Numerical Model for Prediction of Indoor COVID-19 Infection Risk Based on Sensor Data

J Virbulis¹, M Sjomkane¹, M Surovovs¹ and A Jakovics¹

¹Institute of Numerical Modelling, University of Latvia, Riga, Latvia

janis.virbulis@lu.lv

Abstract. In addition to infection with SARS-CoV-2 via direct droplet transmission or contact with contaminated surfaces, infection via aerosol transport is a predominant pathway in indoor environments. The developed numerical model evaluates the risk of a COVID-19 infection in a particular room based on measurements of temperature, humidity, CO₂ and particle concentration, the number of people and instances of speech, coughs and sneezing using a dedicated low-cost sensor system. The model can dynamically provide the predicted risk of infection to the building management system or people in the room. The effect of temperature, humidity and ventilation intensity on the infection risk is shown. Coughing and especially sneezing greatly increase the probability of infection in the room; therefore distinguishing these events is crucial for the applied measurement system.

1. Introduction
Since emerging in Wuhan, China, COVID-19 has killed more than 2.4 million people, infected more than 11 million more and uprooted the life people all over the world once knew. The global roll-out of vaccines does offer some ground for optimism, but many experts believe that COVID-19 is here to stay. It is not yet clear if the vaccines block transmissions and remain effective against newer variants of the virus. Other factors that could potentially drive SARS-COV-2 (the virus that causes COVID-19) circulation in people are an immune escape, waning immunity, uneven vaccine distribution, vaccine hesitancy, animal reservoirs etc. It is believed that SARS COV-2 will likely become endemic, which means that it will continue to circulate in the world and if not contained quickly, it can cause another wave of infections. [1]

SARS COV-2 is transmitted by respiratory droplets [2,3,4]. There are several possible routes for contracting SARS COV-2 - (1) direct transport of droplets exhaled by an infected person to the mouth, nose, or eyes of a person at risk; (2) direct contact of droplets sedimented on surfaces and (3) via aerosol - small droplets that contain virus linger in the air and are then inhaled. The risk of infection is especially high indoors [5,6]. Experimental data have shown SARS COV-2 particles found in ventilation systems [7]. While keeping a safe distance and sanitizing surfaces and hands reduce the routes (1) and (2), aerosol transmission remains the main factor in an indoor environment [8,9].

However, people all over the world are desperate for life to get back to normal and do not always take the precautions suggested by the state [10,11]. To maximise the functionality of society and minimise the infection risks, new solutions are necessary.

Most of the research models compare the benefits of different COVID-19 safety measures regarding the spread of the virus. It was concluded that complete lockdowns and isolating infected
patients would decrease the number of infections the most. These strategies are most effective when combined with contact tracing and group gathering restrictions as well as wearing masks in public [12,13,14]. The impact of COVID-19 on the economy has also been modelled [15] as well as the risks of people with different pre-existing medical conditions getting hospitalized [16,17]. The influence of weather conditions on the virus has been researched and different experiments, as well as models, have been examined to find the safe physical distance to avoid direct SARS COV-2 transmission. As for infection risks indoors, we have found several models to predict the risk of infection with SARS-CoV-2 [18, 19], but only one model that uses carbon dioxide (CO₂) as a proxy [20]. Unlike ours, none of the afore mentioned models calculate the risk factor dynamically as they are not connected to a sensor measurement system run in real-time.

We have built a system of sensors that measures parameters such as temperature, relative humidity (RH), CO₂ concentration, the number of people in the room, particle concentration in the air and others (described in [21]) and a model (described in this article) that determines the risk of infection with COVID-19 for a person in that room.

The sensor systems can be used in auditoriums, offices, public buildings, gyms and other spaces to warn people if the risk of a COVID-19 infection is high and that safety measures should be taken, such as leaving the space or turning up the ventilation capabilities. The sensor systems could be centralized, and automatic monitoring with warning messages could be used (e.g., included in building management systems) to make returning to schools, universities, shops, offices, courts etc. more secure.

2. Infection risk model
The model uses sensor data to evaluate the infection risk for a person in the room. The model is integral and mostly uses the mean parameter values in the room. The key modes of virus transport are illustrated in Figure 1. The expelled droplets (1) lose mass through evaporation (2) and are partially sedimented (3) on the floor. Small particles form an aerosol that can persist for a long time without sedimentation. Virions within the aerosol are transported out of the room via ventilation (4), partially deposited on surfaces (5) and lose viability (6). The droplets and aerosol are inhaled (7) increasing the infection risk of another person.

![Figure 1. A schematic representation of the processes considered in the model](image)

The length, width and height of the room are used for the calculation of volume, surface area and vertical distribution of droplets. The temperature and RH data are taken from the measurement system. The room is also characterized by the total mass of CO₂, the number of small airborne aerosol particles (droplets), the total number of virions in aerosol particles and the number of virions sedimented and
deposited on surfaces (mostly on the floor). The number and size distribution of large droplets in the air is also accounted for in sedimentation, evaporation, and transport calculations.

Droplets of mucus expelled by a potentially infectious person at a certain height through breathing, speech, coughing, and sneezing are characterized by the total amount of expelled liquid, droplet size distribution [22] and virion concentration [23]. The corresponding expelling events are provided to the model by the measurement system analyzing the recorded sound. Droplet evaporation rate depends on temperature and the RH and is modelled as described in [24]. For the evaporating particles, the sedimentation velocity and vertical position are calculated following [25]. When the final size is reached, droplet dynamics are calculated by solving a one-dimensional (vertical room dimension) convection-diffusion equation where convection is described by the sedimentation velocity given above and the diffusion accounts for the turbulent mixing of air in the room. Solving equations for every expelled particle group is not possible in the real-time operational model; therefore, the solution is performed beforehand for all combinations of 16 diameters and 16 turbulent diffusivities. The calculated temporal distributions in the height of 1.2 m are fitted by the least square method using a combination of two exponents and interpolated for any combination of particle diameter and turbulent diffusivity. The turbulent diffusion coefficient is calculated from room volume and ventilation according to [26] or [27]. Deposition of small airborne particles on the surfaces by Brownian diffusion through the laminar boundary layer is calculated according to [28]. If the final droplet diameter is < 5 μm, these particles are assumed airborne and can leave the room only through ventilation or deposition. The effect of ventilation is considered assuming perfect mixing (0D model), the validity of this approach is proved by 3D air flow simulation in Chapter 3.1. The intensity of ventilation is specified if known, otherwise, the ventilation intensity in the model is varied by PID controller so that the measured and calculated CO₂ concentrations are similar. The applicability of the latter approach is demonstrated in Chapter 3.3. The viability of the virus in aerosols and small droplets decreases with time [29]. The person for whom the infection risk is calculated, absorbs between 19% and 95% of inhaled particles depending on their size [30], the effect of wearing a mask is not considered yet but can be added to the model. The risk function (probability of infection) is calculated based on [31], e.g., the probability of infection is 50% when 300 virions have been absorbed. Additionally, an assumption about the virus source is necessary. In this work, it is assumed that the first person in the room is always infected and the infection risk is calculated for the second person. Another method is to apply the prevalence of infection in the population to every person in the room beside the second person.

The model is written in the Python language and is running considerably faster than the real-time on one core of the HPC cluster if a timestep of 0.5 s is used. The most computation time is consumed for the evaporation simulation. The MQTT protocol is used for communicating with the measurement system.

3. Results

3.1 3D air flow simulations

A numerical model of the steady-state airflow in a real room was used for validation of the 0D ventilation model. Transient CO₂ transport was simulated and compared with the 0D model.

A 77.75 m² room was chosen for the modelling, its geometry is depicted in Figure 2. The room has two air inlets, two outlets and some furniture, which was simplified for numerical simulations by omitting irrelevant small details. Standard ventilation rate corresponds to the total volumetric flow rate Q = 120 m³/h or 0.54 Air Change per Hour (ACH). Additionally, calculations with increased ventilation rate Q = 240 m³/h (1.07 ACH) were carried out.

A steady-state incompressible flow of air is considered using standard OpenFOAM solver simpleFoam and k-ω SST turbulence model. The kinematic viscosity v = 1.5 · 10⁻⁵ m²/s, the turbulence intensity of 10% and the mixing length of 3.85 cm are applied at inlets.

The finite element mesh consisting of 7.2 million cells (primarily hexahedral) is generated using OpenFOAM mesh generator snappyHexMesh. The total room air volume is 223.85 m³. About 2000
iterations are required to obtain a steady-state solution, which takes approximately 7 hours of computation on an HPC cluster with 16 cores.

Calculation results with increased ventilation rate in different cross-section planes are shown in Figure 2. The strong jets from the inlets produce a turbulent flow downwards to the floor. Since the cross-section area of the outlets is smaller than that of the inlets, the highest velocity is at the outlets.

Figure 2. Room geometry with calculated velocity in xz and yz cross-sections in case of increased ventilation rate

Transient transport of the CO$_2$ concentration is modelled for a fixed velocity field using a modified OpenFOAM scalar transport solver considering the turbulent diffusion coefficient and sources for the concentration field due to human breathing in user-specified regions. The molecular diffusion coefficient of CO$_2$ in air $D = 1.666 \cdot 10^{-5} \text{ m}^2/\text{s}$, the turbulent Schmidt number of 0.7 is applied. The initial CO$_2$ concentration and the concentration at the inlets is set to 414 ppm.

There are 6 sources of CO$_2$ located 1.2 m above the floor and 2 m apart from each other. It is assumed that each person exhales 28 $\mu$g of CO$_2$ per second, which corresponds to 0.38 ppm/s. Figure 3 shows the iso-surfaces of CO$_2$ concentration field in the air after 100 min in the case of increased ventilation rate. The CO$_2$ concentration is non-uniform and different around each source.

Figure 3. Concentration field in the air at $t = 100$ min after sources turned on in the case of increased ventilation rate. Probe locations that are later used for time-dependent concentration analysis are shown.

The last time instant of the CO$_2$ transport simulation was taken and the concentration sources were turned off, leading to a decrease of the concentration over time. The results are depicted in Figure 4. and show that after disabling CO$_2$ sources, there is a time delay of up to 20 min even with an increased ventilation rate until the concentration starts to change in probe 1. Even though this behavior cannot be described by the 0D model, it predicts the time-dependence of the average concentration rather well and can be used for risk function modelling.
To obtain precise results, large meshes need to be used, and the numerical simulations take considerable time, it makes the presented simulations practically impossible for a real-time modelling. However, the 3D modelling can help to find the most representative place for CO₂ sensor where the measured value is closer to the average value than at the unfavourable location of probe 2 (Figure 4).

3.2 Parameter study for simple scenarios

First, the effects of several model parameters will be demonstrated for a simple scenario when two people (one infected and one healthy) enter a room without any virus contamination. The room size is 3x3x3m, the temperature is 25°C, the RH is 50%, both constant. Different virus expulsion scenarios with continuous breathing and speech, as well as with coughing or sneezing once per minute are investigated. The results are shown in Figure 5-left. The log-scale clearly demonstrates the enormous difference in risk levels depending on the type of virus source. Speaking increases the infection risk roughly tenfold compared to breathing alone. Coughing increases the risk tenfold compared to speaking. Sneezing has the highest associated infection risk that is by an order of magnitude higher than that of coughing. The necessary time for a considerable infection risk (10%) is comparable with the definition of “close contact” – 15 minutes of 2-meter separation.

The effect of virus concentration in the mucus of an infected person on the infection risk is illustrated in Figure 5-right. Three different cases are shown – typical average concentration (50% of tested people exhibit higher values), the upper 20% of infected and upper 5%. Here it is assumed that sneezing occurs once per minute. Staying in a room with a highly infectious person will result in nearly 100% infection probability already after 5 minutes.

The model also reveals the distribution and dynamics of virions within the room. Figure 6-left shows the number of virions in droplets (D>5 μm), aerosol (D<5 μm) and on the surfaces after an infected person (c=10⁸) enters the room and is speaking (speech event is added every 3.5 s). Most virions are contained in droplets, twice as little are sedimented and even fewer are within the aerosol. The effect of RH variations in the above conditions is demonstrated in Figure 6-left. At high RH, fewer virions are within droplets and more are deposited on the floor.
Figure 6-right shows that in the case of coughing once per minute a considerable part of virions are present in droplets ($D>5\ \text{mm}$) and less than 50% are sedimented on surfaces after 1 minute. This is mainly due to turbulent diffusion which counteracts gravitational sedimentation.

![Figure 6](image)

**Figure 6.** Number of virions in room when infected person speaks (left) or coughs once per minute

The effect of ventilation on the probability of infection is shown in Figure 7. If an infected person is coughing regularly once per minute, the infection risk starts to reduce when the ventilation rate goes over 2 ACH with the increase of turbulent diffusion on ventilation rate from [26]. Increased turbulent diffusion reduces the sedimentation and therefore the aerosol concentration grows. At low ventilation rates this effect is stronger than the decrease of concentration due to higher air exchange and only very high ventilation rates reduce the risk considerably. The ventilation rate of $\sim 37$ ACH corresponds to a scenario with a fully open window. However, another research considered the room size and found that ventilation increases turbulent diffusion by a lesser amount [27]. With this turbulent diffusion, the probability of an infection is reduced more strongly at moderate ventilation rates (Figure 7-right). For a more precise parametrization of ventilation, a 3D airflow simulation can be carried out for a room, as shown in Chapter 3.1.

![Figure 7](image)

**Figure 7.** Effect of ventilation and account for turbulent mixing on risk of infection. Left- time dependence using turbulent effect from [27], right – comparison of [27] and [26]

### 3.3 Model results for a room equipped with the measurement system

In this chapter, the prediction of the infection risk in an office with dimensions 7.9x6.2x3.5m equipped with the measurement system is demonstrated. The central ventilation system is similar to the one shown in Figure 2, the unknown and varying ventilation intensity was set to 360 m$^3$/h (2.1 ACH). The simulation was started at midnight and ran for 48 hours. The measured number of persons and CO$_2$ concentration are shown in Figure 8-left together with the simulated CO$_2$ concentration. In Figure 8-right the measured events of sneezing, coughing and speech, as well as the calculated risk of infection, are shown. The worst-case scenario is used, it is assumed that the first person appearing in the room is infectious, and the risk is calculated for the second person. The infection risk is low mainly due to the large room size and the small number of virus expelling events (only 1 sneezing and 18 coughing events in 2 days). This result also emphasizes the importance of measuring expelling events.
Figure 8. Left - measured number of people and measured and simulated CO₂ concentrations. Right – measured speaking, coughing, and sneezing events and predicted infection risk in the office room.

The reason for a disagreement between the measured and simulated CO₂ concentration in the night obviously is the reduced ventilation intensity between 7 PM and 5 AM. The knowledge of ventilation intensity is important for predicting the infection risk, and it can hardly be predicted by the measurement system e.g., due to manual opening of doors and windows. Therefore, the indirect prediction of ventilation using the measured number of people and CO₂ concentration is proposed. The PID controller concept is introduced in the model where measured CO₂ is the desired value or setpoint, the simulated CO₂ value is the plant process value, and the ventilation intensity is the control variable. The PID values were adjusted in several runs to \(K_d=2 \cdot 10^{-6}\), \(T_i=1 \cdot 10^7\) s, and \(T_d=1000\) s. The results with PID control of ventilation intensity are shown in Figure 9. The agreement of CO₂ concentration is considerably improved, the ventilation during the nighttime was strongly reduced in the model and is probably completely turned off in the reality. The risk of infection at the end of the second day is slightly reduced from 0.210% to 0.196% due to higher ventilation in the PID case.

Figure 9. The same as Figure 8, but using adapted ventilation intensity.

4 Conclusions
The developed model can be used for a more precise prediction of the risk of infection with COVID-19 in an indoor environment. The parameter studies using the model show that the infection risk slightly increases for lower humidity and ventilation intensity, whereas intensive ventilation decreases the risk. The coughing but especially the sneezing events strongly increase the risk of infection in the room; therefore, distinguishing these events is very important for risk assessment. The model together with the measurement system can predict the infection risk in real-time and can be used to increase the safety in an indoor environment. A method for determining an unknown ventilation intensity by measuring the number of people and the CO₂ concentration is proposed and tested.

Acknowledgements
The present work has been supported financially by Project No. VPP-COVID-2020/1-0025.

References
[1] Phillips N 2021 Nature 590 382-384
[2] Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X and Cheng Z 2020 The lancet 395(10223) 497-506
[3] Liu J, Liao X, Qian S, Yuan J, Wang F, Liu Y, Wang Z, Wang FS, Liu L and Zhang Z 2020 Emerging infectious diseases 26(6) 1320
[4] Chan JF, Yuan S, Kok KH, To KK, Chu H, Yang J, Xing F, Liu J, Yip CC, Poon RW and Tsai HW 2020 The lancet 395(10223) 514-23
[5] Qian H, Miao T, Liu L, Zheng X, Luo D and Li Y 2020 Indoor air 1–7
[6] Nishiura H, Oshitani H, Kobayashi T, Saito T, Sunagawa T, Matsui T, Wakita T and Suzuki M 2020 MedRxiv DOI 10.1101/2020.02.28.20029272
[7] Ong SW, Tan YK, Chia PY, Lee TH, Ng OT, Wong MS and Marimuthu K 2020 Jama 323(16)
[8] Asadi S, Bouvier N, Wexler AS and Ristenpart WD 2020 Aerosol Science and Technology 54(6) 635-638
[9] Santarpia JL, Herrera VL, Rivera DN, Ratnesar-Shumate S, Denton PW, Martens JW, Fang Y, Connoo N, Callahan MV, Lawler JV and Brett-Major DM 2020 MedRxiv DOI 10.1101/2020.07.13.20041632
[10] Li Z, Ge J, Yang M, Feng J, Qiao M, Jiang R, Bi J, Zhan G, Xu X, Wang L and Zhou Q 2020 Brain, behavior and immunity 88 916-9
[11] Lima CK, de Medeiros Carvalho PM, Lima ID, de Oliveira Nunes JV, Saraiva JS, de Souza RI, da Silva CG and Neto ML 2020 Psychiatry research 287 112915
[12] Kucharski AJ, Klepac P, Conlan AJ, Kissler SM, Tang ML, Fry H, Gog JR, Edmunds WJ, Emery JC, Medley G and Munday JD 2020 The Lancet Infectious Diseases 20(10) 1151-60
[13] Tomar A and Gupta N 2020 Science of The Total Environment 728 138762.
[14] Howard J, Huang A, Li Z, Tufekci Z, Zdimal V, van der Westhuizen HM, von Delft A, Price A, Tomar A and Phillips N 2021 1(1) 1-9
[15] Hajifathalian K, Shariati RZ, Kumar S, Krisko T, Skaf D, Ang B, Redd WD, Zhou JC, Hathorn KE, McCarty TR and Bazarbashi AN 2020 Plos one 15(9)
[16] Bargaz MT and Bush JW 2020 medRxiv DOI 10.1101/2020.08.26.20182824
[17] Peng Z, Bahnfleth W, Buonanno G, Dancer SJ, Kurnitski J, Li Y, Loomans MG, Marr LC, Morawska L, Nazaroff W and Noakes C 2021 medRxiv DOI 10.1101/2021.04.21.21255898
[18] Peng Z and Jimenez JL 2021 Environmental Science & Technology Letters 2021 8(5) 392-7.
[19] Tellicko J, Vidulejs DD and Jakovics A 2021 A monitoring system for evaluation of COVID-19 infection risk (Preprint Paper for 8th International Building Physics Conference in Copenhagen)
[20] Duguid JP 1946 Epidemiology & Infection 44(6) 471-9
[21] Schijven JF, Vermeulen LC, Swart A, Meijer A, Duizer E and de Roda Husman AM 2020 medRxiv DOI 10.1101/2020.07.02.1914832
[22] Chaudhuri S, Basu S, Kabir P, Unni VR and Saha A 2020 Physics of Fluids 32(6) 063309
[23] Holterman HJ 2003 Kinetics and evaporation of water drops in air (Wageningen: IMAG)
[24] Foat T, Drodge J, Nally J and Parker S 2020 Building and Environment 169 106591
[25] Cheng KC, Acevedo-Bolton V, Jiang RT, Klepeis NE, Ott WR, Fringer OB and Hildemann LM 2011 Environmental science & technology 45(9) 4016-22
[26] Park SH, Kim HO, Han YT, Kwon SB and Lee KW 2001 Aerosol Science & Technology 35(3)
[27] Van Doremalen N, Bushmaker T, Morris DH, Holbrook MG, Gamble A, Williamson BN, Tamir A, Harcourt JL, Thornburg NJ, Gerber SI and Lloyd-Smith JO 2020 New England journal of medicine 382(16) 1564-7
[28] Stahlhohfen WG, Rudolf G and James AC 1989 Journal of Aerosol Medicine 2(3) 285-308
[29] Basu S 2020 medRxiv DOI 10.1101/2020.07.27.20162362