Discrete-Event Modeling of Human Behavior for Spread of Diseases on University Campuses

Hazel Griffith[1], Cristina Ruiz-Martin[1], and Gabriel Wainer[1]

[1] Carleton University, Ottawa, ON, CANADA
cristinaruizmartin@sce.carleton.ca

Abstract. The COVID-19 pandemic has highlighted the importance of defining sound policies to make attending workplaces safe. Sometimes, deciding on different policies is challenging as this highly depends on the behavior of the individuals. We introduce a Discrete Event based method to study such policies, including human behavior along with information about the workplace layout and building characteristics such as ventilation rate or room capacity. We exemplify how to use this method using the case study of Carleton's University Campus. We introduce a case study focusing on the effect of the ventilation policy on the number of disease cases on campus.

Keywords: DEVS, disease spread, human behavior.

1 Introduction

The COVID pandemic has revealed that crowded events or locations are hot spots for the spread of airborne viruses. When functioning at normal capacity, workplaces, including university campuses, can be considered crowded places where people congregate for a long period of time, usually for eight hours or more. For example, Carleton has over 30 000 students attending lectures and traveling the halls. Some lectures have over 200 students sitting in a closed space for at least 90 minutes.

On top of complying with the regulations, workplaces and university campuses cannot afford to get the disease spread among their employees or students because that will highly impact the daily activities of the organization. Therefore, a safe environment should be provided.

To provide a safer environment, we need to collect data on how different policies affect the spread of the disease. Doing this with real-life experiments is not viable as we may risk the health of the employees/students, seeing the effect of policies takes time, and many variables may affect the result in unpredictable ways. We may collect this data by running experiments using simulation models that realistically model how COVID (or other diseases) spread across the workplace or university campuses. Using these models, we can run experiments to study the effect of different parameters on the spread of the disease. For example, different ventilation rates in rooms or offices, the number of infected people attending work, or different room capacity limits. The data obtained from these experiments can be used to inform new strategies, policies, and identify hotspots in the workplace.

Although there are already many simulation models to study the spread of COVID-19, there is limited work focusing on workplaces, including human behavior, workplace layout, and building characteristics in the study.

In this research, we approach this limitation by building a model that includes the above-mentioned aspects. More specifically, we developed a method to study the spread of diseases in workplaces considering human behavior and workplace characteristics. We base our method on the architecture to study diffusion processes in dynamic multiplex networks (ADPM) presented in [1]. We adapted the architecture to study the spread of diseases in a workplace and exemplify the use with the case study of the Carleton University Campus.

2 Background

Different simulation models have been built and executed to study the spread of disease during the COVID-19 pandemic. Such simulations were useful for determining the impact of COVID-19 depending upon many factors, which include control policies, the area's physical layout, citizens' mobility, etc. Many of these models are based on the well-known Susceptible-Infected-Recovered models [2,3]. These SIR models have evolved, and now they include other states (e.g., exposed, deceased) as well as geographical level transmission dynamics [4,5,6,7,8].

Other studies include the use of a novel Monte Carlo simulation procedure for modeling the spread of COVID-19 over time [9]. This study focuses on simulating the rate at which cases will appear in Australia and the UK based on knowledge of the virus and the initial number of cases, over a series of arbitrarily created scenarios. They calculated the day when the number of new cases per day would peak for both countries. Their results were found to be accurate, indicating that their model could be applied to other nations and pandemics.

In [10], the authors focused on the impact of urban structure on the spread of COVID-19. They focused on individual cities and how their physical layout affects the capacity of citizens to respond quickly to mobility-related policies. Such policies include stay-at-home orders, social distancing, etc. They found that while densely packed cities experience a greater initial infection rate, they are also easier to enforce and transmit mobility policies to citizens. They use a SIR-type compartmental model where simulated individuals flow between compartments that may be labeled as susceptible, infectious, or recovered. Their results proved that investing resources in early monitoring and prompt ad-hoc interventions in more vulnerable cities could make future pandemics easier to contain.

Many other works, as presented by Loring et. al., in their literature review [11] consider human behavior and social relations such as workplace, profession, or household, among others. However, they do not focus on developing specific models to evaluate the risk of getting covid in the workplace. Some other studies have focused on addressing the risk of getting covid at the workplace by developing high-level probabilistic models [12].

In this work, we focus on addressing the above-mentioned limitation by developing a method to study the spread of diseases in workplaces considering human behavior and workplace characteristics.

To do so, we consider the spread of a disease as a diffusion process. Diffusion processes are phenomena that represent how an element may spread within a given medium. For example, you could consider the diffusion of traffic across a network of roads, or how information travels between people in an emergency response system. The connections over a multiplex dynamic network (i.e., a network with different types of connections) determine the medium through which the element travels and how it travels.

In [1], the authors propose ADPM (Figure 1) to model these types of processes. There are components to model the nodes, the direct and indirect connections between nodes, how the connections between nodes change over time, how the behavior of the nodes changes over time, and how the diffusion process starts. They also proposed a development process to instantiate this architecture, as detailed in [1]. We base our method on this architecture. We adapt the architecture to study the spread of diseases in a workplace and exemplify the use with the case study of the Carleton University Campus. Following the original research in [1], we also define the models in DEVS [13] and implement them using Cadmium Simulator [14].

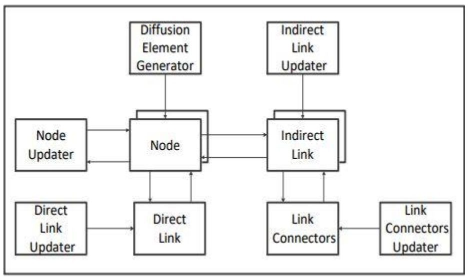

Fig. 1. Complete ADPM architecture.

3 An Architecture to Simulate the Spread of Diseases in Workplaces

In this section, we explain how we adapted ADPM [1] to the case study of the spread of diseases.

Figure 2 shows the elements of the ADPM used to study the spread of an airborne virus. We selected three of the components: Node, Direct Link and Node Updated. The Node model is instantiated with a Person model that will get and transmit the disease. The Node Updater model is instantiated with a Weather model as the changes in the weather will influence the behavior of people. Finally, the Direct Links model is instantiated with several Room models because interactions between people will happen in rooms. In the case of an airborne virus being spread across a population, an interaction in a Room could represent sneezing near another person.

In this case, Indirect links would represent an infected person handling an item and passing it to another person. With airborne viruses, the odds of a person becoming sick through indirect contact with a sick person are very low. Therefore, we have not included the part of the architecture that handles indirect interactions.

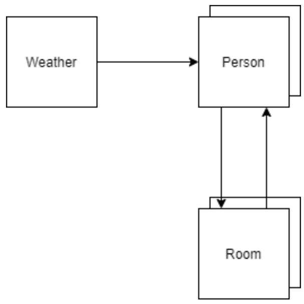

Fig. 2. The adapted ADPM architecture

Each model present in figure 2 is further expanded, as shown in figure 3 and detailed in the rest of the section. Each component is defined as parameterized models using the DEVS formalisms.

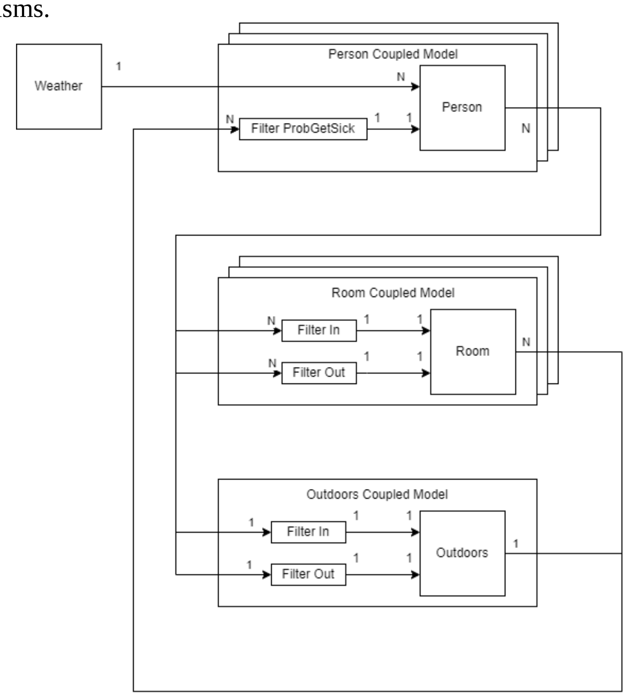

Fig. 3. Decomposition of the components in the adapted ADPM architecture

3.1 Person Model

The Person component is defined as a coupled model with two components: a filter to determine which messages are for that specific person and a person atomic model to represent the person's behavior.

The behavior of a person includes their daily schedules, interpersonal relationships, personal choices in terms of masking, social distance, how to move around the workplace, and their probability of being infected after exposure. The explained behavior is a function of the weather. For example, when the weather is mild, a person may choose a safer path to move around the workplace, but if it rains or snows, they will favor being inside.

Each person model will have a general relationship (e.g., family, acquittance, stranger, etc.) established with each other person to realistically model how they engage in safe behaviors or not.

In this case, the main behavioral factors we consider are if people would wear masks, social distance, and comply with maximum occupancy policies.

Although we have focused on those behavioral factors, the model can be extended to include others. The behavioral components to be included will depend on the disease under study and the experiments to be performed.

The Person model is defined as a parameterized model whose parameters are specified in an XML file, as shown in figure 4.

Each person has the following attributes:

- *ID*: a unique ID identifying the person
- *location*: the location of the person at the beginning of the simulation
- *currStartTime*: the time the person becomes active in the simulation
- *timeInFirstLocation*: the time the person will spend in the current location
- *isSick*: identifies if the person has the disease or not
- *exposed*: identifies if the person has been exposed to the disease or not
- *vaccinated*: identifies if the person is vaccinated or not
- *wearingMaskCorrectly*: identifies if the person, when wearing a mask, wears the mask properly fitted or not
- *socialDistance*: identifies if the person is prone to keep social distance or not
- *weatherThreshold*: identifies how prone the person is to engage in unsafe behavior when the weather conditions are not favorable. It is a value between 0 and 10. Zero represents low tolerance to bad weather.
- *relationship*: identifies the type of relationship with other persons in the model.
- *behaviorRulesPerson*: identifies the behavior patterns in terms of maintaining a safe social distance, wearing a mask, and entering a room at a maximum occupancy based on the type of relationship with a given person
- *locationPlan*: determines the person's schedule

```
<DecisionMakerBehavior>
<ID>3</ID>
<location>home</location>
<currStartTime>1280</currStartTime>
<timeInFirstLocation>760</timeInFirstLocation>
<isSick>False</isSick>
<exposed>False</exposed>
<vaccinated>False</vaccinated>
<wearingMaskCorrectly>True</wearingMaskCorrectly>
<socialDistance>True</socialDistance>
<weatherThreshold>6</weatherThreshold>
<relationship>
     <relationship ID=”1” type=”friends” />
     <relationship ID=”4” type=”acquaintances” />
     <relationship ID=”5” type=”acquaintances” />
     …
</relationship>
<behaviorRulesPerson>
     <personRelations status=”acquaintance” safeDistanceProb=”50”
          maskWearingProb=”50” enterMaxOccRoomProb=”50” />
     <personRelations status=”friends” safeDistanceProb=”20”
          maskWearingProb=”20” enterMaxOccRoomProb=”20” />
   …
</behaviorRulesPerson>
<locationPlan>
     <locationPlan room=”38-VS - 2285” timeinroom=”90” startTime=”610 />
     <locationPlan room=”Outdoors” timeinroom=”10” startTime=”700” />
     <locationPlan room=”home” timeinroom=”490” startTime=”710” />
   …
</locationPlan>
</DecisionMakerBehavior>
```


Fig. 4. Person XML file

3.2 Room Model

The Room component is defined as a DEVS coupled model with three atomic models, two filters to determine if the persons are coming or leaving that specific room, and a room atomic model modeling the room itself. Note that we are distinguishing a specific type of room called outdoors to represent outdoor locations where the probability of getting infected with an airborne virus is very low.

Each room atomic model determines the probability of a person being exposed to the virus based on several factors. These factors include whether the person and other people in the room wear a mask and maintain social distance, and how many sick people are in the room. We also use the current concentration of CO2 in the room as CO2 is usually used as a proxy for the number of viral particles in a room when there are sick people.

The Room model is also defined as a parameterized model whose parameters are specified in an XML file, as shown in figure 5. The XML specifies the following characteristics: the room's ID, its ventilation rate, social distance threshold, maximum occupancy, several adjustable factors that contribute to the probability of exposure calculations (mask-wearing, social distance, vaccination, etc.), the respiratory increase per minute, the size in square meters and the height.

```xml
<RoomParameters>
 <ID>5,RH - 1100</ID>
 <ventilationRating>3</ventilationRating>
 <socialDistanceThreshold>35</socialDistanceThreshold>
 <maxOccupancy>26</maxOccupancy>
 <wearsMaskFactor>1</wearsMaskFactor>
 <socialDistanceFactor>1</socialDistanceFactor>
 <vaccinatedFactor>-2</vaccinatedFactor>
 <sickPeopleCO2Factor>2</sickPeopleCO2Factor>
<highCO2FactorThresholds>1001,1840,1857,1904</highCO2FactorThresh-
olds>
<highCO2Factors>1,2,3,4</highCO2Factors>
<respIncreasePerMin>340000</respIncreasePerMin>
<squareMetres>71.019997</squareMetres>
<height>2.438000</height>
 </RoomParameters>
```

Fig. 5. Room XML file

Modeling CO2 Concentration.

To model the CO2 concentration in the room, we first calculate the increase of CO2 because of breathing. According to Environmental Health Perspectives, "*Although typical outdoor CO2 concentrations are approximately 380 ppm, outdoor levels in urban areas as high as 500 ppm have been reported (Persily 1997).*"[15]. For our model, we define the outdoor concentration as 400 ppm. In [16], the authors state that "*an average adult exhale contains 35,000 to 50,000 parts per million (ppm) of CO 2 on each breath*"; in [17], the authors define the volume of a breath at 500 mL per breath; and in [18], the authors state that a person breaths between 12 and 20 times per minute. Using these values, we calculate the respiratory increase per minute as shown in the following equation. We get a respiratory increase of 340000 mg of CO2 per minute.

$$respIncPerMin(\frac{mg}{min}) = (500\left(\frac{mL}{Breath}\right) * \left(\frac{35000ppm+50000ppm}{2}\right)\left(\frac{\frac{1mg}{L}}{1ppm}\right) * \left(\frac{12\left(\frac{breaths}{min}\right)+20\left(\frac{breaths}{min}\right)}{2}\right) = 340000\,\frac{mg}{min}.$$

We then calculate the decrease in CO2 because of ventilation. The air changes per hour (ACH) are usually anywhere between 1 and 8, but this will be a parameter of our room model since different buildings and workplaces can choose different rates. The ventilation rate per minute is calculated as follows:

$$ventilationRatePerMin\left(\frac{L}{min}\right) = \frac{ACH * volumeOfRoom(m^3)}{60minutes} * \frac{1000L}{m^3}$$

The new CO2 concentration is calculated linearly based on the CO2 concentration flow as follows:

$$CO2Concentration\left(\frac{mg}{L}\right) = CO2ConcentrationFlow\left(\frac{mg}{L}\right) + PreviousCO2Concentration\left(\frac{mg}{L}\right)$$

CO2ConcentrationFlow represents the change in the CO2 concentration since the previous CO2 concentration was calculated. The CO2ConcentrationFlow is calculated by adding the CO2 entering the room from its ventilation per minute, the CO2 being breathed out by everyone in the room per minute, and subtracting the CO2 leaving the room per minute due to ventilation.

$$CO2ConcentrationFlow\left(\frac{mg}{L}\right) = \frac{ElapsedTime(min)}{volumeOfRoom(m^3) * \frac{1000L}{m^3}} * \left(CventilationRatePerMin\left(\frac{L}{min}\right) * averageCO2\left(\frac{mg}{L}\right) + respIncPerMin\left(\frac{mg}{min}\right) * numberOfPeople - ventilationRatePerMin\left(\frac{L}{min}\right) * PreviousCO2Concentration\left(\frac{mg}{L}\right)\right)$$

The limitation of this equation is that the longer the elapsed time variable is, the less accurate it becomes. We have tested that for intervals of 10 minutes or less, and the formula is accurate. Therefore, we are sticking to those intervals.

The CO2 concentration equations were validated using historical data from a room at Carleton University Campus. We collected the CO2 concentration values at half-hour intervals over 24 hours, the volume of the room, and the number of people in the room. The ACH value was unknown. We calibrated the model to find the ACH value. Then, we validated our formula by conducting a t-test to judge if there were any inconsistencies between the historical data set and the data set the model produced.

3.3 Outdoors Model

The Outdoors is an atomic model that represents outdoors locations where the probability of being exposed to the virus is really low. This model is similar to the room model but with a really small probability of being infected as long as there is no close contact.

3.4 Weather Model

The Weather atomic model simulates general weather patterns such as rain and snow. In this version of the model, it generates a random weather pattern. This model can be adapted to generate weather patterns that matches the obverted weather of given locations. This model is important because the behavior of a person is usually influenced by the weather. For example, in cold climate weather, where the temperatures can reach -30C, people will prefer to move around through indoor corridors that may be crowded and not well ventilated instead of going outdoors.

4 Implementation

The model was implemented in Cadmium [14] and it is available at the following link: https://github.com/SimulationEverywhere-Models/COVID_Campus_Simulation.

The model is parameterized with the number of people and number of rooms. That way, we can run a simulation with any number of people, over any duration, and have any number of rooms.

Each instance of the Person atomic model is created the XML file described above that contains the person's schedule, relationships with each other person, and several traits that determine their behavior. These traits include their ID, whether or not they are vaccinated, are sick, have been exposed, will wear a mask correctly if they are alone in a room, and the severity of the weather necessary for them to choose to travel via the tunnels. Each instance of the room is also created from an XML as described in the previous section.

In order to run different scenarios, we just need to update the XML describing the behavior of the people and the rooms.

4.1 Visualization of the Simulation Results

Once the simulation is complete, some data logs are generated. This data is then parsed by a separate program implemented in Python, and different graphs and metrics are generated based on the data obtained. These graphs will allow showing statistical analysis done on the results of the chosen policies. It will help identify areas where there is an increased risk of infection or safer policies.

Currently, the Python graph generator generates some graphs such as the rooms grouped by average exposure probability vs ventilation rate, or probability of exposure and occupancy vs time for each room, among others. These graphs give insights into which rooms pose the greatest risk for exposure and what virus mitigation policies may be effective.

5 Case Study

We show how to use the model with the case study of Carleton's University Campus.

In this case study, the rooms accurately resemble Carleton University's campus. We got the dimensions for 4352 rooms from a Building Information Model (BIM) of the campus. This model did not contain ventilation data. Therefore, this will be a parameter for our experiments. We did not consider all the rooms. We focused on the rooms where students would congregate, so only rooms with an area greater than 40 square meters were considered. Also, many rooms were missing the height of the room and this value is important to calculate the CO_2 concentration in the room. This brought it down to

434 usable rooms with over 40 square meters and complete dimensions. With the information extracted from the BIM model, XML files for every room were generated.

Carleton Campus has a special feature; students can move from one room to the other going out or through a set of tunnels. We have modeled the tunnels as an instance of the Room atomic model where there is a chance of being exposed to the virus.

Our simulation can also consider a varied number of users, and we define the schedules of each person to accurately resemble the schedules of students and faculty on Carleton University's campus. We were not able to gather actual data from scheduling services. Therefore, we had to implement our own scheduling.

We implemented an event-based scheduling system for students by obtaining real data on rooms at Carleton's campus. To implement the event-based scheduling system, we created events (e.g., lectures, tutorials, etc.) for every room. The events were labeled as being a tutorial, lab, or lecture, depending upon the size of the room. Lectures were scheduled in the largest rooms, followed by labs, and tutorials were assigned to the smallest rooms. The events were given durations according to their type. Lectures are 90 minutes long, labs are 180 minutes, and tutorials are 60 minutes long. Events are created to fill a regular school day from 8:30 am to 9:00 pm. These events were then passed to the students being generated, where students are assigned schedules for events on a first-come, first-serve basis. A boolean is used to determine whether an event should be booked over its max occupancy or if it should only book at most a number of students equal to the room's max occupancy.

A possible limitation of this approach could be if there are too many students and not enough rooms with events for them to be given schedules. For example, if we were going to consider the first 30 rooms from our selection, we could only generate a population of 1350 people. This can change depending on what rooms we choose to use in a simulation. Despite this limitation, if we focus on a set of people, we can simulate the interactions within a faculty or the students in a given set of programs.

We use this scenario to study the effect of ventilation on the spread of COVID on campus.

5.1 Ventilation Experiments

Although we already know that ventilation has a strong impact on the transmission of COVID-19, we use the above mention case study to determine, through simulation data, how strong is the effect of ventilation on the probability of exposure to COVID-19. We define the probability of exposure as the chance of a person being exposed to COVID-19 particles. After exposure, different people have different probability of becoming sick, and this depends on many factors such as the person's medical history, but it cannot be influenced by any COVID-19 safety protocols. In this analysis, we only focus on the person's probability of being exposed to the virus.

We will consider two scenarios over a two-week period as we assume that in two weeks a person infected/exposed to COVID will most likely identify that has been exposed and would test for the disease. Both scenarios include 30 rooms, where 10 are lecture halls, 10 are student's labs, and 10 rooms are for tutorials. Both scenarios consider 1200 people, as this is the maximum number of people that can be generated with the chosen rooms.

The parameter that changes between both scenarios is the ACH (Air Changes per Hour). In the first scenario, we set the number of ACH to 1 for every room, while in the second scenario, we set ACH to 8 for every room. The room representing the tunnels will remain the same, and no change in the ventilation rate will be applied.

Table 1 shows the data we have used to initialize the rooms, and Table 2 the rest of the parameters used in our study.

Table 1. Data of Rooms used in Experiments

Lecture Halls		Laboratories		Tutorials	
Area (m3)	**Height (m)**	**Area (m3)**	**Heigh (m)**	**Area (m3)**	**Height (m)**
313.46	3048	121.98	3200	54.77	3048
185.27	3200	143.65	2438	45.91	3048
198.31	3200	122.46	2438	53.67	3048
238.53	3200	134.33	2438	72.91	3048
286.38	2438	150.28	2438	52.48	3048
568.02	2438	120.25	2438	65.27	3048
208.14	2438	112.86	2438	52.36	3200
323.87	2438	132.82	2438	54.92	3200
339.39	2438	132.82	2438	55.48	3200
209.48	2438	132.84	2438	53.68	3200

Table 2. Parameters of the Simulation

Max occupancy	¾ of the social distance threshold
Social distance threshold	½ of room's area
Wears mask factor	Uniform distribution that is either 1 or 2
Social distance factor	Uniform distribution that it is either 1 or 2
Vaccinated factor	Uniform distribution from -1 to -4
Sick People CO2 Factor	Uniform distribution from 1 to 3
CO2 Factor Thresholds	3 values with uniform distribution between 1000 and 2000 in order from lowest to highest
CO2 Factors	1, 2, and 3 assigned to thresholds from lowest to highest
Respiratory CO2 Increase per Minute	340.000mg of CO2
Room over capacity	30% probability that a room is assigned more students than its max occupancy allows
Relationships	20% Friends; 30% Acquaintances; 50% Strangers
People sick at start	0%
People vaccinated	50%
People wears mask when alone	50%
Weather threshold	Uniform distribution from 0 to 10
Probabilities of wearing a mask, social distancing, and entering a room at max occupancy with Friends	20%, 20%, and 80%
Probabilities of wearing a mask, social distancing, and entering a room at max occupancy with Acquaintance	50%, 50% and 50%

Probabilities of wearing a mask, social distancing, and entering a room at max occupancy with Strangers	80%, 80%, and 20%
Probability of becoming sick after exposure	30%
Time to become sick	Uniform distribution from 0 minutes to 10080 minutes (two weeks)
Abandons schedule and stays home when sick	50% chance

Simulation Results

From each simulation scenario, we ran five replications and obtained the CO2 concentration at each half-hour interval for every room, and the probabilities of exposure at each half-hour for every person. Five replications were enough to achieve a 95% confidence interval.

We calculated the mean, sample variance, and half-width confidence intervals with 95% confidence for the probability of exposure values for all 1200 people. Then an across-replication, we also calculated the sample mean, sample variance, and half-width confidence interval with 95% confidence. We followed this same approach to calculate the average CO2 concentration among rooms.

Table 3 summarizes this data for the scenario with ACH = 1 and Table 4 the data for the scenario with ACH = 8.

Table 3. Data obtained for Experiment with ACH = 1

ACH=1	**Exposure Probability (%)**			**CO2 Concentration (mg/L)**		
Experiment Replications	**Mean**	**Variance**	**Conf. Int.**	**Mean**	**Variance**	**Conf. Int.**
E1R1	29.9771	259.0067	±0.9115	889.2212	88433.4321	±111.0426
E1R2	29.1751	250.9616	±0.8972	879.8302	83292.0315	±107.7664
E1R3	28.868	237.5691	±0.8730	880.686	88638.6487	±111.1714
E1R4	30.1844	266.403	±0.9244	894.845	87977.8172	±110.7562
E1R5	28.5901	229.0607	±0.8572	880.77	92257.5773	±113.4181
Overall	29.3589	0.48236	±0.8624	885.0705	44.4870	±8.2817

Table 4. Data obtained for Experiment with ACH = 8

ACH=8	**Exposure Probability (%)**			**CO2 Concentration (mg/L)**		
Experiment Replications	**Mean**	**Variance**	**Conf. Int.**	**Mean**	**Variance**	**Conf. Int.**
E2R1	23.4795	154.3914	±0.7037	445.8642	1179.5802	±12.8246
E2R2	23.7178	161.6669	±0.7201	444.9765	1070.3994	±12.2167
E2R3	24.2372	171.1704	±0.7410	445.4648	1052.7961	±12.1158
E2R4	23.6137	153.7463	±0.7023	445.7014	1131.4423	±12.5602
E2R5	24.561	178.8042	±0.7573	444.4135	1101.6124	±12.3936
Overall	23.9218	0.2100562	±0.5691	445.2841	0.34897	±0.7335

If figure 6, we show the above data graphically. We plot every room's ventilation rate compared to its average probability of exposure values. The graph represents the scenario with an ACH value of 8, and the graph on the right the scenario with an ACH value of 1.

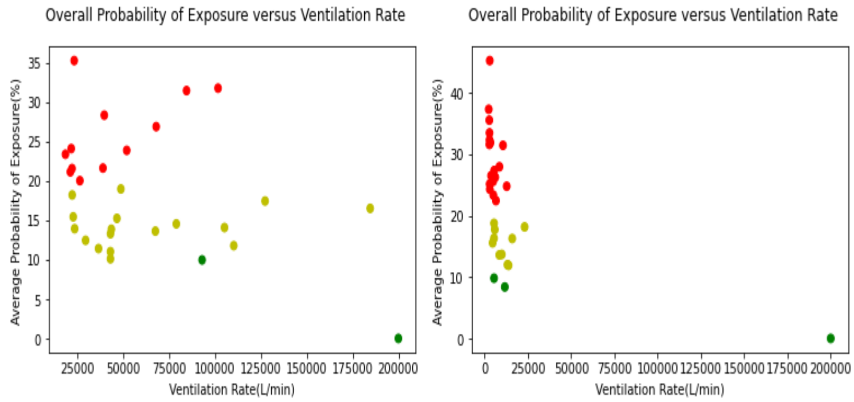

Fig. 6 Average Probability of exposure in each room versus ventilation rate per room. (Left) ACH = 8 (Right) ACH = 1

The green dot in the bottom right that is the same for both graphs represent the tunnels on Carleton's campus which are very large and well ventilated so the odds of becoming exposed to COVID-19 remain low. From the graph, we can see that when more points have a lower ventilation rate, they tend to have a higher average probability of exposure. The green, yellow, and red dots represent rooms with an average probability of exposure smaller than 10%, between 10 and 20% and over 20% respectively.

The results of first scenario (ACH = 1) show an overall average probability of exposure equal to 29.3589 ± 0.8624, and an overall average CO2 concentration of 885.0705 ± 8.2817 mg/L. The results of the second scenario (ACH = 8) show an overall average probability of exposure equal to 23.9218 ± 0.5691 and an overall average CO2 concentration of 445.2841 ± 0.7335 mg/L. Comparing these averages, we can conclude that when the ventilation of all rooms on campus are improved by 7 ACH, we would see the average probability of becoming exposed to COVID reduce by 5.4371 ± 1.0346.

Although around 5% is not a lot, the results prove that implementing a policy where the ventilation rates of rooms on Carleton's campus are standardized at a high ACH value would improve safety and limit the spread of the virus.

It is important to note that this improvement if for the population defined in table 2, where only 50% of people are vaccinated where the probability of wearing a mask in the presence of friend and acquaintance is relatively low.

With this model, we can also examine the probability of exposure of a specific person (Figure 7) or the CO2 concentration on specific rooms (Figure 8). This is relevant because we can analyze the behavior of people with high risk of exposure and the locations they have visited to give further insights on the factors that contribute to the exposure of COVID on campus.

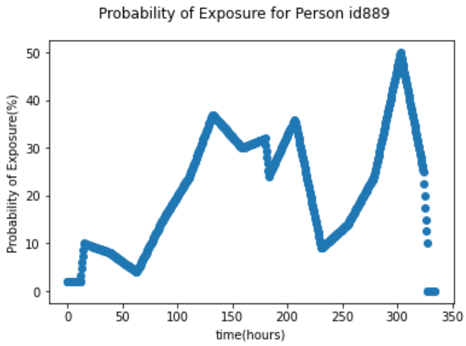

Fig. 7: Probability of Exposure over 2 weeks for Person 889 when ACH = 1

In figure 8, we can see large spikes then linear dips. During the day, when people are using the room and breathing CO2 into the air but with poor ventilation, the CO2 levels only keep increasing. Then once the room is empty for the night the ventilation can bring CO2 back down to normal levels.

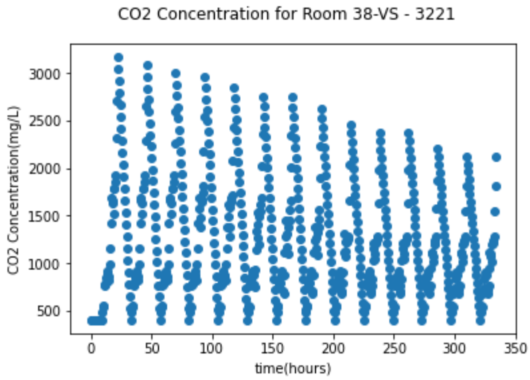

Fig. 8: CO2 Concentration for Room 38-VS - 3221 over two weeks with ACH = 1

6 Conclusions

Being able to define policies to keep workplaces safe is critical as they cannot afford to have many employees sick at the same time. These policies should be supported by experimental data. However, doing real life experiments to collect data is not feasible.

In this paper, we have presented an architecture and a model to study the spread of a disease in a workplace and analyze the effect of different policies. We have shown how to use this model through a case study using real data from Carleton University Campus to simulate the workplace environment.

Some limitations of this research include the validation of the human behavior implemented in the model as well as the factors used to correct the probability of infection based on the different behaviors such as social distance or mask wearing.

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