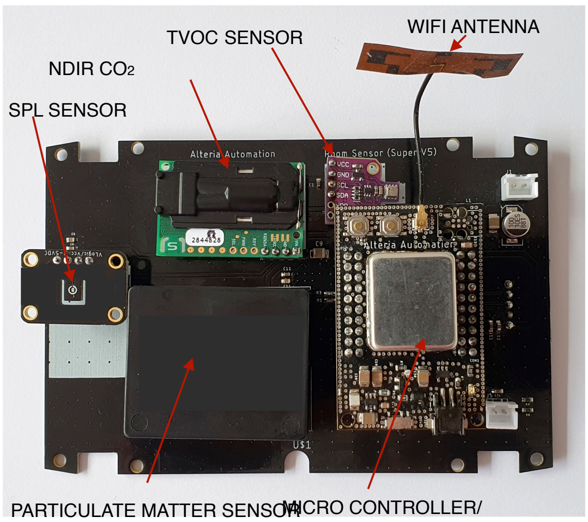


IMAGE OF ONE OF THE SEVERAL SENSOR DEVICE PCB PROTOTYPES BUILT

Firmware

The logic was written in C/C++ using RTOS (Real-Time Operating System). The data fed from the sensors is parsed, creating a string that is transmitted using Wi-Fi connectivity via TCP/IP.

Server

The data string is then organized before feeding the database using a JSON declarative language.

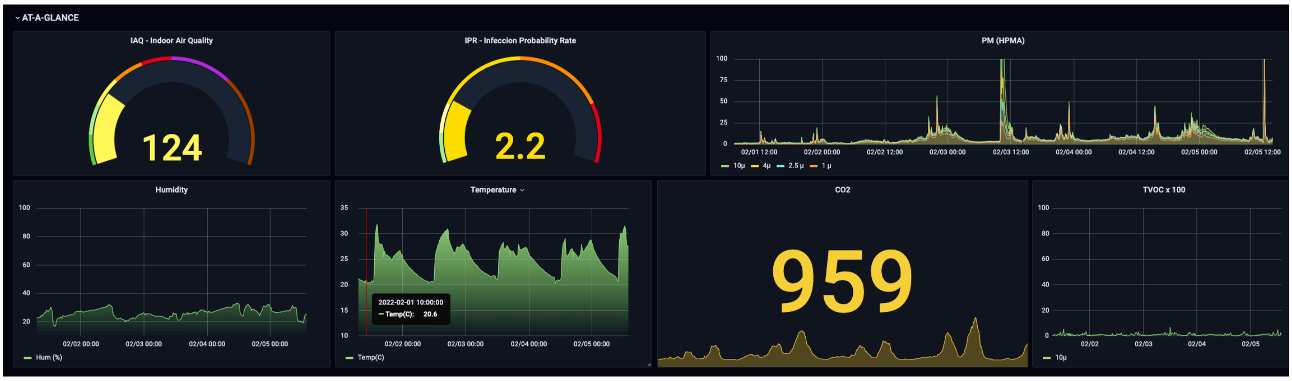
A non-SQL database is used to store the data. Non-SQL type databases offer a better search speed while providing historian reports when the amount of data stored is huge such in this case. The data is secured by installing an SSL certificate on the server.

Client

An agnostic client set-up was used from the beginning. The data stored in the database can be searched from any password-authorized device. A smartphone, computer, or tablet using any O.S. can be used for this purpose.

A GUI (graphic user interface) is used to visualize the data. GRAFANA is used in the first application but other apps such as TABLEAU can be used to provide further statistical analysis.

Below, we show an at-a-Glance data visualization using GRAFANA from a restaurant for a period of 4 days.



COMBINED DATA VIEWER AT-A-GLANCE

This at-a-glance view shows the principal values and two algorithms (Indoor IAQ & IPR) for instant feedback interpretation.

PART 3 Case Studies

In order to evaluate the success of our approach, we installed the air monitoring sensor system in a restaurant in Madrid, Spain (Case Study 1) and in a public Hospital in Valladolid, Spain (Case Study 2).

Data was monitored for several days.

The information gathered surprised the team members, as the mere visualization of the data lead to important findings.

Case Study 1

Our first case study was a large Restaurant in downtown Madrid, Spain.

The screenshot below shows sensor data from 4 consecutive days of readings.

CASE STUDY 1: DATA VIEWER, BUSY RESTAURANT

With a simple analysis, the following findings are noted:

- High levels of CO2 (top left) denote regular meal times and are directly related to occupancy levels. With this information, we can infer the number of people in the restaurant at a certain time.
- TVOC levels (top right) remain stable with minor increases outside business hours, representing the cleaning of the premises. TVOC levels are affected by disinfectants and cleaning materials.
- Particulate Matter (bottom left) shows very high particulate matter concentration levels that leaked from the kitchen into the dining room of the restaurant. We can clearly see the three highest peaks occurring just before and during lunch timeframe 12:00 to 15:00.
- WIFI coverage (bottom right), is also shown, not an air-related variable that shows optimal connectivity at all times.

In the middle row, IIAQ index and IPR algorithms are shown.

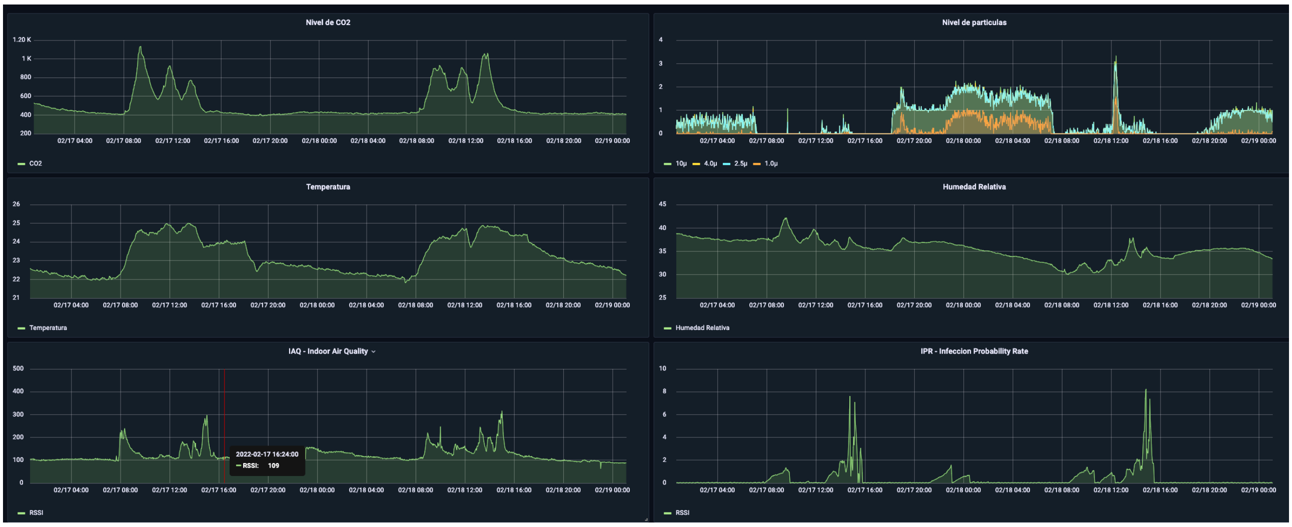
High levels of CO2 and Particulate Matter (PM) quickly rise to a high Infection Probability over time.

We can conclude that the IIAQ and IPR measurements are completely different and complementary in order to assess the Indoor Air Quality and the IPR over time.

Case Study 2

Our second case study was in a rehabilitation section of a Public Hospital in Valladolid, Spain.

The screenshot below shows sensor data from 2 consecutive days of readings.



CASE STUDY 2: DATA VIEWER, HOSPITAL

With a simple at-a-glance analysis, the following findings are noted:

- Moderate levels of CO2 (top left) denote medium occupancy levels. Ventilation can be improved to assure values under 800 ppm as desirable at all times. Improved ventilation will minimize IPR reading exponentially.
- Particulate Matter (top right) shows very low particulate matter concentration levels given the moderate occupancy and low exercise levels. Please note that rehabilitation hospital rooms have passive therapies with low movement. The place looks clean with no dust.
- At the bottom row, IIAQ index and IPR algorithms are shown. Moderate levels of CO2 and low Particulate Matter (PM) accumulated over time results in isolated peaks of the Infection Probability Rate registered during high occupancy time frames.

Summary of General findings

1.- Overall, the concentration of carbon dioxide found (CO2) was much higher than expected in schools, food courts, gyms, and other public places. That revealed outdated HVAC systems, designed with the economy in mind instead of providing clean air to the public.

After checking some installations to get corrective actions with HVAC professionals we have found filters that were never changed or cleaned, providing load loss. We found damaged ducts and malfunctioning impellers.

2.- However, some public indoor environments were much better than we expect. We checked the air quality and the IPR at the Madrid trade show center (IFEMA) where all the air feeding the HVAC units is 100% from outside.

We have also checked the air quality and IPR in the Madrid- METRO underground transport system, where new ventilation units were installed after the first Covid outbreak, surprisingly finding that the air quality and the IPR were excellent at most times.That does not include the trains, that were not monitored.

3.- Including the Particulate Matter (PM) count in the IIAQ and the IPR was found to be relevant. In restaurants, the PM levels were found to be very high denoting poor isolation of the kitchen HVAC system to the dining room, even if there was no cooking smell. The amount of PM in school lunchrooms was found to be excessive at all times, denoting poor isolation and ventilation systems.

4.- The IPR algorithm was found to work well to show unhealthy indoor environments over time something the IIAQ doesn’t do. The risk accumulation rate overtime reveals that with just a 60 minute (and higher) exposure to an unhealthy indoor environment, there is a significant probability to inhale stale air with harmful viral loads.

5.- There is an evident societal demand for clean, healthy air that goes beyond city pollution-related issues that are monitored by existing IAQ standards.

Combustion gases emissions are a certain thread for health. But what we are seeing now is a different thread that is related to indoor environments and the existence airborne spread diseases.

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