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Cell-DEVS models with BIM integration for airborne transmission of COVID-19 indoors

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ABSTRACT

The spread of viral particles as a primary cause of infection indoors is an open problem under investigation. Physical experimentation for studying infection spread in variable indoor configurations are very complex; instead, modeling and simulation provide a way to conduct the required studies in a safe environment. We present a method for modeling, simulating, and visualizing the infection risks in closed spaces. We present models to estimate the dynamics of indoor infection under different conditions. We use Cellular Discrete Event Specifications and integrate the results with Building Information Modeling.

1 INTRODUCTION

The ongoing pandemic of COVID-19, which started in 2019 in the city of Wuhan, Central China, resulted in human and economic loss and imposed numerous efforts in epidemiological research. It has been shown that one of the main sources of the disease is Airborne transmission (also called infectious aerosols) which refers to the infection caused by small droplets aerosols and droplets nuclei. Airborne transmission plays a crucial role in the spreading of COVID-19, in particular in poorly ventilated spaces [12], as shown by links to superspreading events [15].

Aerosol contagion occurs when an infected subject sheds infectious particles exposes others [22]. Infectious aerosols are emitted in different sizes by people when they breathe, cough, talk or sneeze [12]. The viability of the virus in these airborne particles depend on environmental factors such as humidity, temperature, sunlight, and ventilation [17]. Aerosols stay suspended in the air and infect people by inhalation; and their activity produces different effects: for instance, particles emission during normal speaking increases with loudness [5]. Particles smaller than 5 μm (micrometer) diameter are more infectious than large ones emitted by coughing or sneezing. These small particles can live in air longer before settling on surfaces (or dying), increasing the chance of inhaling them. They can penetrate far into the respiratory tract and cause infection easily.

Aerosol transmission not only depends on the number of particles shed by different respiratory activities (e.g., breathing, speaking, and coughing), but also by the different levels emitted while resting or exercising [6]. Research has shown that ventilation also plays a crucial role in infection spread [7]. The research presented here explores the impact of airflow and the exposure time of susceptible people to different indoor environmental conditions. The effect of infected individuals shedding infectious aerosols through respiratory activity can be studied by analyzing the spread of viral particles. Similarly, we can use the amount of carbon dioxide (CO_2) concentration as a proxy for the disease [23,25]. Measuring CO_2 is simple for real-world analysis, as its concentration can be measured by low-cost sensors. This is a good alternative to actual physical experimentation. Studying infection effects in variable indoor configurations is not feasible due to the lack of information on the nature of SARS-CoV-2, as well as the risks and ethical issues related to studying the biological aspects of the disease in real settings. Modeling and simulation is thus an attractive method to conduct studies in a risk-free environment.

We present indoor models that provide a practical representation of different indoor conditions and considers different configuration parameters to facilitate studying and understanding airborne transmission in indoor environments. The research focuses on new methods to understand airborne transmission behavior indoors (considering different parameters such as respiratory activity, the number of emitted particles, ventilation, and indoor place dimension) and defining new techniques for simulating and visualizing airborne transmission to help decision-makers (architects, designers, construction and operation) to explore different solutions for improving ventilation conditions, decide on the maximum number of occupants, and masks' usage. The models mimic the dynamics of viral spread and the CO_2 diffusion indoors by replicating real-life scenarios,

combining Cellular Discrete-Event Specifications (Cell-DEVS) [29] and a variety of Building Information Modeling (BIM) models and tools. The research shows the integration of Cell-DEVS formal models and BIM software. We define a workflow that starts by extracting BIM data from buildings' models (including vents' locations, building elements like windows and doors, building properties like size, and contextual information). This data is then used to build Cell-DEVS models to obtain different results depending on different configurations and using the simulation to provide a variety of visualizations (for instance, using DEVSWeb viewer [4], AutoDesk Forge, etc.). In this paper, we introduce a new method for rapid prototyping applications using integration of Cell-DEVS formal models and BIM software. We discuss potential extensions and improvements for the proposed indoor models and the integration with BIM tools. We present two case studies for indoor modeling, and their variations for studying airborne transmission indoors. One is based on viral particles (VP) in a closed area (including different types and levels of respiratory activity). The other case study uses the spread of CO_2 and its concentration, which can be used as a proxy to indicate the risk of infection in a room [23]. Both models can be easily extended to other scenarios. We show the application of the VP model in a well-known outbreak scenario of the effects of air conditioning in a restaurant in Guangzhou, China [20]. The simulation results align with the infection patterns found in the real-life scenarios, and the method shows how to integrate a BIM model of the building with the corresponding epidemiological models.

The rest of the paper is organized as follows. Section 2 provides background about airborne particles' behavior indoors, the Cell-DEVS formalism, and BIM integration. Section 3 briefly describes BIM data extraction and visualization of the simulation results using Autodesk Forge API. In section3, we present the conceptual and formal specification of the VP model and the CO_2 model. Section 4 discusses the simulation results and proposes future work. Section 5 concludes the paper.

2 BACKGROUND

Airborne transmission indoors plays a role in infection spread and is still an open problem and needs an extra effort and investigation [17]. Proximity, airflow, respiratory activity, and the exposure of an infection medium (e.g., mouth, nose, and eyes) are a few of the different factors that may play a role in superspreading events [15,17].

First, the effect of proximity on infection is influenced by many factors (e.g., the size of the infectious particle and airflow direction). Aerosols and droplets are defined as particles of saliva or respiratory fluid emitted by an infected person due to different respiratory activities [17,12]. However, particles' behavior differs in closed spaces based on their sizes. Particles with sizes larger than 100 (micrometer) μm can be called "ballistic droplets" as they can move through the air and infect people through the mouth, nostrils, or eyes. At the point when droplets contain infectious bioaerosols, like viruses, those bioaerosols stay in the air even after the fluid substance vanishes. In any case, the period that a virus can survive is different from one kind of bioaerosol to another [17]. Those droplets can travel less than 2 m and fall to the ground at 1-2 m from the source if they do not meet a host (e.g., another occupant).

On the one hand, if the particles are larger than ~100 μm and are produced by talking (not coughing or sneezing), they can reach someone else at a 0.5-1 m distance. On the other hand, particles smaller than 100 μm are called aerosols and live in the air for an interval between 10 s up to hours and can travel more than 2 m. The concentration of aerosol particles is usually highest near a source and decreases as they get further. Besides, the speed and direction by which air moves in the closed space affect who gets infected or not based on their location relative to the source of infection [20]. A person gets infected by inhaling them through the nose and/or mouth. One may get infected through the eyes but with a lower probability than other means of infection. Finally, various respiratory activities (breathing, speaking, coughing) and different physical situations, such as resting or exercising, can shed particles with different numbers and sizes.

To estimate the number of emitted particles by an infected person, the Wells–Riley equation [30] defines a quantum as a dose of airborne droplet nuclei required to infect a susceptible person. Based on this, Buonanno et al. [6,7] calculate the quanta emission rates of SARS-CoV-2 to estimate the number of infectious quanta in the viral load emitted by an infected person. The quanta are classified according to respiratory activity types, inhalation rate, and activity level. They conclude that the lowest aerosol emission rate is in breathing while resting (0.36 quanta per hour), increasing with the inhalation rate while doing heavy exercising to reach 2.4 quanta per hour. The research also suggests that singing or speaking loudly, emits 31 quanta per hour, which is the highest number compared to other activities. The emission rate of particles is positively correlated with the loudness of human speech [5].

As discussed in the introduction, conducting experiments to measure the impact of those factors (i.e., proximity, activity levels, etc.) on infection is not feasible by physical means. Instead, Modeling and Simulation (M&S) permits defining advanced studies in a risk-free environment. Numerous models have been built since the start of the pandemic of COVID-19, which permit simulating various scenarios of spreading of the disease. Gressman and Peck built agent-based models in university environments [16]. This study does not consider factors such as the size of classes and transmission from out-of-campus sources. Others have used classic Susceptible-Infectious-Recovered (SIR) models to account for population densities and contact tracing apps effect on the spread of the virus [13] or to simulate the spread based on data from specific countries [10]. Such

macrosimulation models do not consider individual contact factors, HVAC influence or mobility of occupants.

In this research we have used Cell-DEVS [29], a M&S methodology that has been shown to be robust modeling indoor spaces [18]. Cell-DEVS is an extension to the Discrete EVent Specifications (DEVS) formalism, a mathematical formalization for modeling real systems as a composition of a hierarchy of modular models [29].

As such, Cell-DEVS has the advantages of being a discrete-event approach. Unlike time-stepped M&S methods that update all components of the model even when the update is not needed, Cell-DEVS scheduling improves the performance by skipping unnecessary updates of asynchronous events. Being an extension of DEVS also allows coupling a Cell-DEVS model with other models representing external factors (e.g., a model of an HVAC unit). Other advantages of Cell-DEVS include the availability of a wide variety of tools that facilitates translating formal, easier to verify, mathematical models into executable models [19], as well as providing a well-defined specification of timing delays [29].

We use Cadmium, a DEVS and Cell-DEVS simulator [9] to implement the indoor models presented in later sections. Cadmium is a C++ header library simulator that defines general models based on the Cell-DEVS and DEVS formal specifications. Cell-DEVS models are defined in C++ combined with model configuration parameters defined using JavaScript Object Notation (JSON). The model configuration (such as the cell's neighborhood shape, dimensions of the room, or occupants), are specified in a JSON file (the models are available online in [1] and [4]). DEVS and Cell-DEVS are also useful for design decision making in architecture. The formalisms allow considering a whole physical system as a composition of different subsystems. An application presented in [14] is an example that shows how to define an automated lighting system based on its subsystems' functionality: a detector, a lighting fixture, and employees. Similarly, Autodesk Design DEVS defines a new method to make it easy for the experts in architecture and urban design to understand DEVS concepts by integrating visual interface design for easy interaction [21].

Tools like Autodesk Revit and 3Ds Max, used for BIM, have often been used for either data extraction or visualization; but both aspects in the same environment still need some exploration [2]. In our research, we use the API of Autodesk Forge to build Cell-DEVS models in BIM. We use BIM information to convert the building's model into Cell-DEVS model, then use the simulation results for BIM visualization.

3 A WORKFLOW FOR INTEGRATION OF MODELS AND INTEGRATION WORKFLOW

This section describes a workflow for extracting BIM data and visualizing the simulation results under a common platform. In the absence of a BIM model, other formats can be used, for instance, an image of a building plan or an AutoCAD file [19]. Figure 1 shows the workflow using Autodesk Forge, a web service API that allows access to BIM 360, a repository of BIM models.

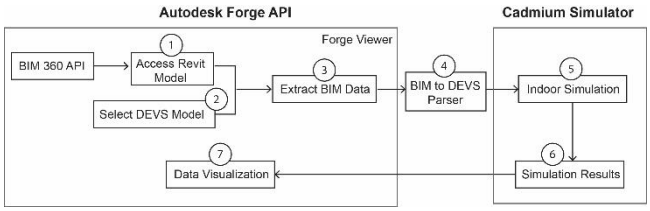

Figure 1 Workflow for BIM data extraction and visualization.

The workflow shows how to integrate the different tools, allowing designers to explore models for different buildings. The Revit models are accessed from BIM 360. When the user selects the simulation model type to run, like CO_2 diffusion or viral spread, the BIM data integrated with the DEVS scenario is extracted to a JSON file, and it is automatically downloaded from the Forge viewer. The Cadmium simulator is run using the JSON file as an input, and the simulation output is integrated back into the BIM for data visualization. We will discuss the conceptual specification for two models built to study aerosol particles' behavior in indoor environments: a Viral Particle (VP) and a CO_2 diffusion model. Both models use the workflow discussed above: we use a BIM model to define the built environment for the simulation study (which can be uploaded to BIM 360 and accessed through Autodesk Forge, as discussed in step 1 above). We then choose the simulation model to be executed (step 2), extract the BIM data (step 3) and convert the BIM to DEVS [24] (step 4) to create input files to run the simulation in Cadmium (step 5). The results (step 6) can be visualized in Autodesk Forge (step 7) or other tools. Both Cell-DEVS models use a set of parameters that can be adjusted to understand the spread of infection indoors for different building types. In the following section, we explain the complete process of BIM data extraction and conversion to Cell-DEVS and how to convert the simulation results obtained to visualization data that can be viewed in a BIM model.

3.1 CO_2 Diffusion Models for Estimating Infection

As occupants of any indoor space breathe, they exhale air that contains CO_2 mixed with aerosols; possibly containing viral particles. A higher CO_2 concentration in a closed space indicates that the occupants of that space are inhaling more CO_2 and hence more viral particles if they exist [25]. Researchers have derived mathematical expressions from calculating the risk of indoor infection for different viruses based on CO_2 concentration levels. The motivation for using such expressions is the ease of measuring CO_2 concentration using low-cost CO_2 sensors. Peng and Jimenez provide some guidelines for safe indoor CO_2 concentration levels that reduce indoor COVID-19 infection risk [23]. For everyday activity levels (e.g., office work), researchers suggest 700 particles per minute (ppm) when the outdoor concentration is around 420 ppm. Others suggest 1000 ppm as a maximum

concentration for CO_2 in a closed space [8]. The model presented here is for implementing the concept of using CO_2 concentration level as an indicator of the possibility of infection. The suggested model and future versions can be used to put a cap on the number of occupants in modeled indoor spaces to reduce infection probability. It can also be used to set the required ventilation for each modeled indoor space separately.

The CO_2 infection model presented in this section is a modification of a Cell-DEVS CO_2 diffusion model presented in [18]. The authors' CO_2 diffusion model mimics an indoor space while considering different settings of the space. The model considers the dimensions of the modeled space, ambient CO_2 concentration (outdoors CO_2 level), locations and status of windows and doors, locations and dimensions of ventilation ports, and occupants' presence. The model also considers different arrival times, departure times, and the period spent by each occupant in different indoor spaces. In this research, the focus is on the 2-dimensional version of the model [18].

In this research, we have added a new type of occupants: potentially infected occupants who are at higher risk of infection because of their presence in an area where CO_2 concentration has been high for a certain period. The model now uses a risk concentration threshold (RCT) and an exposure time threshold (ET). An occupant is potentially infected if they are present in an area where the CO_2 concentration level has been above the RCT for a period exceeding the ET. Table 1 lists the cell types that are specified in the formal description of the model. The table also lists the default concentration values for each cell type.

Cell type	CO_2 **concentration (ppm)**
impermeable structure	0
windows (outdoor concentration)	400
Vents	400
air and workstations	Depending on airflow, CO_2 concentration is distributed among the neighboring cells.
rest of the building (indoor concentration)	500
CO_2 source	+0.31 l/minute/person

Table 1. CO_2 concentration in all cell types in the model.

Experimental research conducted at the start of COVID-19 breakout predicted that airflow could change the way people could get infected in a closed space [20]. Therefore, we also incorporate airflow in the model. To do so, we use the air direction (AD) and the rate of airflow (RAF) in that direction. AD is a vector of two components (x, y) where x and y represent the horizontal and vertical airflow direction, respectively. For example, if the AD in a model is (-1,1), this means that the air flows from the southeast to the northwest of a 2D model. RAF indicates the portion of CO_2 concentration from the current cell distributed to the cell in AD's direction. If AD is (-1,0) and RAF is 0.8, this means that 80% of the CO_2, of the current cell, is distributed to the west direction. In comparison, the rest of the CO_2 concentration (20% of the current concentration) is calculated by averaging the CO_2 concentration in the remaining neighborhood cells. Different directions and strength of airflow may affect whether a person in a specific location in the room may be potentially infected or not.

The Cell-DEVS local computation function calculates the new CO_2 concentration and the infection risk in each cell based on the model configuration and the current CO_2 concentration. The following pseudocode snippet shows a portion of the model found on our GitHub repository [11], which calculates the concentration of CO_2 in the air based on the AD and RAF. We also show how a healthy occupant (CO_2_SOURCE) switches to a potentially infected occupant (SUSC_CO_2_SOURCE) based on the RCT and ET.

```
CO2 local_computation() {
 CASE cell_type of {
  air:
    flow_c = concentration of cell in AD direction
    nbrs_c = avg concentrations of other neighbors
    concent = (1-RAF) x nbrs_c + RAF x flow_c
  co2_source:
    IF breathing counter mod breathing rate == 0
       concent = concent + breathing increase
    IF concent ≥ RCT {
         exposure_time++
         IF exposure_time ≥ ET
                cell_type = potentially_infected
     } // IF
  } // case
} // function
```

The values of RCT, ET, AD, and RAF, as well as the room configuration, are specified in the configuration file. Similarly, the breathing settings (CO2 production per breath and breathing rate) are specified by the user based on the activity level of the occupants.

Next, we show the results of running this code on two case studies for the same indoor space, with the same number of occupants (25 persons). In both scenarios, RCT = 700 ppm, and ET = 50 minutes. The threshold choices are based on examples of real-life scenarios [21] and research findings [23] respectively. Occupants arrive at different rates. In the first scenario, the airflow direction is from south to North (i.e., AD = (0,1)) with an RAF of 80%. Figure 2 shows the simulation results after around 52 minutes (i.e., 2 minutes after the threshold). The simulation results show seven occupants at a higher risk of getting infected. All those occupants are clustered on the upper third portion (i.e., North of the floorplan) of the room.

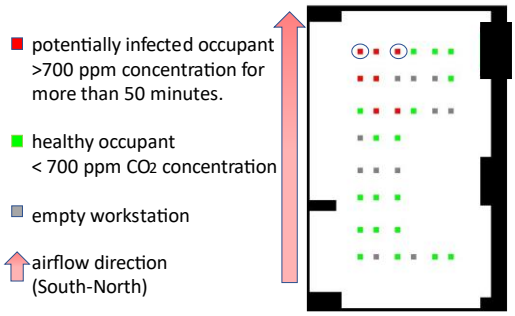

Figure 2 Simulation of CO2 concentration as an indicator of infection in a room with the effect of vent airflow.

In the second scenario (Figure 3), CO_2 concentration is diffused equally among all neighboring cells to mimic a uniform air distribution room. Figure 3 shows the simulation result at the same time displayed in Figure 2 (i.e., at minute 52). Comparing the two results, one observes that more occupants in the area towards which the air is flowing are potentially infected.

Note that the occupants arrive at different times. Therefore, some areas in the room may have more CO_2 concentration than in other areas. However, the pattern and timing of occupants' arrivals are the same in both scenarios. Occupants who appear to be at risk in one scenario and not in the other are circled in the figures. For example, the occupant at risk on the left upper corner of the floorplan of Figure 2 is not at risk in the scenario where the air is uniformly distributed (Figure 3). The simulation results of the Cell-DEVS model presented here align with the results that Lu et al. reported about the effect of the airflow direction on infection scenarios in a closed space [20].

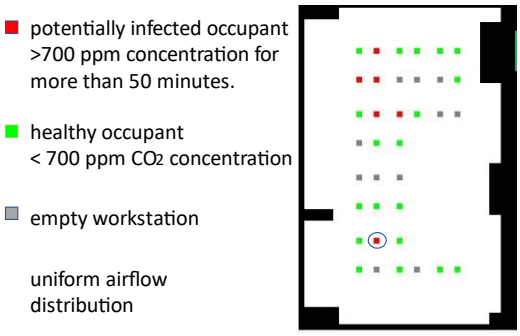

Figure 3 Simulation of CO2 concentration as an indicator of infection in a room with uniform airflow distribution.

The model uses diffusion equations, and it has been validated and calibrated based on ground truth data, the equations have been also validated in a previous publication and have shown to mimic real-life scenarios [18]. Another option would be to use our previous CFD implementation in Cell-DEVS [26], which would require improved performance and will be experimented in future versions of this model. The current model shows how to conduct rapid prototyping of Cell-DEVS models in this application domain.

3.2 Viral Particles Spread model

The model we propose represents a closed indoor area with one (asymptomatic) infected person. In the beginning, the area has zero infectious particles, then the infected person (shown in red color in Figure 4 (A)) starts breathing and emits 33 particles per minute [27]. We used a breathing rate of one breath every 5 s and defined viral particle production as another parameter chosen. We considered the dimensions of the closed area, the number of infected people, the infection threshold as a total number of particles it takes to infect a healthy person, and vents representing the AC flow, that can be set to On or Off. The direction of airflow is calculated based on the vents' positions. For example, if the vent is in the east of the room, then particles spread in the same direction of the air flowing from the vent (represented by blue arrows in Figure 4 (B)). The indoor closed space is represented as a set of neighboring cells in a 2D Cell-DEVS model. The accumulated number of particles is distributed between the total number of neighboring cells in all directions when there is a uniform airflow, no ventilation (i.e., AC is Off), and the remainder stays in the center cell as shown in Figure 4 (C).

In the case of existing ventilation, a percentage of particles identified by a model parameter (flow weight) travel in the vent airflow direction. The rest of the particles stay in the cell until it has enough particles to distribute them evenly between their neighboring cells. Each cell in the model represents 25cm × 25cm spaces. The restaurant application scenario dimensions are 17.5 m x 8.3 m in 2D, and a 70 x 33 cells grid can reflect those dimensions. The VP model uses the eight closest neighbors. The restaurant scenario can use uniform airflow (when the vent is Off) and we can change the vent's location based on the original BIM data.

The following pseudocode snippet shows how the local computation function calculates the total number of viral particles for each cell type. Those particles are generated with each breath every 5 seconds. The complete source code for the VP model is available in [28].

```
vp_cell local_computation() {
 CASE cell_type {
  IMPERMEABLE_STRUCTURE:  num_particles = 0;
  VP_SOURCE:
    FOR each neighbor {
      // assign a direction based on its position
      setDirection(s', neighbors);
      loopThroughNeighbors(neighbors);
      computeParticles(s', neighbors);
        calculate how many particles should be
          distributed to the neighboring cells
    } // FOR
   } // CASE
} // function
```

The model uses different types of cells: open-air, vp_source (represents an infected person), impermeable_structure (such as walls, ventilation), and vp_receiver (a susceptible individual). The function uses three main functions:

- *setDirection* assigns a direction to the cell based on its position (for example, if a vp_source is located in the airflow

zone, a percentage of the particles, identified by a flow weight parameter, will spread in that direction);

- *loopThroughNeighbors* loops through all cell's neighbors and checks if they have any viral particles; and

- *computeParticles* calculates how many particles should be distributed to the neighboring cells.

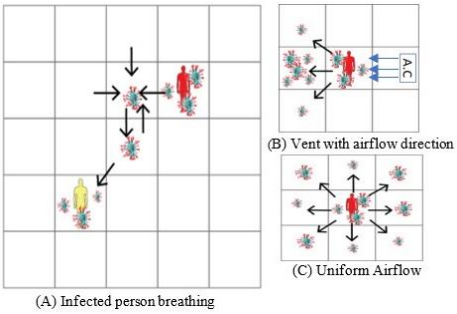

Figure 4 Viral particles (VP) Conceptual Model.

Figure 5 shows the restaurant's floorplan extracted from [20]. Wall cells translate have impermeable structure. Tables are shown in yellow; chairs are shown in grey when they are empty and blue if they are occupied. Cells representing vents are shown as light blue rectangles and located at the east of the restaurant floor plan. The vents' precise location in the physical system presented in [20] is not available.

We run the simulation for 3600 timesteps, equivalent to the one-hour exposure time (average exposure time for family B and family C). Figure 5 shows the infected person (index case) has started breathing every 5 s and is emitting particles. 80% of them are spread in the room in the same direction of the vent airflow from east to west. Figure 5 (a) shows the simulation results after 30 minutes. The table where the index case (red color) is sitting is in the vent airflow zone with chairs occupied by susceptible people (blue color). One of them sitting beside the index case has changed to brown color, which means this susceptible person has become infected. Figure 5 (b) shows the results after one hour of simulation, and four susceptible persons got infected.

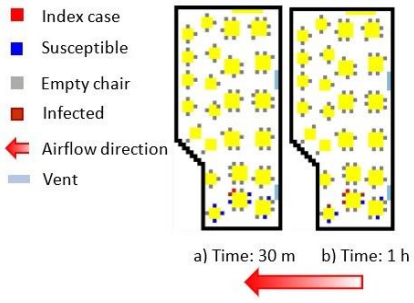

Figure 5 Viral particles spread with the effect of vent airflow.

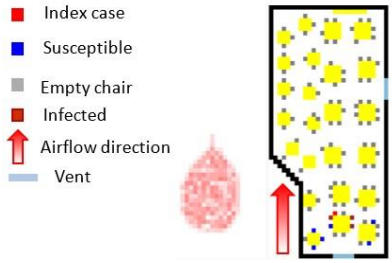

Figure 6 Simulation results with vent in the south.

In the scenario presented in Figure 6, we changed the vent location and kept the other parameters as in the previous scenario. The vent located in the south is turned On, prompting 80% of the particles to follow the AC airflow. As a result, three susceptible persons, who shared the index case (red color) the same table, which is in the airflow zone, became infected (brown color).

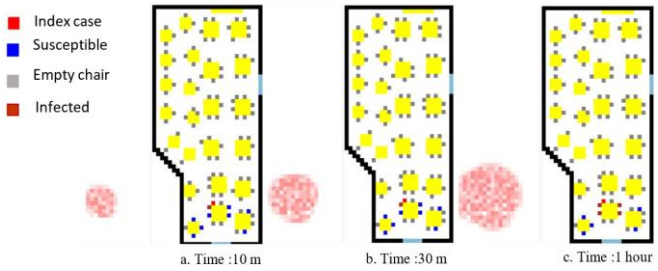

Figure 7 Uniform airflow.

In the scenario presented in Figure 7, the vent is Off. Therefore, the particles are distributed evenly between the total number of neighboring cells in all directions when there is a uniform airflow. As we see in Figure 7 (a, b, c), the number of particles increases with every breath exhaled from the index case. Figure 7 (c) shows that the four persons sharing the table with the index case got infected.

3.3 BIM to Cell-DEVS Integration

The VP spread model presented here uses, as example, a real-world case extracted from the scientific literature for COVID-19 research. On January 23rd, 2020 [6, 20], an asymptomatic index patient traveled from Wuhan, the center of the COVID-19 pandemic, to Guangzhou, China. On the next day, January 24th, 2020, the index patient had lunch in a restaurant with three people from his family (family A) sharing the same table. In the same restaurant and at the same time, there were two other families (family B and family C) having lunch and seated at the neighboring tables of family A table. Later, the same day, the index patient experienced fever and coughing and diagnosed with a COVID-19 infection. By February 5th, four people of family A, three of family B, and two of family C were diagnosed with COVID-19, which increased the total number of confirmed cases with COVID-19 to ten (including the index case). The restaurant where the index patient had lunch is located on the third floor within a 5-floor building and occupies 145m^2. Each floor in the building has its ventilation system and does not have

windows. On the day of the lunch, eight staff members and 83 customers sat at 15 tables. The tables were arranged with about 1 m between them. Out of 83 customers, ten confirmed cases with COVID-19, the other 73 had no symptoms, and their tests returned negative.

The airborne transmission was the main factor causing the restaurant outbreak since the index patient had no symptoms during the time they spent in the restaurant [6,20]. The airflow direction was another critical factor in the outbreak. AC ventilation prompted particles to follow the direction of AC airflow. This explains why other customers who sat on the tables outside the AC airflow zone did not get infected, and five people who sat on the tables in the AC airflow zone, including the index patient table, got infected.

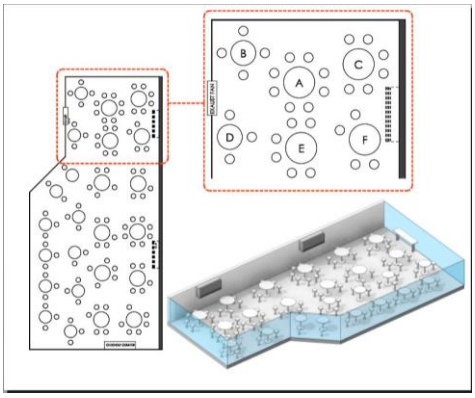

Figure 8 Revit model a restaurant in Guangzhou, China [20]

We designed a BIM model of the restaurant using Autodesk Revit based on the dimensions and interior details provided in the floor plan of the restaurant, presented in Figure 8.

The results presented in the simulation results section are generated based on different model variations to study the effect of airflow on the viral particles spread, which cause the infection. The simulation results are read in the BIM model using D3.js and visualize the data using three.js files in the Autodesk Forge API.

As shown in Figure 9, the red color gradient represents the viral aerosol particle concentration. Light red represents less concentration (one viral particle), and dark red represents a high concentration (20 viral particles). The model represents three conditions: infected (red; the index patient), exposed (brown), and susceptible individuals (cream). People exposed to a high concentration of particles eventually become infected; anyone present in the room with an infected person is susceptible. The BIM integration model allows the spatial analysis of the simulation results. For example, the spread is faster in location A of the restaurant than in location B. Location A is compact in comparison to location B. The model clearly shows how the infection spreads in the direction of the airflow of the vents.

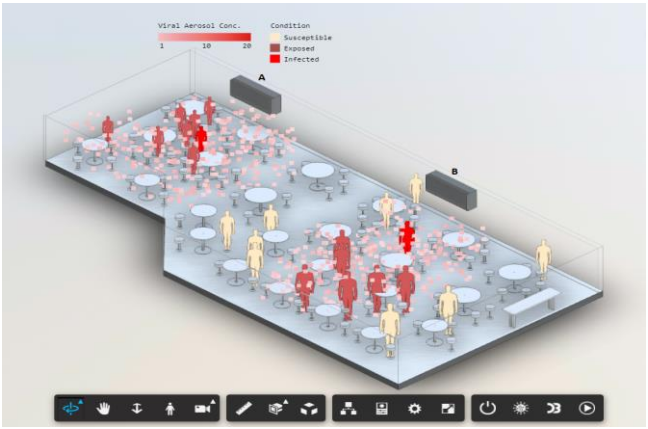

Figure 9 BIM model showing the family seating and vent details.

Figure 10 (a) shows the simulation results at the start time: 0 of the simulation with the infected people in the built environment. At 15 time units, the particle concentration increases resulting in occupants' exposure to a high concentration (Figure 10 (b)).

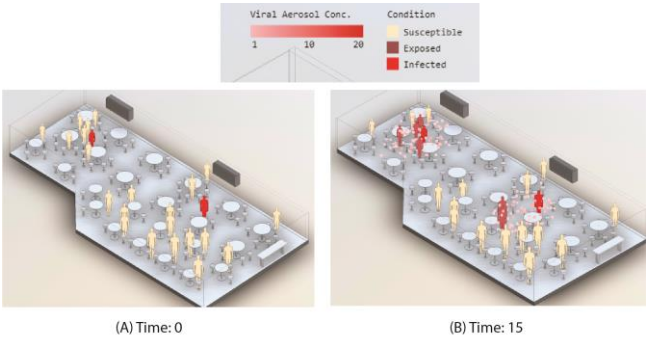

Figure 10. Simulation at different time steps.

4 DISCUSSION

The results of the two models presented and their variations show the impact of indoor configuration on occupants' infection. We use the airflow direction as an example that influences the infection spread. By varying the parameters, these models can simulate the implications of any airborne disease.

The two models are backed by supporting real data from physical systems. However, there are some validity threats as in any other experiment. For example, we represented a physical 3D space in a 2D model which may be argued as a construct threat to validity. We overcome this threat by considering the 2D model as a cross-section. We calculate the concentrations of VP and CO_2 with the assumption that this cross-section has a depth of 25 cm at the breathing occupants' height. In future versions, we plan to reproduce the models in 3D versions, which we have used Cell-DEVS for before in other indoor models [18].

Another limitation is that the airflow is considered similar in the whole space, while airflow direction and speed may vary from one place to the other in a closed room. Airflow

properties (i.e., speed, direction) is also another aspect that we plan to incorporate in future models. Nevertheless, in the current state, the simulation results comply with the corresponding physical systems' data. Thus, the presented limitations do not significantly affect the results.

The simulation results are easily analyzed further by combining the models with generative design. This combining allows the architects or designers to evaluate physical distancing performance with infection rate. Also, the integration of BIM to Cell-DEVS allows non-domain experts to use the formalism with ease. In the future, we will implement additional parameters in Forge viewer for the advanced user who can formulate their own rule for DEVS simulation. These models help in building operation, automation, and designing for a healthy environment.

5 CONCLUSION

The ongoing pandemic has disrupted everyday life. As companies, universities, and schools plan for re-opening their buildings, evaluating the spread of the virus in the building takes a priority. Simulating airborne transmission in indoor places helps the building industry stakeholders understand its design implications and performance. Building managers can foresee the hotspots for infection and make changes to the building design by increasing ventilation or air-infiltration. In the worst-case, they can reduce the occupancy count or incorporate building design changes. Hence, visualizing simulation results with BIM helps architects, engineers, and building managers to make informed decisions. The two models presented in this research, viral particle spread and CO_2 diffusion, aids in this process. Combining the proposed models with the parametric design is a powerful tool for design-decision, risk assessment, and maintaining good indoor air quality.

Indoor environmental quality plays a crucial role in a healthy environment for occupants. Studies show that adequate ventilation reduces the spread of infection [6,7,14]. If the building does not have a proper ventilation design system, it fails and causes health hazards. The presence of a high concentration of CO_2 in the building poses more danger during a pandemic. The CO_2 diffusion model helps track occupants' presence and may support the building facility manager to identify hot spots for the spread of infection. Both models help understand the spread of disease in the buildings. The viral particle spread uses a person's infected condition, while the CO_2 diffusion model uses the CO_2 concentration level in buildings as a proxy for the risk of infection.

As the research of the spread of COVID develops, more factors can be incorporated into the proposed prototype models, allowing the simulation to render more accurate future models. In future versions, we will consider the quanta emission rates (ERq) to estimate the number of infectious quanta in viral load emitted by an infected person. ERq considers infectious removal rate in a space representing the sum of the air exchange rate (AER) via ventilation and particle deposition on surfaces and the viral inactivation [6,7]. We will also consider other respiratory activity types such as speaking and coughing at different levels, for instance, speaking loudly, speaking, or breathing while exercising. Also, masks' efficacy will be evaluated by introducing other parameters to represent different mask types with their shedding rate (percentage of particles exhaled) and efficiency (percentage of particles blocked from being inhaled). Another area of improvement is considering the spread of CO_2 produced by occupants between different rooms through different connections (e.g., ventilation ducts). The effect of such connections on the spread of viral particles, with the breath, from a closed space to another is a significant research area that we foresee pursuing soon.

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