# CELL-DEVS MODELS FOR $CO_2$ SENSORS LOCATIONS IN CLOSED SPACES

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## ABSTRACT

With the global warming crisis and its correlation to levels of energy consumption, it is paramount to find ways to reduce energy consumption in closed spaces with minimal disruption to occupants' comfort. Thus, researchers are working to improve methodologies for occupant-based demand-control heating, ventilation, and air conditioning. Sensor usage for occupancy detection is among the methodologies researched for controlling consumption. Carbon dioxide sensors proved to be effective but overly sensitive to configuration. Research also proved that there is an undetermined latency period between the changes of the number of occupants and the carbon dioxide sensors detection of that change. We present a work in progress method to determine the best placement of carbon dioxide sensors for the accurate occupants' detection and calculation of latency using the Cellular Discrete-Event Specifications formalism. We present several case studies showing resemblance between physical closed spaces and the models and how the simulation replicates real-life scenarios.

## 1    INTRODUCTION

Limiting global warming requires maintaining a substantive decrease in carbon dioxide $CO_2$ emission (Rogelj et al. 2018), to which energy consumption is closely related. A recent Energy Technology Perspective (ETP) report stated that three-quarters of global electricity demand can be saved by using high-efficiency lighting, cooling, and appliances (IEA 2017). This perspective is one of the several reasons why researchers investigate ways to optimize energy consumption in buildings. One of the most expensive energy-consuming functions in buildings is heating, ventilation, and air conditioning (HVAC). One way that has been proposed to achieve high-efficiency energy consumption of HVAC is the demand-driven HVAC control, where the use of the HVAC system depends on accurate occupancy information and measurement (Huang and Mao 2016). Occupants with energy-conscious behavior can contribute to saving up to one-third of a building's energy (Nguyen and Aiello 2013). However, trusting occupant's behavior for better energy consumption is unrealistic, especially in commercial buildings where occupants are not directly affected by the cost of energy consumption. Therefore, demand-driven control of lighting and HVAC systems are often chosen as a solution to reduce the consumption in buildings. Many studies have been conducted to develop demand-driven control of lighting and HVAC systems. The objective in most cases is that the total energy consumed is kept at the minimum possible value without disturbing the comfort conditions of the occupants of the building (Labeodan et al. 2015). Demand-driven control systems depend on sensors data for indoor occupancy detection. Many kinds of sensors are used in such systems either individually or in combination with other types of sensors. Among those sensors are $CO_2$ sensors.

  $CO_2$ sensors have advantages and disadvantages in terms of occupants' detection when compared to other sensors. In addition to not being non-intrusive, they do not require motion or any special action, and they do not have extra cost as they are installed as part of the building code in many cases. However, there are a few concerns with $CO_2$ sensors as a means for detecting occupants. First, the demand-driven control

systems should account for the latency needed for the sensor to detect an increase or decrease in $CO_2$ levels in the closed space. Second, although $CO_2$ sensors achieve up to 91% accuracy in detecting the existence of occupants in closed spaces, they are not very accurate in detecting the precise number of occupants in the space (Arief-Ang et al. 2018) because they are highly sensitive to the configuration (Labeodan et al. 2015; Hobson et al 2019). With the variability of configuration parameters and the impracticality of collecting ground truth data for each space, there is a great motivation for simulation models for occupants' detection (Arief-Ang et al. 2018). Models are also the only solution at the design stage when the buildings are yet to exist when it is impossible to collect ground truth data using the physical space. In this research, we use modeling and simulation (M&S) to achieve two major objectives: (1) Based on the room dimensions, and other parameters of the occupied space, determine the best placement of $CO_2$ sensors for the most accurate occupancy detection and (2) based on the placement and the room, calculate the latency between the arrival/departure of an occupant and the detection of an increase/decrease in $CO_2$ levels. We propose using the Cellular Discrete-Event Specifications (Cell-DEVS) formalism (Wainer 2009) as a way of modeling and studying the relation between configuration parameters (e.g. room dimensions and window locations) and the ability of $CO_2$ sensors to detect occupants and how this relationship can be used to determine the best placement of $CO_2$ sensors. In section 2, we explain the necessary background to put our research into context. In section 3, we define the research problem. Then, we explain the current experimental setup including the scope and the model specifications in section 4. The preliminary simulation results of our work in progress research are presented in section 5 and discussed in section 6. Finally, we conclude and list the future steps in section 7.

## 2    BACKGROUND

In this section, we provide the necessary background needed to contextualize our research. We start by describing several types of sensor-based occupancy detection, we explain the theoretical concepts for the modeling techniques we are using in this research and discuss a brief literature review.

### 2.1    Sensor-Based Occupancy Detection

There are two possible outcomes of sensor-based occupancy detection: binary detection and the estimate of the number of occupants. Binary occupants' detection determines the presence of any occupant. For example, passive infrared (PIR) sensors detect only binary information to indicate whether a room is occupied or not, which makes it useful only for non-individualized demand-control systems (e.g. light switching) (Li et al. 2012). On the other hand, the use of such types of sensors for demand-control HVAC systems is limited since it does not give an estimate of the number of people occupying the space (Labeodan et al. 2015). Binary occupant detection versus occupants count estimate is only one criterion for classifying sensor-based occupancy detection systems. Labeodan et al. (2015) categorize sensor-based occupancy detecting systems based on (1) method: the need for a device attached to the occupant, (2) function: the ability to individualize occupants, and (3) infrastructure: this differentiates between sensors that are part of the infrastructure and sensors that must be installed just for occupants detection.

Listing all the types of sensors-based systems in all categories is out of the context of this paper. Instead, we list a few examples in comparison to $CO_2$ sensors that are the focus of our paper. For example, unlike detection systems such as electromagnetic (EM) signals that require the occupant to carry a device for the system to detect the presence of that occupant, $CO_2$ sensors and PIR sensors do not. For the function criterion, cameras, for example, can detect individual occupants, and consequently, the demand-driven control system can adjust the comfort level based on the preference of the detected individual. However, the privacy of the occupants is compromised in this case. On the other hand, $CO_2$ sensors are non-intrusive as they preserve the privacy of the occupant. Also, $CO_2$ sensors are part of the infrastructure in many cases. For example, in the province of Ontario, Canada, $CO_2$ sensors installation has been part of the building codes since 2014 (Carbon Monoxide Questions and Answers 2019).

Based on the advantages of $CO_2$ sensors, they are one of the best types of sensors to measure indoor occupancy, but most indoor occupancy papers using $CO_2$ provide binary occupancy analysis, not real people

counting analysis (Arief-Ang 2018). Although $CO_2$ levels in the room change based on the number of occupants present in that room and hence, they are not binary by nature, their sensitivity to room configuration limits their accuracy ( Labeodan 2015; Hobson et al. 2019). Many configuration parameters may affect $CO_2$ levels in closed spaces. Among those parameters are the room size (Arief-Ang 2018), and sensor location. For example, temperature differences in surfaces affect airflow especially close to windows which in turn affect the uniformity of $CO_2$ distribution in the whole space (Batog and Badura 2013).

## 2.2    DEVS and Cell-DEVS

We chose for our modeling of $CO_2$ dynamics DEVS and Cell-DEVS. DEVS is a mathematical formalization of the system and therefore it is independent of any tool or programming language. DEVS formalizes the definition of systems using the hierarchical composition of behavioral (atomic) and structural (coupled) models (Wainer 2009). An atomic model consists of input/output ports to communicate with other models, internal/external transitions, and a time-advance function. Each atomic model has a set of state variables that represent the current state of the model. After the time-advance (ta) has elapsed, the output function ($\lambda$) is triggered which sends an output to the output port (y) based on the current state. Then, the internal transition function ($\delta_{int}$) which updates the next state of the atomic model based on its current state gets fired. The external transition function ($\delta_{ext}$) updates the state of the model based on inputs received from other models and collected through the input ports. Atomic models can be combined in a hierarchy to form a coupled model. Cell-DEVS is an extension of the DEVS formalism that combines Cellular Automata (CA) and DEVS. A Cell-DEVS model is composed of multiple atomic models where each atomic model is represented in a cell in an n-dimensional lattice of cells. The complete cell space is a coupled DEVS model formed by combining the individual atomic models (Wainer 2009). An atomic model in a Cell-DEVS space is formally defined as TDC=< X, Y, S, N, delay, $\delta_{int}$, $\delta_{ext}$, t, $\lambda$, D > where X is the input events set, Y is the output events set, S is the set of states, N is the set of input values, delay is the type of delay, $\delta_{int}$ is the internal transition function; $\delta_{ext}$ is the external transition function, t is the local computing function, $\lambda$ is the output function, and D is the state's duration function (Wainer 2002). The local computing function t calculates the next state of the cell (s $\in$ S). Each cell is associated with a delay that can either be transport or inertial. Transport delay defines the duration after which, the output values are transmitted. The inertial delay d is used as a preemptive mechanism; it prevents any scheduled change from taking place upon receiving an external event from a neighbor cell before the scheduled time. A complete Cell-DEVS space is defined as GCC=< $X_{list}$, $Y_{list}$, I, X, Y, $\eta$, {$t_1$,…,$t_n$}, N, C, B, Z> where $X_{list}$ is the list of external input coupling, $Y_{list}$ is the list of external output coupling, I is the set of states, X is the set of external input events set, Y is the set of external output events set, $\eta \in$ N is the neighborhood size, {$t_1$,…,$t_n$} is the number of cells in each dimension, N is the neighborhood set, C is the cell space, B is the set of border cells, and Z is the translation function. The border cells B can have different behavior than the rest of the cell space (e.g., borders can be wrapped). The translation function Z defines the internal and external coupling of the model (Wainer 2002). Figure 1 illustrates the basic behavior of a Cell-DEVS model.
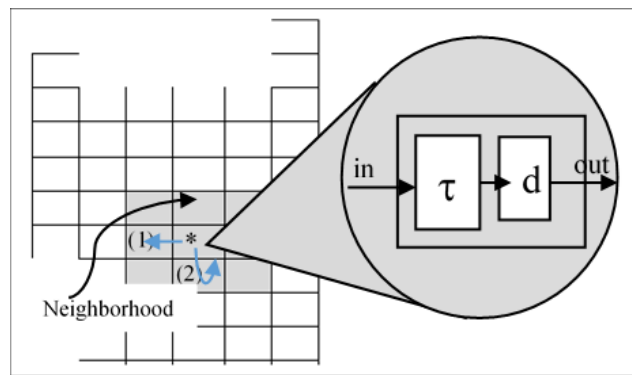


Figure 1: Basic Cell-DEVS model.

There are many advantages to using Cell-DEVS to model $CO_2$ dispersion. Cell-DEVS is proven to be suitable for modeling systems like what we are trying to model in our research. For example, unlike agent-based models that are not adaptable to different environmental settings such as diverse types of room (Arief-Ang et al. 2018), Cell-DEVS can easily incorporate the different environmental settings in the model. Also, in comparison to cellular automata (CS) modeling, Cell-DEVS has several advantages (e.g. CellDEVS provides asynchronous execution, which results in better execution time). Examples Cell-DEVS environmental and social models are available through ARSLab (2020) and in the literature (Wainer 2006; Khalil and Wainer 2020). The discrete nature of the modeling formalism allows for skipping periods of inactivity in simulation and hence achieves better performance. This formality is simpler to verify and validate. Besides, Cell-DEVS and its tools provide a complete modeling and simulation solution that includes formal model specification, simulation by independent tools, and visualization (Wainer and Giambiasi 2005).

## 2.3    Literature Review

Labeodan et al. (2015) provide a review of different occupancy detection systems and claim that obtaining information for use in building control can be challenging due to different environmental factors and stochastic human behavior. To compensate for this, the authors install chair sensors in the form of micro switches wired to a transmitter. The system is assessed in a conference room for eight hours and the 100% accuracy is recorded. The drawbacks of the proposed method are failure to detect standing occupants, the change of sensors' states due to occupants' frequent adjustments in their seats, and occupants' resistance. Cali et al. (2015) present an algorithm to detect occupants based on $CO_2$ levels in indoor environments. The algorithm was validated against ground truth data in five different environments: an office with no mechanical ventilation, two offices with mechanical ventilation, a residential living room, and a kitchen without mechanical ventilation. The algorithm scored 95% and 80.6% success for detecting the presence of occupants, and the number of occupants, respectively. The authors conclude that to maximize the precision of their algorithm, detailed knowledge about the value for air change rate through windows, doors, and the outdoor $CO_2$ concentration is important. Ryu and Moon (2016) use a statistical decision tree model and Hidden Markov Model to detect occupancy based on indoor climate sensors. The authors conclude that $CO_2$ sensors while considering the ratio of indoor and outdoor $CO_2$ concentrations, provide the highest level of information. The study presented by Pedersen et al. (2017) offers a binary occupant detection plug-and-play method. The proposed method uses PIR, noise, $CO_2$, temperature, humidity, and volatile organic compound (VOC) measurements to detect the presence of occupants. The study uses a simple test room and a three-room apartment to validate the method. The maximum detection accuracy is 98% for the former and 78% for the latte. Huang and Mao (2016) combined $CO_2$ and light sensors with a wireless sensor platform to estimate the number of occupants in an office building. The authors suggest that the integration of the different sensors can compensate for the fluctuation of $CO_2$ levels due to environmental factors (e.g. location of $CO_2$ sensor and HVAC operations).

Batog and Badura (2013) present a model that corresponds to a simplified version of a real bedroom containing only big solid surfaces (e.g. bed and wardrobe). The authors consider the different $CO_2$ production rates during sleep from one sleeping object along the course of eight hours. Two simulations are performed; a simulation without fresh air inlets and a simulation where airflow gaps around windows and doors are considered. The simulations show that the proper placement of $CO_2$ sensors is essential for accurate measures. The authors suggest the $CO_2$ sensors should not be in corners, below bed level, nor near doors and windows. The authors observe that $CO_2$ concentration may differ significantly in a room between consecutive nights and this is caused by outdoor air that flows through minor gaps around windows. Pantazaras et al. (2016) suggest a method to create models tailored for specific spaces. The model designed for a specific room, $CO_2$ concentration, ventilation, and some occupants can then be used to predict the $CO_2$ concentration level in that room. The possibility of predicting future $CO_2$ levels allows for further operational efficiency as opposed to using reactive energy systems. The predictive model is proven effective for short term predictions. The author warns that the location of $CO_2$ sensors must be carefully chosen for the method to be effective. To the best of our knowledge, there is no significant work that models and

simulates indoor $CO_2$ dynamics in closed spaces using cellular automata neither there is modeling and simulation research work that takes into consideration sensor placement and room configuration, and this is the focus of the research we present the initial phase of.

## 3 PROBLEM DEFINITION

The fact that $CO_2$ sensors are an effective, affordable, and non-intrusive means of accurately detecting occupants on one hand, and that they are very sensitive to the environment on the other hand (section 2) motivates our research. In our work, we aim at utilizing the advantages of $CO_2$ occupant detection, while overcoming the concerns associated with those sensors. First, we use M&S to overcome the problem of lack of and difficulty in collecting ground truth data for different indoor environments. For this objective, we make use of Cell-DEVS advantages and its applicability for the objectives of our work (section 2). Second, we aim at incorporating factors that affect the accuracy of occupants' estimation using $CO_2$ sensors such as locations of sensors, window and door locations, and volume of the occupied space. Third, we aim at finding a way to calculate the latency required for $CO_2$ sensors to pick up the change in the number of occupants. To achieve this, we propose the following two research questions (RQs). RQ1: Is it possible to determine the best $CO_2$ sensors location for most accurate occupancy detection based on room configuration using M&S? RQ2: What is the latency between the arrival/departure of an occupant and the detection of the change in the $CO_2$ concentration level?

## 4 CURRENT STATUS EXPERIMENTAL FRAME

In this paper, we present the initial version of our work where we limit our scope to (1) closed spaces of size 3.5m × 5.75m × 2.5m (width × length × height), (2) one to two occupants, (3) presence of means for $CO_2$ to escape (an open door, a window or a ventilation port), and (4) the placement of one or two $CO_2$ sensors in constant locations.

The hypotheses that we are trying to prove at this stage to allow us to proceed with our research to answer the RQs introduced in section 3 are (1) Cell-DEVS M&S complies with ground truth data in the sense that $CO_2$ levels are sensitive to configuration and hence Cell-DEVS can be used to answer the RQs in section 3, (2) $CO_2$ sensors placement in the models affect the occupants' detection, and (3) sensors' locations affect the latency between introducing an occupant and detecting the presence of that occupant.

### 4.1 Conceptual Model

In this section, we describe the conceptual model for our scope. Figure 2 illustrates the elements that could be present in the model. Parameters that we consider at this stage are the dimensions of the room, the locations of window/door and ventilation ports, the $CO_2$ sensor placement, and the presence of occupants.
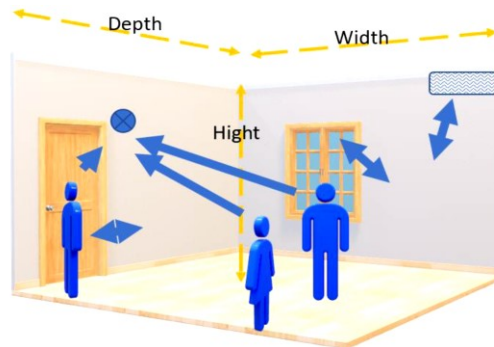


Figure 2: Conceptual model.

We represent the closed space as a set of neighboring cells in a 2-dimensional Cell-DEVS model with different $CO_2$ levels. We note here that we base our calculations on the facts that normal background $CO_2$

levels measured in particle per million (ppm) range from 300 to 400, while CO2 levels in an occupied space with normal ventilation range from 400 to 1,000 ppm (Teleszewski and Gładyszewska-Fiedoruk 2019), and the average person produces 0.5l of air per breath of which 3.8% (or 38,000 ppm) is $CO_2$ (Jung et al. 2017). Most people breathe once every 5 seconds corresponding to an output of 228 mL of carbon dioxide every minute. Hence, we have in the model six types of spaces where the gas diffuses according to different rules: (1) open-air spaces with constant 500 ppm $CO_2$ level, (2) walls that are impermeable and do not allow $CO_2$ to diffuse through them, (3) $CO_2$ sources with a fixed level of $CO_2$ added at an interval to mimic breathing, (4) open doors that diffuse $CO_2$ to the rest of the building with a fixed indoor background $CO_2$ level of 500 ppm, (5) open windows that are also $CO_2$ sinks with a fixed outdoor background $CO_2$ of 400 ppm, and (6) vents that diffuses gas through HVAC system with a reduced $CO_2$ background level <300 ppm.

CO₂ sinks in our model maintain constant $CO_2$ levels based on their type and are unaffected by the concentration of $CO_2$ in the closed space represented by our model. This approximation is very reasonable since outside (such as the rest of the building or outside a window) is large compared to the volume of air inside the confined spaces. Thus, diffusion of gas from inside the spaces into such large spaces should not significantly change the levels of $CO_2$. Determining the amount of $CO_2$ that is added to source cells from breathing requires some basic calculations. Each in the model represents 25 cm × 25 cm × 25 cm spaces and therefore has a 15.625 L volume of air. The average person produces 0.5 l of air with every breath at a concentration of 3.8% resulting in 19 mL of $CO_2$ being added to the surrounding air volume with each breath. The increase in $CO_2$ percentage for a standard cell volume is, therefore (0.019 l/15.635 l) = 0.001216% (note that the conversion between percentage and ppm is a factor of 10,000). Therefore, every 5 seconds (the average time between exhalations), approximately 12.16 ppm of $CO_2$ should be added to the current concentration in source cells. This rate of respiration reflects a single occupant who is not exercising. For our preliminary model, we average $CO_2$ levels of all cells in the local neighborhood including the center cell. The rate of diffusion is then controlled explicitly by the delay between each averaging event. In the future, more robust diffusion laws could be added, or the delay times adjusted to reflect the rate of diffusion in real life. For this stage of the research, diffusion averaging delays have been arbitrarily set to 1 second. The cell space should reflect the size of an average small office space or room. For a room measuring 3.5 m × 5.75 m and 2.5 m in height, which translates to a cell space of 14 × 23 × 10 cells in 3D.

## 4.2 Formal Model Specification

The two-dimensional Cell-DEVS space of the $CO_2$ model is: $CO_2$ = < $X_{list}$, $Y_{list}$, S, X, Y, η, N, {$t_1$, $t_2$}, C, B, Z >, where $X_{list}$ = $Y_{list}$ = {Ø}; S = *type*: {0, 1, 2, 3, 4, 5} and *conc*: {double}; X = Y = Ø; η = 5; N = {(0,0), (-1, 0), (0, -1), (0, 1), (1, 0)}; $t_1$ = 14; $t_2$ = 20; C = {$C_{ij}$ | i ∈ [0, 14[ ∧ j ∈ [0, 23[}; and B = {Ø} (unwrapped cell space. The local computing function $\tau$ of the atomic model of each cell and the duration function D are shown in Table 1 and Table 2 respectively. We use the Von Neumann neighborhood; we consider only the North (N), East (E), West (W), and South (S) neighbors. The cells have 2 distinct state variables: *type* and *conc*. *Type* has six possible numeric values which represent the type of cell: 0 for open-air, 1 for $CO_2$ sources, 2 for walls/impermeable objects, 3 for open doors, 4 for open windows, and 5 for ventilation. *Conc* is a double value that represents the $CO_2$ concentration in ppm within a cell. If a cell is impermeable, its *conc* variable is assigned a value of -10. All cells have a default delay of 1,000 ms except for $CO_2$ sources which represent human breathing; these cells have an additional 12.16 ppm of $CO_2$ added every 5,000 ms to mimic normal exhalation. Type 0 (open-air) and type 1 cells ($CO_2$ sources) are the only cells that undergo concentration changes due to diffusion. In the implementation of the formal specification, type 2 cells (walls/impermeable objects) are excluded from the averaging calculation. To reduce the complexity of the model rules, it can be reasonably assumed that source cells (type 1) are always separated

from walls by at least 1 cell buffer, which is a reasonable assumption since it is not common for a person to be breathing directly against a wall.

Table 1: Values of $\tau$(N).

| $\tau$(N) | N |
|---|---|
| *conc* = average of neighbors | *type = 0* |
| *conc* = neighbors average + 12.16 ppm | *type = 1* |
| *conc* = −10 | *type = 2* |
| *conc* = 500 ppm | *type = 3* |
| *conc* = 400 ppm | *type = 4* |
| *conc* = 300 ppm | *type = 5* |

Table 2: Values of *D*(S).

| **D(S)** | S |
|---|---|
| R0 += 1,000 | *type = 0* |
| R0 += 5,000 | *type = 1* |
| R0 += 1,000 | *type = 2* |
| R0 += 1,000 | *type = 3* |
| R0 += 1,000 | *type = 4* |
| R0 += 1,000 | *type = 5* |

## 4.3    Experimental Setup

After the formal specification is defined, we implement our model using CD++ (López and Wainer 2004); a toolkit that implements DEVS and Cell-DEVS theoretical concepts. In CD++, Cell-DEVS models are specified using a specification language provided by the tool. The simulator version of CD++ we use to execute the cellular models in this research features the ability for a cell to store multiple state variables and uses RESTful Interoperability Simulation Environment (RISE) middleware that allows for the remote execution of models over a distributed computing platform (Al-Zoubi and Wainer 2015). For visualizing, we use ARSLab Simulation Viewer (St-Aubin et al. 2018).

## 5    SIMULATION RESULTS

We present in this section variations of the model we introduced in section 4. Videos of the simulations can be viewed through ARSLab (2020). Diffusion rules for open-air and source cells are performed by averaging the *conc* values of the center cell with the four neighboring cells. Open-air cells need to check the local neighborhood in case one or more wall/impermeable cells are present. If this is the case, the diffusion computation is adjusted to exclude the unwanted cells from the average calculation. There are 8 cases to consider for an open-air cell: 4 cases when the cell is directly against a wall and not in a corner, and 4 cases of being in a corner where walls meet. To check if a given neighbor cell is a wall, its *conc* value is compared in the rule's conditions: if the concentration is negative, it must be a wall or other solid object (recall that type 2 cells have a fixed conc value of -10). As stated previously, $CO_2$ sources are assumed to have a 1 cell buffer from walls or other solid objects so only a single rule is needed. One key change in the rule for source cells is that in addition to averaging the concentration of neighbor cells, an additional 12.16 ppm of $CO_2$ is added every 5 seconds. Remaining cells including walls, open doors, open windows, and vents all have fixed values throughout the simulation. Note that for the model presented in this paper, HVAC is turned on, windows are open to the outdoor space, and doors are open to the rest of the building throughout the simulation. These simple rules are combined with varying initial conditions to observe the effect of multiple occupants and varying room configurations. With many different possibilities for initial configurations, a variety of complex behavior is expected to emerge.

## 5.1    Model Variations

In this section, we present several variations of the model described in section 4.2, and we show the simulation outcome of the presented models. All the simulations presented are run for a 30-minute duration. In all the simulation figures (Figure 4 to Figure 7(a)), we present four snapshots for each model variation (M1 to M10). The snapshots are at 7.5, 15, 22.5, and 30 minutes ordered clockwise in each figure. Figure 3 is the legend that summarizes the color scheme used in the simulations (Figure 4 to Figure 7(a)) to represent $CO_2$ concentration levels.
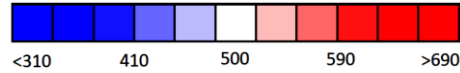
Figure 3: Color legend for $CO_2$ levels shown in the simulation (ppm).

The initial model (M1) is a closed space with no structures/walls other than the four enclosing walls and a single occupant placed in the center of the room. As shown in Figure 4(a), $CO_2$ diffusion occurs isotopically in all directions, spreading out from the central source cell. $CO_2$ levels continue to steadily rise over time due to the lack of outlets. The source cell is closer to the bottom wall than the top wall by a single cell and consequently, $CO_2$ levels south of the occupant rise slightly faster than in the cells north of it. The next model variation (M2) adds partitions to subdivide the space into two cubicle type areas. A single occupant is present close to the center of the right cubical with no $CO_2$ outlets. The simulation of Figure 4(b) shows how $CO_2$ begins to build up in the right cubicle and diffuses around the dividing wall since the model defines the zones that represent the walls as impermeable to the gas. At the end of the simulation, concentrations are much higher near the source than on the far side of the room; wall configuration, therefore, plays a key role even with the existence of open space. Model M3 adds a second occupant to M2 in the left cubicle. As shown in Figure 4(c), $CO_2$ levels rise very quickly compared to M2 where only one occupant is present. The concentration of $CO_2$ is symmetric due to the symmetry of the walls and occupant positions. The lack of outlets (sink cells) causes high buildups of $CO_2$ in a brief period.
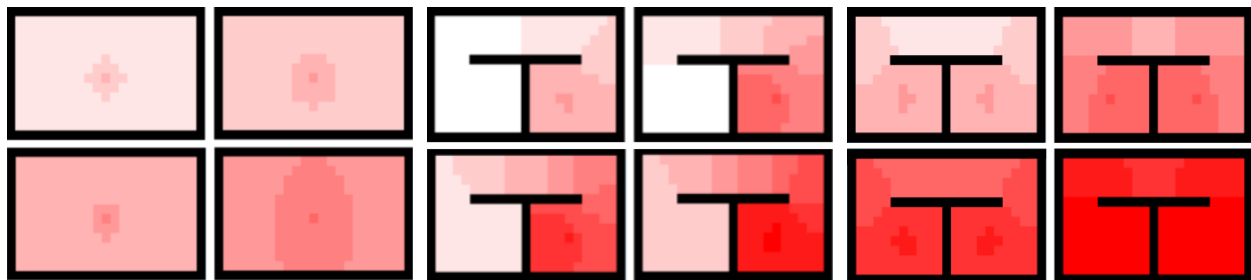


(a) M1-an occupant in a closed space.

(b) M2-an occupant in a two cubical room.

(c) M3-two occupants in a two cubical room.

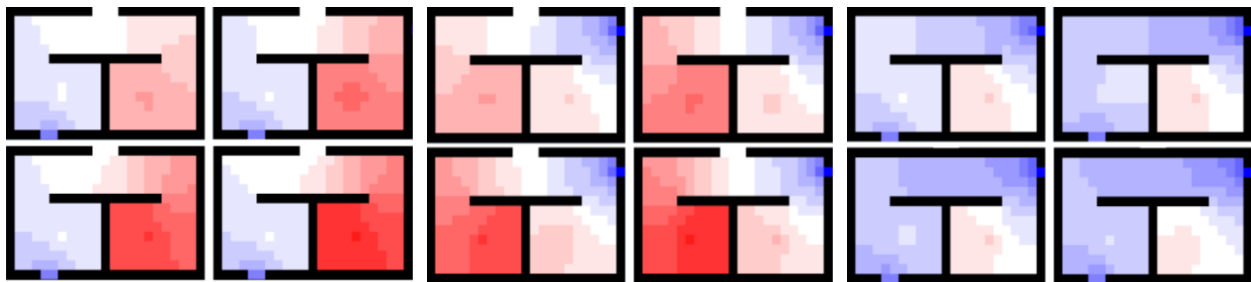Figure 4: Simulation results for M1, M2, and M3.

In model variation M4, we add to M3 a sink zone to the center north wall to represent an open door (3 cells = 75 cm wide). Figure 5(a) shows how the ventilation from the open door reduces the overall concentrations compared to the simulation of M3. The rise of $CO_2$ levels still reflects poor air quality indicating that additional ventilation sources may be needed.



(a) M4-two occupants in an open-door room.

(b) M5-two occupants in a room with a window.

(c) M6-two occupants in a room with a vent.

Figure 5: Simulation results for M4, M5, and M6.

In the variation model M5, we simulate the effect of multiple $CO_2$ sink zones by adding an open window to M3 to the south wall around the center of the left cubical (see Figure 5(b)). The open window initially lowers the $CO_2$ concentrations in the left cubicle despite its occupant adding to the $CO_2$ levels with each breath. As time progresses, the levels in the right cubicle increase due to lack of ventilation and $CO_2$ begins diffusing around the walls from the right cubicle to the left. Figure 5(c) shows M6 that varies M3 by adding a 25 cm wide ventilation port to the north of the eastern wall. The port (one cell) maintains a constant $CO_2$ level at 300 ppm but reduces the $CO_2$ level around it. In models M7 and M8 (Figure 6(a) and Figure 6(b) respectively), we investigate the effect of having two sink zones in the closed room. The increased number of $CO_2$ outlets and their location in the simulation shown in Figure 6(a) keep concentrations low in the left cubicle making it difficult to detect the occupant. Levels in the right cubicle rise steadily making it a better location for a potential sensor. However, further investigation is required to differentiate between the increase in $CO_2$ levels due to the longer presence of occupants and the increase in $CO_2$ levels that is due to a larger number of occupants. M8 of Figure 6(b) combines the M4 and M6. Having a door and a ventilation port reduces the $CO_2$ levels in one of the cubicles like M7 simulation. However, the location of the vent in M8 is different from the window in M7 and the two sinks have different sizes and different background concentration levels (one cell for the vent/25cm and two cells/50cm for the window) which results in a net increase in $CO_2$ levels for both cubicles in M8 as opposed to M7 which makes placing a sensor in either cubical in the latter case possible. M9 of Figure 6(c) is a closed room with two cubical areas, a ventilation port, and a window. With an open window and an active ventilation port, the decrease rate of $CO_2$ from the environment is significant despite the presence of 2 occupants which makes finding an acceptable position for the $CO_2$ sensors more challenging.
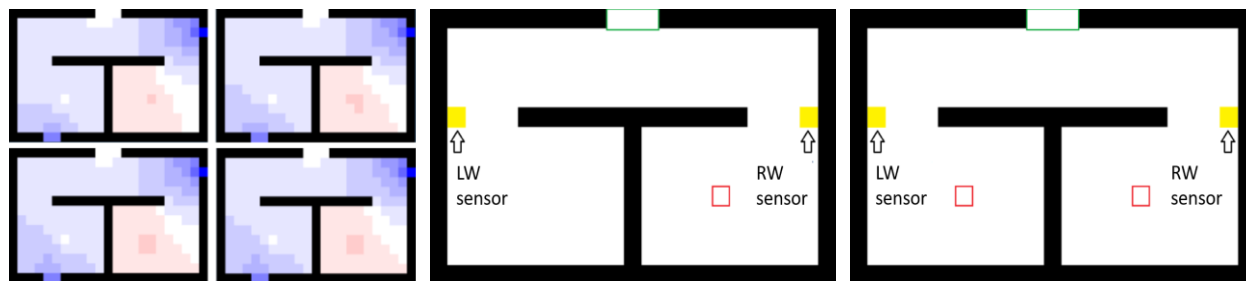


(a) M7-two occupant, window, and a door.  (b) M8-two occupants, ventilation port, and a door.  (c) M9-two occupants, window, and ventilation port.

Figure 6: Simulation results for M7, M8, and M9.

M10 of Figure 7(a) adds an open door to the center of the north wall of the room. In this model, we have three possible outlets for $CO_2$. Interestingly, the open door which has normal indoor background $CO_2$ levels acts as a source drawing fresh $CO_2$ into the room in the presence of decreased concentrations due to the window and vent. There are slightly higher $CO_2$ levels in all parts of the room when compared to M9.

## 5.2    Sensor Placement

We placed a sensor on the right wall (RW) and another on the left wall (LW) of the room with a single occupant in the right cubicle and an open door is the only $CO_2$ outlet (Figure 7(b)). Plots of the concentration levels over time are shown in Figure 8(a) for the two sensors. The RW sensor nearest to the only occupant detects $CO_2$ levels that rise very quickly before eventually stabilizing, while the LW sensor detects only minor $CO_2$ increases and has difficulty detecting the occupant. This is due to the ventilation provided from the open door in the only pathway connecting the two halves of the room. Over 30 minutes, the LW sensor detects a rise of only 10 ppm compared to a rise of 117 ppm in the RW sensor. In Figure 7(c), we show the same model used in the simulation of Figure 7(a), with an additional occupant. Due to the symmetry of the room configuration, $CO_2$ levels for both sensors rise in unison. The results are plotted in Figure 8(b).
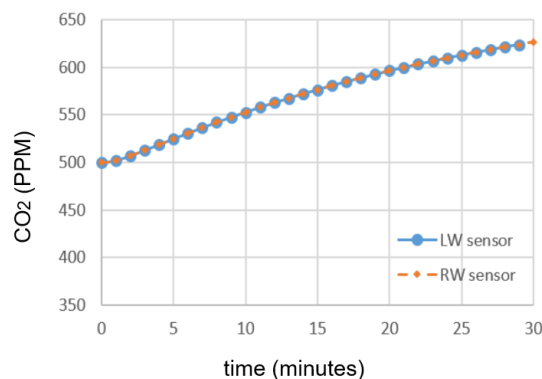
(a) M10- 2 occupants, window, vent, and a door.

(b) One occupant, a door, and two $CO_2$ sensors.

(c) Two occupants, a door, and two sensors.

Figure 7: Simulation results for M10 and sensors locations.
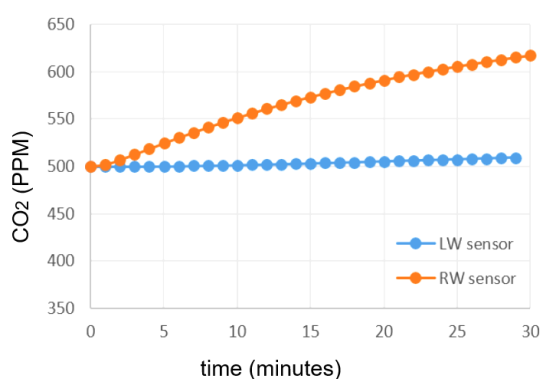


(a) $CO_2$ Vs. Time plot for Figure 7(b)

(b) $CO_2$ Vs. Time plot for Figure 7(c)

Figure 8: Time plot of $CO_2$ levels for sensors in two locations.

## 6    DISCUSSION

In this section, we discuss the simulation results and the threats to the validity of the performed simulation.

### 6.1    Results Analysis

From the simulation results, we observe that from a basic set of rules, complex behavior emerges. The emerging behavior is dependent on the initial configuration of the room and its occupants. Placing $CO_2$ outlets in one location versus another drastically affects the ability of the gas to diffuse throughout the room. Additionally, impermeable walls affect the rate at which $CO_2$ can spread throughout the room. Dividing the open rectangular room into cubicles results in the gas building up on one side of the wall and having difficulty reaching the opposite side. One general conclusion is that simulating the exact layout of a confined space is important for determining how $CO_2$ will spread and build up. This shows how the models comply with the ground truth experience that $CO_2$ sensors are indeed sensitive to room configuration (Labeodan et al. 2015; Hobson et al. 2019). Even minor changes in the configuration result in widely varying distributions of $CO_2$. This confirms that the exact distribution of changing gas levels in confined spaces is indeed a non-linear complex process that needs to be investigated on a case-by-case basis.

Determining the latency for a sensor to detect significant $CO_2$ changes is also heavily dependent on the layout of the room. The plot of Figure 8(a) illustrates how one of the sensors can quickly determine the presence of the occupant while the sensor on the opposite side barely detects any noticeable change. Additionally, having two occupants versus a single occupant may not make significant changes in the $CO_2$ levels detected by a sensor if there is a source of air shifts. One consistent outcome of all simulations is that

placing a $CO_2$ sensor near a $CO_2$ sink zone introduces a notable change in concentration. Thus, to determine the ideal location of a sensor, the specific conditions present in the real world must be simulated.

## 6.2    Threats to Validity

Although simplifying a 3-dimensional space in the form of the 2-dimensional model is a common practice in M&S, in a situation where the third dimension may change the results this can be considered a construct validity threat. In our case, the $CO_2$ concentration and best placement may differ based on the height of the closed space. Thus, adding a third dimension to our model is a step that is included in our research plan. Another construct validity threat is that we do not use precise fluid dynamics methods. In our next step, this threat can easily be corrected by adjusting the time step used between diffusion calculations and by updating the diffusion calculation to reflect fluid dynamics equations. However, the calculations we use are reasonable at this stage of proving the concept as discussed in section 4.1. For example, the assumption of modeling $CO_2$ outlets/sinks as constant concentrations may not be a precise representation of reality, but the simplicity of this assumption facilitates implementing rules that mimic real behavior. In M10 (Figure 7(a)), the open door acted as a $CO_2$ source due to the low levels of $CO_2$ surrounding it due to an open window and a vent which reflects reality in the sense that a door should operate in two ways: drawing $CO_2$ from high concentration to low concentration areas. Also, an external validity threat is that the number of models and configurations we assessed so far are not representative of all the possible configurations for closed spaces and offices. Therefore, we also plan to experiment with several types of spaces to enable the analytical generalization of the results. Finally, although the initial results of our preliminary work conform with previous research results, the models presented here are not validated against ground truth data which is considered a reliability threat to our results. To overcome this, we plan to model real spaces that we have ground-truth data collected from to validate our models. For external validity, in the modeling environment, we introduce here where all the variables are controlled, we do not see an external validity threat that is worthy of reporting. Other parameters that we are considering for our research to enhance the construct validity of our experiments are the effects of air shifts and the effect of variable temperature.

## 7    CONCLUSION AND FUTURE WORK

In conclusion, although this $CO_2$ model is basic, it provides insights into the basic pattern for the diffusion of the gas within a room and the feasibility of continuing our study through M&S to answer the proposed RQs (section 3). The simulations we executed showed compliance with the real-life situations that proved the sensitivity of $CO_2$ to rooms configuration. For every unique room configuration, minor changes may result in a significant difference in the resulting $CO_2$ levels and extra care should be taken when choosing a location for a potential sensor. Additionally, the latency for the detection of $CO_2$ can vary greatly based on room layout and sensor configuration. The next stage in our research is to incorporate more precise fluid dynamics calculations, consider other configuration parameters, consider $CO_2$ concentration reduction when occupants leave the space and run a variety of model configurations (e.g. lack of HVAC) with a larger number of occupants, and validate the models. Then, the collected results can be used to automatically determine the best sensor locations depending on the configuration and number of occupants. A second stage of the research would feature using statistical analysis to calculate the correlation between the latency of detecting occupants' presence and sensor location.

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