Carleton University

Department of Systems and Computer Engineering

Term Project

Cell-DEVS: Model and Simulation of Corporate Building Energy Consumption and Waste in Post-Pandemic Work Practices

SYSC 4906 G

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Professor: Dr. Gabriel Wainer

Submitted By:

Michael De Santis: 101213450

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1. Introduction

The motivation for this project is to use formally proven methodologies in the modeling and simulation of a corporate building office floor in order to assess the effect of post-pandemic work practices on corporate building energy consumption and waste. The methodology for modeling and simulation used in this project is the Discrete Event System Specification (DEVS) methodology. DEVS is formally proven to be able to simulate any finite set of discrete events within a modeled system [1]. Another property of the DEVS methodology is its propensity for high modularity, allowing individual atomic models to be combined along input and output ports into coupled models, with coupled models themselves also capable of combination in hierarchy [1]. DEVS is also highly integrable with other methodologies, providing the ability to model and simulate scenarios of different types and complexities. One such methodology is Cellular Automata (CA), which may be combined with DEVS to form the Cell-DEVS methodology [1], enabling additional event-based modeling and simulation techniques. Cell-DEVS is particularly useful in studying emergent behaviour arising from the simulation of many atomic models cells situated within the coupled model of the cell space.

This report documents the design and use of a tool to model and simulate the energy consumption behaviour of heating a single corporate office floor under different occupancy and operational conditions. The underlying model and simulation are formed using the Cell-DEVS methodology [1] and implemented in C++ using the Cadmium V2 library [2]. The project's source code, documentation, and experiments referenced within this report are available at the project repository[3].

The research goals of this project are to seek answers to the following questions:

1. What effects do post-pandemic work practices have on corporate building energy consumption and waste?
2. Should building maintenance systems employ different energy strategies based on work policies and occupancy patterns?
3. Can Cell-DEVS modeling and simulation provide guidance towards more efficient post-pandemic corporate building maintenance practices?

This project intends to contribute to the field of Building Information Modeling (BIM) by applying a Cell-DEVS methodology to understand the effect of post-pandemic work practices on corporate office building energy consumption and waste. By building on previous models and simulation methodologies, the Cell-DEVS implementation here seeks to establish a means of understanding how corporate building Heating, Ventilation, and Air Conditioning (HVAC) systems may be modified to improve efficiency, minimize waste, and maintain occupant comfort in light of the new work practices ushered in by the global Covid-19 pandemic. While the scope of this project is limited to the study of heating systems within a narrow experimental frame, the modeling, simulation, and analysis techniques used herein may inform broader efforts in understanding and mitigating wasteful corporate building practices, and may have import to other academic works or to facility managers accommodating hybrid work solutions in their own corporate offices.

2. Background

2.1. Building Information Modeling (BIM)

Building Information Modeling (BIM) is described as the socio-technical system that involves the broad processes of design, construction, and facility management of buildings [4]. In the 21^{st} century, BIM has been seen as providing a significant opportunity for societies to achieve more sustainable building construction processes and higher performance facilities with less risk and resources when compared to traditional practices [4].

Corporate buildings have been selected as the focus of this project, as they are responsible for significant energy consumption and waste globally. Buildings (of all types) account for approximately 70% of all electricity consumed in the U.S. [5], with 80% of that usage during occupancy [5]. Heating, Ventilation, and Air Conditioning (HVAC) is estimated to account for approximately 50% of building energy expenditures [6], and as such, represents a large area for improvement in terms of energy efficiency.

In regards to corporate office buildings, where a primary purpose of the building is to house employees and enable productive work, occupancy modeling is a significant feature of BIM [4]. Occupant numbers, configurations, and behaviours are all important factors that contribute to energy practices, consumption, and waste, and there is a wealth of research dedicated to studying the diverse effects of occupancy in BIM [7-23]. Current research shows significant discrepancy between building energy use as designed and during actual operation, with a large portion of this discrepancy attributed to shortcomings in the consideration of occupant behaviour [23]. Many different modeling and simulation methodologies have been employed to help understand these occupant-energy relationships in BIM with the goal of narrowing the gap between design and actual operation, including a proliferation of Agent-Based Modeling (ABM) applications in recent years [5, 24-27].

2.2. Cell-DEVS and BIM

Cellular automata have previously been used in the context of BIM [28], and the Cell-DEVS methodology in particular has been shown as highly integrable with BIM [29]. Cell-DEVS has found extensive application in BIM projects, some of which have informed the efforts here [30-32].

In [30], Cell-DEVS was used to predict room occupancy based on the model and simulation of CO_2 diffusion in enclosed spaces. CO_2 sensors were tested as a means to detect room occupancy based on occupant emissions. While the binary detection of occupants (ie. the presence or absence of occupants) was deemed to be reliable, the estimation of the number of occupants based purely on CO_2 levels was found to be less reliable [30]. Although CO_2 monitoring is out of the scope of the model and simulation developed herein, the mechanism is assumed as reliable for binary occupancy detection based on this earlier work: the HVAC elements within the model are equipped with binary occupancy sensors that can accurately determine whether their zone of governance is occupied (by one or more occupant) or wholly unoccupied. Since occupant numbers and their distribution within indoor space is a controlled input to the models and simulation herein, binary detection is sufficient for the purpose of demand-driven HVAC control tested in this project's simulations.

The work of [31] extends the work of [30] discussed above, studying the effect of the space settings on the measurement and the dispersion behaviour of CO_2, particularly in regards to how vents and ducts may affect dispersion rates and occupancy detection. Again, this project's model assumes reliable CO_2 occupancy detection and does not seek to optimize detection with vents and ducts; it does, however, draw from the Cell-DEVS modeling of CO_2 dispersion in relation to its modeling of heat diffusion within an indoor space [31].

While the project here is informed by these earlier efforts, the goal of this project is not occupant detection; rather, this work assumes known occupancies within a given space to study the effects of different occupancy levels and configurations on the energy expenditures of demand-driven building HVAC maintenance systems.

2.3. Post-Pandemic Work Practices

Globally, places and practices of work were irrevocably changed by the Covid-19 pandemic. During the pandemic, many corporate spaces denied or discouraged employees from working out of central offices, leaving empty floors and even entire buildings all over the world. In the wake of the pandemic, work did not return to the prior status quo. Many companies adopted wholly remote work practices, or hybrid work practices consisting of "work-from-home" days where office attendance is optional, and "in-office" work days where attendance is expected. It is the effect of these changing work practices on corporate building occupancy patterns that this project intends to study, with a focus on how these new patterns in turn influence corporate energy consumption and waste.

Many researchers see the pandemic as an opportunity or catalyst for change in regards to environmental improvements in many diverse fields [6, 33-36]. Some studies primarily focus on the home work environment that displaced office workers have increasingly begun to inhabit [37-41]; however, in these works and in general, it seems that less attention is given to studying the office spaces that they have left. As such, this project offers one foray into how BIM may incorporate post-pandemic work practices to study what kind of effect such practices may have on the energy consumption and waste of corporate buildings with lower and irregular occupancy patterns.

3. Models

3.1. Conceptual Model

To inform the development of a Cell-DEVS specification that may be used to guide modeling, simulation, and implementation, a conceptual model is first described. The scenario for the model will be a single office floor within a corporate building, which will be represented by the total cell space of the Cell-DEVS model as per Fig. 1 below (explained in more detail in Section 4).

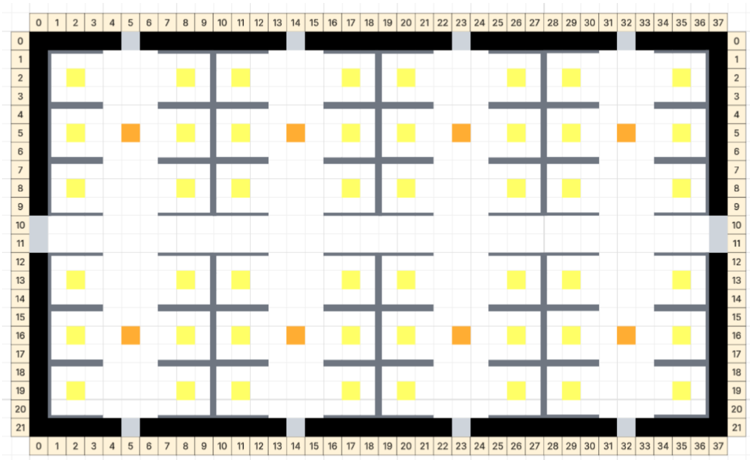

Figure 1: Office Floor Plan

The space of the office floor is enclosed by exterior walls with windows, and is segregated internally by cubicles. Each cubicle represents an employee's work station, and each station may be occupied by an employee or may remain unoccupied. Work stations will be designated as occupied or unoccupied by specifications of the experiment being conducted. For this model, occupants remain at their work station for the duration of the work day, and no occupants may leave or enter the space. Occupant employees have a climate comfort zone of between 21°C and 24°C, and can represent themselves as comfortable or uncomfortable based on whether or not the temperature around them is within this range. Empty office spaces will be visualized with a color gradient (described below) to indicate their temperature relative to the the target temperature (shades of blue for below the target range; white for within the target range; and shades of red for above the target range).

HVAC heaters are present within the office floor, with each corresponding to a zone of governance that encapsulates six cubicled work stations. Heaters can activate to supply heat if their temperature sensors register a temperature lower than the configured target. These heaters are equipped with binary occupancy sensors capable of determining whether or not their corresponding zone is occupied. If the sensors are enabled in the heaters, the heaters will only engage to supply heat if their occupancy sensor reports the zone as occupied. Otherwise, if the sensors are disabled, the heaters will consider only temperature in their activation algorithm, and will therefore supply heat indiscriminately to both occupied and unoccupied zones.

Heat diffuses throughout the space of the office using an averaging algorithm supplemented by heat generation and dissipation functions associated with each type of space. All spaces have a dissipation function that causes some heat to be lost (if above a threshold), which uses dissipation constants associated with the type of space. For example, external windows and walls dissipate more heat than internal spaces. Some spaces have heat generation functions as well. Heaters generate large amounts of heat when activated. Windows generate a small amount of heat from solar radiation, as do occupants as a result of their internal body temperatures being higher than the room temperature targets.

This model is simulated over a typical eight hour work day, with each time unit representative of a five minute interval for a total of 96 time units. Experiments are designed to test this office space under different occupancy loads to simulate optional "work-from-home" days and mandatory "in-office" days with different attendance. Each occupancy load may also be distributed across the space of the office, with occupants scattered randomly, or consolidated in minimal areas. The model allows for the activation or deactivation of the heater's sensors in order to test the effect of occupant detection on HVAC performance.

3.2. Cell-DEVS Formal Specification

Based on the conceptual model described above, a formal Cell-DEVS model specification can be constructed for use in simulation and experimentation. Cell-DEVS formal specifications for atomic model components (ie. individual cells in the coupled model of the entire cell space) are presented according to the following formal definition [1]:

$$\langle TDC = X, Y, S, N, delay, d, \delta_{int}, \delta_{ext}, \tau, \lambda, D \rangle$$

where:

- X = the set of input external events
- Y = the set of output external events
- S = the state set
- N = the set of input values
- d = the type of delay for each cell
- $delay$ = the delay duration for each cell
- δ_{int} = the internal transition function
- δ_{ext} = the external transition function
- τ = the local computing function
- λ = the output function
- D = the delay function

3.2.1. Atomic Model: Cell

The Cell-DEVS formal specification for each cellular atomic model is as follows:

- $X = \emptyset$
- $Y = \emptyset$
- $S = \{0, 1, 2, ..., 12\}$ where:

  0 = EMPTY_CELL_COLD_0
  1 = EMPTY_CELL_COLD_1
  2 = EMPTY_CELL_COLD_2
  3 = EMPTY_CELL_OK_3
  4 = EMPTY_CELL_HOT_4
  5 = EMPTY_CELL_HOT_5
  6 = EMPTY_CELL_HOT_6
  7 = OCCUPANT_COMFORTABLE
  8 = OCCUPANT_UNCOMFORTABLE
  9 = HEATER_ON
  10 = HEATER_OFF
  11 = WALL
  12 = WINDOW
- $delay$ = inertial
- N = Moore's Neighbourhood ($r = 4$)
- $d = 1$ time unit
- $\tau = \{$

```
/* Local Variables */

// Accumulators
int neighbours = 0;
int occupant_neighbours = 0;
double neighbourhood_temperature = 0.0;

/* Canvas the Neighborhood */

// Canvas this cell's neighborhood and record required values for determining
// temperature and occupancy
for (const auto& [neighborId, neighborData]: neighborhood) {
    // State of the neighbor cell for this iteration
    auto nState = neighborData.state;
```

```
    // Accumulate neighbours for temperature averaging calculation
    neighbours++;
    // Accumulate occupant neighbours for sensor use in controlling heaters
    if (nState->type == BimSimStateName::OCCUPANT_COMFORTABLE ||
        nState->type == BimSimStateName::OCCUPANT_UNCOMFORTABLE) {
        occupant_neighbours++;
    }
    // Accumulate neighbour temperatures
    neighbourhood_temperature += nState->temperature;
}
// Take the average neighbourhood temperature as the new cell temperature
state.temperature = neighbourhood_temperature / neighbours;

/* Mutate State Based on Rules and Return */

// Case: EMPTY cells
// 0  EMPTY_COLD_0
// 1  EMPTY_COLD_1
// 2  EMPTY_COLD_2
// 3  EMPTY_OK_3
// 4  EMPTY_HOT_4
// 5  EMPTY_HOT_5
// 6  EMPTY_HOT_6
if(state.type >= BimSimStateName::EMPTY_COLD_0 &&
   state.type <= BimSimStateName::EMPTY_HOT_6) {
    // Dissipate and/or generate heat as required
    if (state.temperature >= MIN_TEMP) {
        state.dissipate(DEFAULT_DISSIPATION_MIN, DEFAULT_DISSIPATION_MAX);
    }
    // Update the state based on new temperature
    updateEmptyCellStateByTemperature(state);
}
// Case: Occupants
// 7  OCCUPANT_COMFORTABLE
// 8  OCCUPANT_UNCOMFORTABLE
else if(state.type == BimSimStateName::OCCUPANT_COMFORTABLE ||
        state.type == BimSimStateName::OCCUPANT_UNCOMFORTABLE) {
    // Dissipate and/or generate heat as required
    if (state.temperature >= MIN_TEMP) {
        state.dissipate(DEFAULT_DISSIPATION_MIN, DEFAULT_DISSIPATION_MAX);
    }
    state.generate(OCCUPANT_GENERATION_MIN, OCCUPANT_GENERATION_MAX);
    // Update the occupant's state based on climate comfort level
    updateOccupantCellState(state);
}
// Case: Active Heater
// 9  HEATER_ON
else if(state.type == BimSimStateName::HEATER_ON) {
    // Dissipate and/or generate heat as required
    if (state.temperature >= MIN_TEMP) {
        state.dissipate(DEFAULT_DISSIPATION_MIN, DEFAULT_DISSIPATION_MAX);
```

```
        }
        state.generate(HEATER_GENERATION_MIN, HEATER_GENERATION_MAX);
        // Turn the heater ON or OFF as required
        updateHeaterCellState(state, occupant_neighbours);
    }
    // Case: Unactive Heater
    // 10  HEATER_OFF
    else if(state.type == BimSimStateName::HEATER_OFF) {
        // Dissipate and/or generate heat as required
        if (state.temperature >= MIN_TEMP) {
            state.dissipate(DEFAULT_DISSIPATION_MIN, DEFAULT_DISSIPATION_MAX);
        }
        // Turn the heater ON or OFF as required
        updateHeaterCellState(state, occupant_neighbours);
    }
    // Case: Wall
    // 11 WALL
    else if(state.type == BimSimStateName::WALL) {
        // Dissipate and/or generate heat as required
        if (state.temperature >= MIN_TEMP) {
            state.dissipate(WALL_DISSIPATION_MIN, WALL_DISSIPATION_MAX);
        }
    }
    // Case: Window
    // 12 WINDOW
    else {
        // Dissipate and/or generate heat as required
        if (state.temperature >= MIN_TEMP) {
            state.dissipate(WINDOW_DISSIPATION_MIN, WINDOW_DISSIPATION_MAX);
        }
        state.generate(WINDOW_GENERATION_MIN, WINDOW_GENERATION_MAX);
    }

    // Return the state with its updated temperature
    return state;

}
```

- D = inertial delay of 1 time unit
- $\delta_{int}, \delta_{ext}, \lambda$ are defined according to the Cell-DEVS specifications [1].

An extended Moore's Neighbourhood with ($r = 4$), as in Fig. 2 below, was selected to aid in modeling the heat diffusion through an indoor space. Each section of six cubicles with up to six occupants is classed as a climate zone, and contains a single central heater. Each heater is equipped with an occupancy sensor that, if enabled, can determine whether its corresponding climate zone is wholly unoccupied or contains one or more occupants. If the heater's sensors are disabled, it will function irrespective of occupancy, engaging when the detected temperature is below the target threshold. If the heater's sensors are enabled, it will additionally consider occupancy in its heating algorithm, only engaging if its respective climate zone is below the target threshold and occupied by one or more employee.

(i-4, j-4)	(i-3, j-4)	(i-2, j-4)	(i-1, j-4)	(i, j-4)	(i+1, j-4)	(i+2, j-4)	(i+3, j-4)	(i+4, j-4)
(i-4, j-3)	(i-3, j-3)	(i-2, j-3)	(i-1, j-3)	(i, j-3)	(i+1, j-3)	(i+2, j-3)	(i+3, j-3)	(i+4, j-3)
(i-4, j-2)	(i-3, j-2)	(i-2, j-2)	(i-1, j-2)	(i, j-2)	(i+1, j-2)	(i+2, j-2)	(i+3, j-2)	(i+4, j-2)
(i-4, j-1)	(i-3, j-1)	(i-2, j-1)	(i-1, j-1)	(i, j-1)	(i+1, j-1)	(i+2, j-1)	(i+3, j-1)	(i+4, j-1)
(i-4, j)	(i-3, j)	(i-2, j)	(i-1, j)	(i, j)	(i+1, j)	(i+2, j-1)	(i+3, j)	(i+4, j)
(i-4, j+1)	(i-3, j+1)	(i-2, j+1)	(i-1, j+1)	(i, j+1)	(i+1, j+1)	(i+2, j+1)	(i+3, j+1)	(i+4, j+1)
(i-4, j+2)	(i-3, j+2)	(i-2, j+2)	(i-1, j+2)	(i, j+2)	(i+1, j+2)	(i+2, j+2)	(i+3, j+2)	(i+4, j+2)
(i-4, j+3)	(i-3, j+3)	(i-2, j+3)	(i-1, j+3)	(i, j+3)	(i+1, j+3)	(i+2, j+3)	(i+3, j+3)	(i+4, j+3)
(i-4, j+4)	(i-3, j+4)	(i-2, j+4)	(i-1, j+4)	(i, j+4)	(i+1, j+4)	(i+2, j+4)	(i+3, j+4)	(i+4, j+4)

Figure 2: Moore Neighbourhood ($r = 4$)

4. Simulation

The model defined above was implemented in C++ using the Cadmium V2 library to create the `bimsim` tool binary. This tool allows for configuration of the initial state of the cell space to provide customizable starting points for simulation. The occupancy load and distribution may be statically configured within the floor plan. Heater occupancy sensors may also be configured as active or inactive. Via configuration, additional experiments to those presented below may be run within the experimental frame, and new experimental frames may be developed. Runtime options for the `binary` permit the setting of input configuration and output log files, as well as the simulation duration.

Simulation outputs for each experiment under different configurations and variations were logged to files for analysis, and given to the Cell-DEVS Visualizer to generate images of the initial and final states of the simulation, as well as videos showing the simulation unfold dynamically. Select images corresponding to experiments are provided inline below; however, as individual frames of the simulation are not particularly useful in representing the dynamic simulation, it is recommended to view the videos of the entire simulation for each experiment. All simulation videos are aggregated and available on the repository's sample results page.

4.1. Experimental Frame

Each experiment in the experimental frame is simulated for 96 time units, representing an eight hour uninterrupted work day in increments of five minutes. Each experiment uses the floor plan of Fig. 3 below, where each cell on the grid has state in $S = \{0, 1, 2, ..., 12\}$ as per the formal specification in section 3.2.1 above.

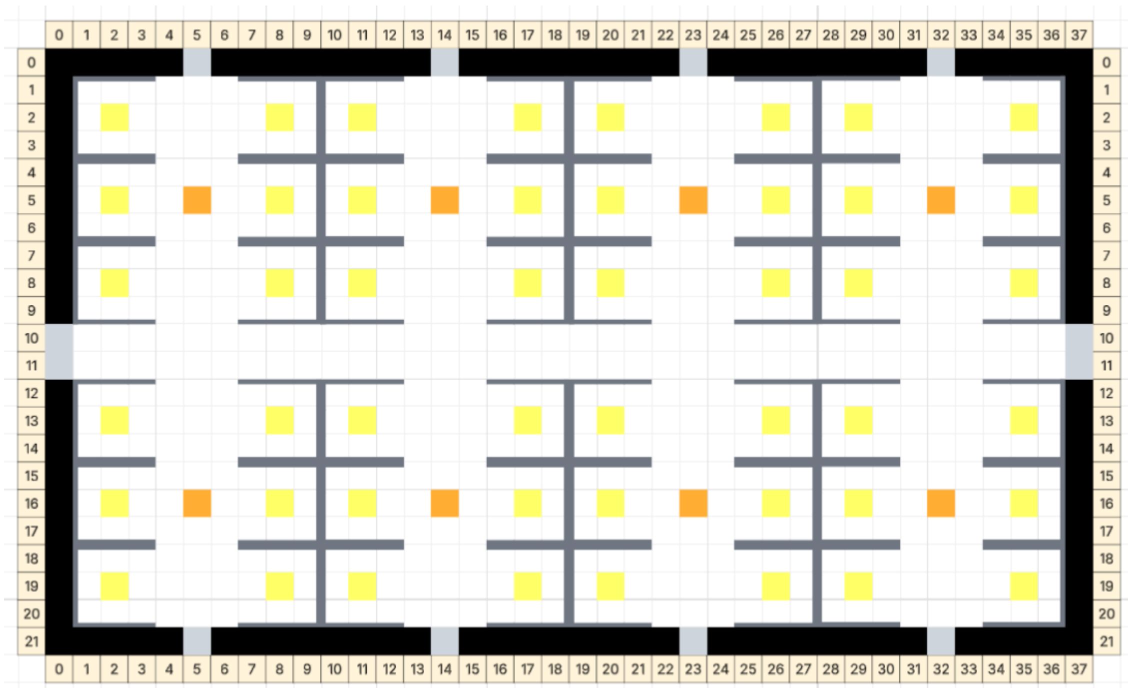

Figure 3: Experimental Frame Office Floor Plan

In order to visualize each cell state during simulation, the cell colour scheme in Fig. 4 below is used:

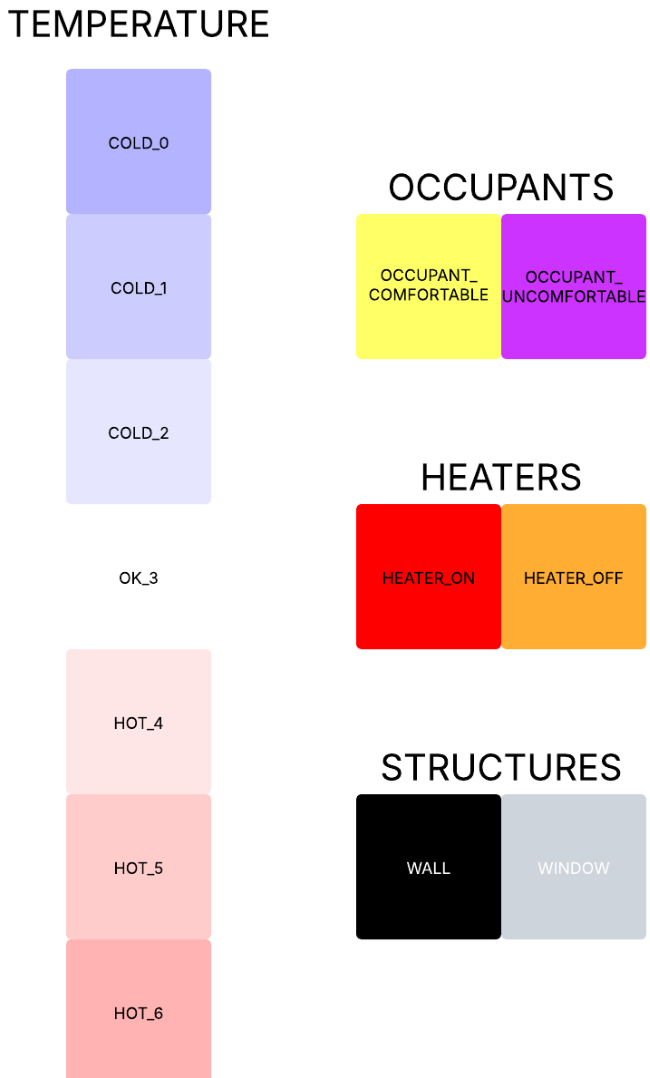

Figure 4: Cell Legend for Simulation Visualization

4.2. Experimental Organization

Experiments within this simulation are broken down into configurations and variations in order to test different phenomena through comparison. The terminology of this structure is as follows:

1. **Experiment**: Each experiment corresponds to an occupancy level (ie. number of occupants). All configurations and variations under an experiment are run with this same number of occupants. Different examples therefore permit the analysis of the effects of occupancy levels in the experimental frame.
2. **Configuration**: Each configuration corresponds to an occupancy distribution pattern (randomly scattered or condensed). All variations under a configuration are run with this same occupancy distribution pattern. Different configurations therefore permit the analysis of the effects of occupancy distribution patterns within an experiment.
3. **Variation**: Each variation corresponds to HVAC systems operating with their binary occupancy sensors either disabled (static) or enabled (demand-driven based on occupancy). Different variations therefore permit the analysis of the effects of different HVAC operational modes within a configuration.

Simulation results for all experiments, configurations, and variations are presented below according to the following organization:

1. **Experiment 1: High Occupancy Work Day**
   Occupancy: 44/48 Workstations Occupied
   - 1.1. Configuration 1: Scattered Occupancy Pattern
     - 1.1.1. Variation 1: Occupancy Sensors Disabled
     - 1.1.2. Variation 2: Occupancy Sensors Enabled
   - 1.2. Configuration 2: Condensed Occupancy Pattern
     - 1.2.1. Variation 1: Occupancy Sensors Disabled
     - 1.2.2. Variation 2: Occupancy Sensors Enabled
2. **Experiment 2: Half Occupancy Work Day**
   Occupancy: 24/48 Workstations Occupied
   - 2.1. Configuration 1: Scattered Occupancy Pattern
     - 2.1.1. Variation 1: Occupancy Sensors Disabled
     - 2.1.2. Variation 2: Occupancy Sensors Enabled
   - 2.2. Configuration 2: Condensed Occupancy Pattern
     - 2.2.1. Variation 1: Occupancy Sensors Disabled
     - 2.2.2. Variation 2: Occupancy Sensors Enabled

3. **Experiment 3: Low Occupancy Work Day**
   Occupancy: 8/48 Workstations Occupied

   3.1. Configuration 1: Scattered Occupancy Pattern
      3.1.1. Variation 1: Occupancy Sensors Disabled
      3.1.2. Variation 2: Occupancy Sensors Enabled
   3.2. Configuration 2: Condensed Occupancy Pattern
      3.2.1. Variation 1: Occupancy Sensors Disabled
      3.2.2. Variation 2: Occupancy Sensors Enabled

4.3. Experiment 1: High Occupancy Work Day

This experiment tests an occupancy load of 44/48 employees under two occupancy configurations of two variations each:

1. Configuration 1: Scattered Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled
2. Configuration 2: Consolidated Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled

This experiment was designed to model a traditional "in-office" work day of almost full occupancy. As nearly all workstations are occupied, there is little difference between the scattered and condensed occupancy pattern configurations. The same is true for the results of the variations: since every zone is occupied by at least one occupant in both configurations, HVAC operational modes do not incur notable difference. The experiments here were conducted primarily to provide a benchmark for later experiments with reduced occupancy.

4.3.1. Configuration 1: Scattered Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

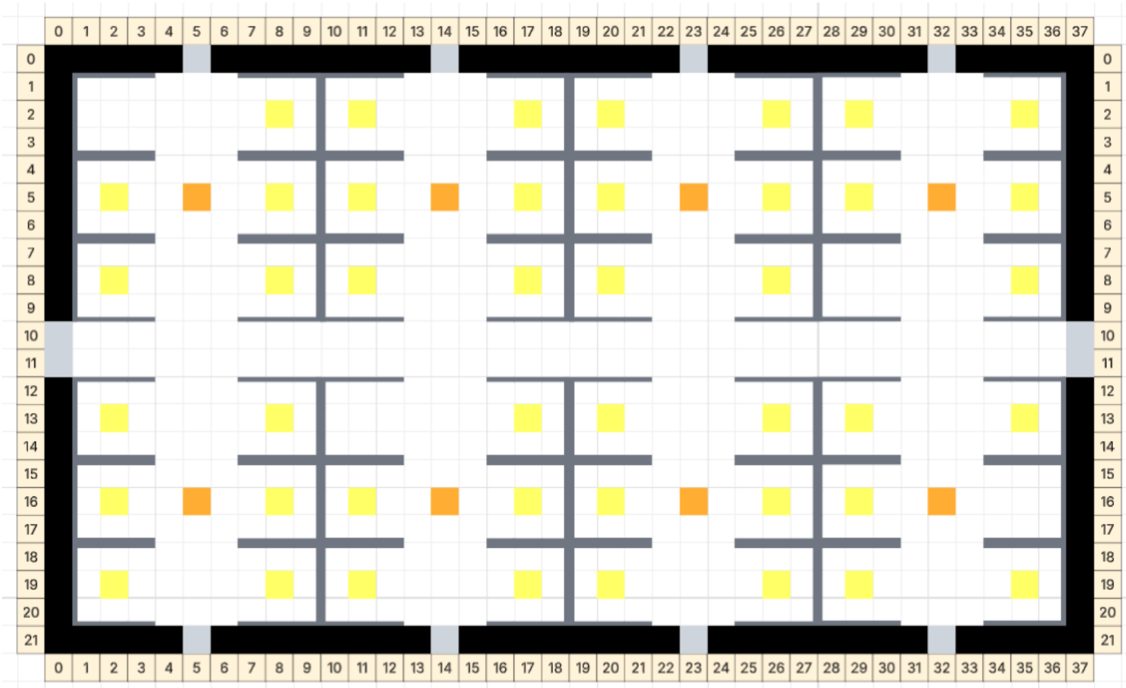

Figure 5: Experiment 1 Configuration 1 Floor Plan

4.3.1.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

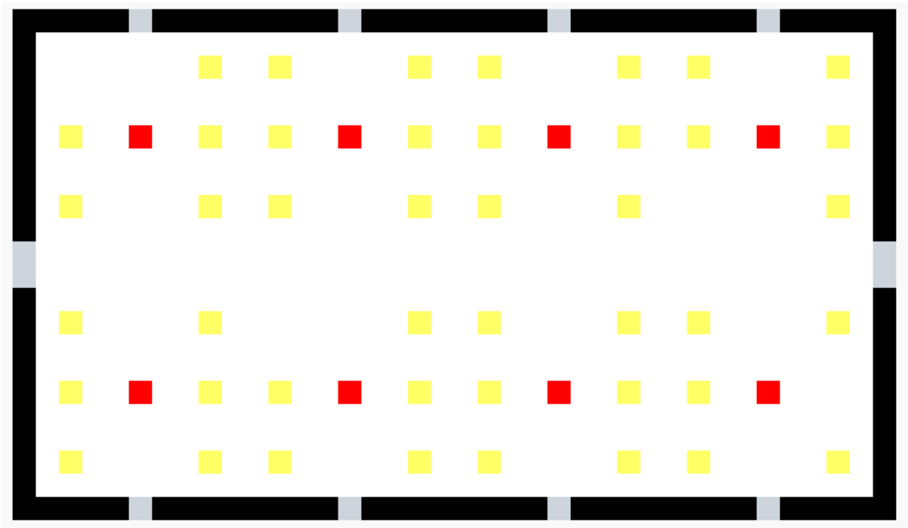

Figure 6: Experiment 1 Configuration 1 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

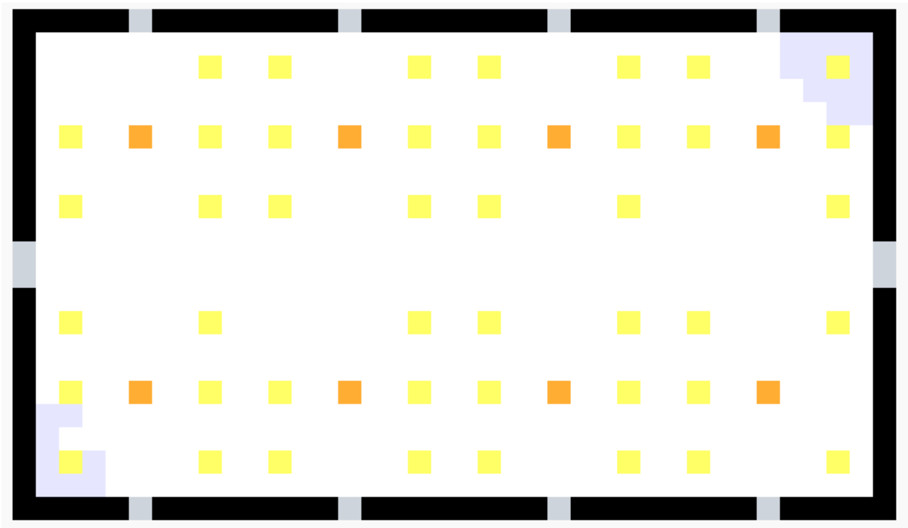

Figure 7: Experiment 1 Configuration 1 Variation 1 at $t = 95$

4.3.1.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

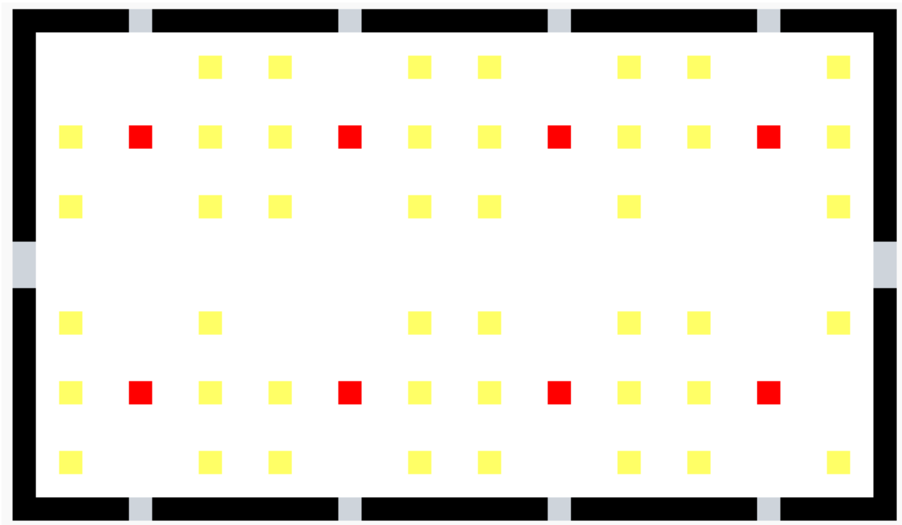

Figure 8: Experiment 1 Configuration 1 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

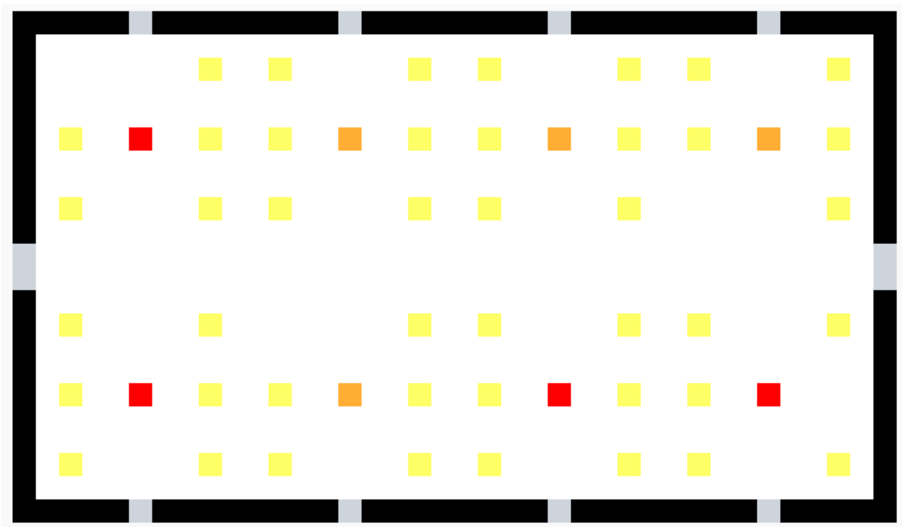

Figure 9: Experiment 1 Configuration 1 Variation 2 at $t = 95$

4.3.2. Configuration 2: Consolidated Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

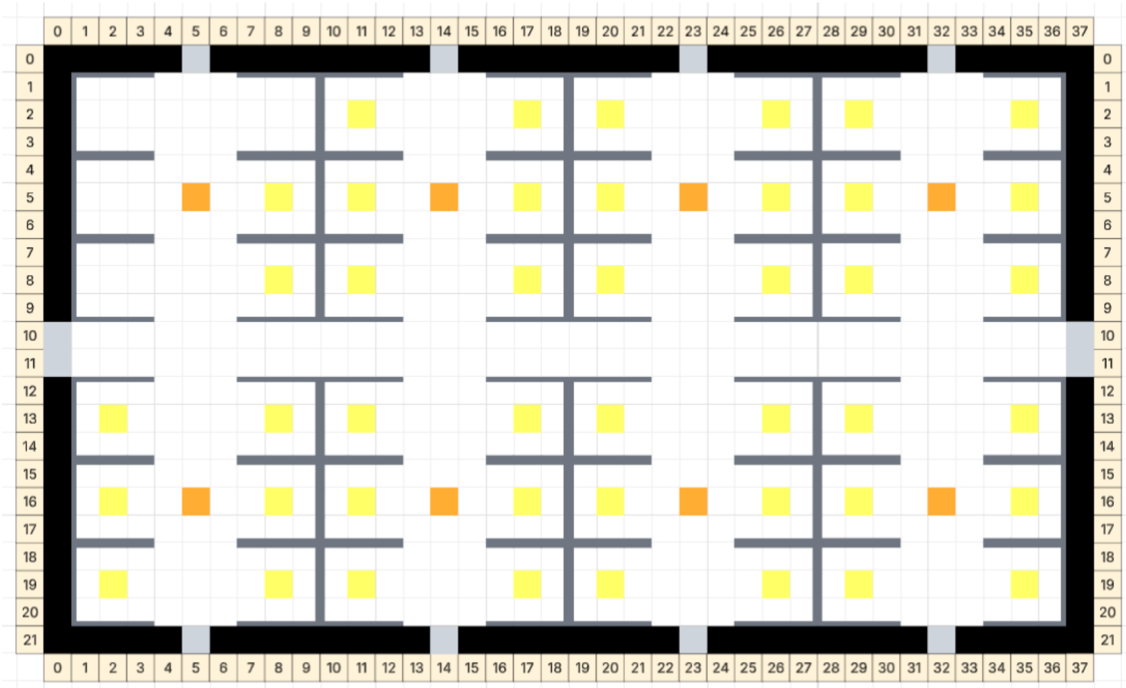

Figure 10: Experiment 1 Configuration 2 Floor Plan

4.3.2.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

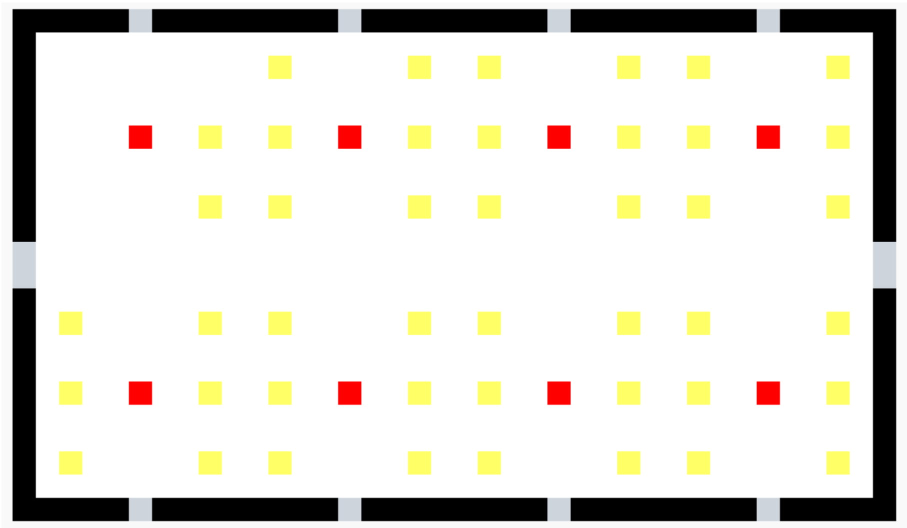

Figure 11: Experiment 1 Configuration 2 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

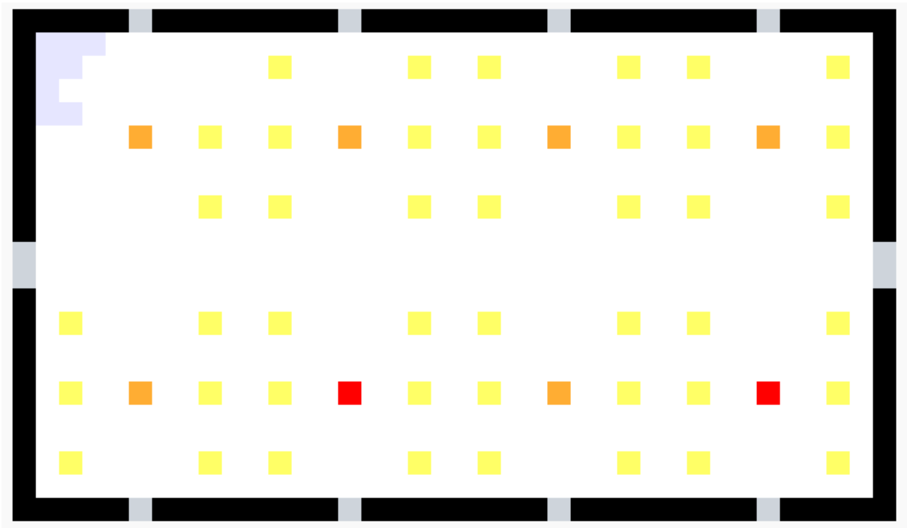

Figure 12: Experiment 1 Configuration 2 Variation 1 at $t = 95$

4.3.2.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

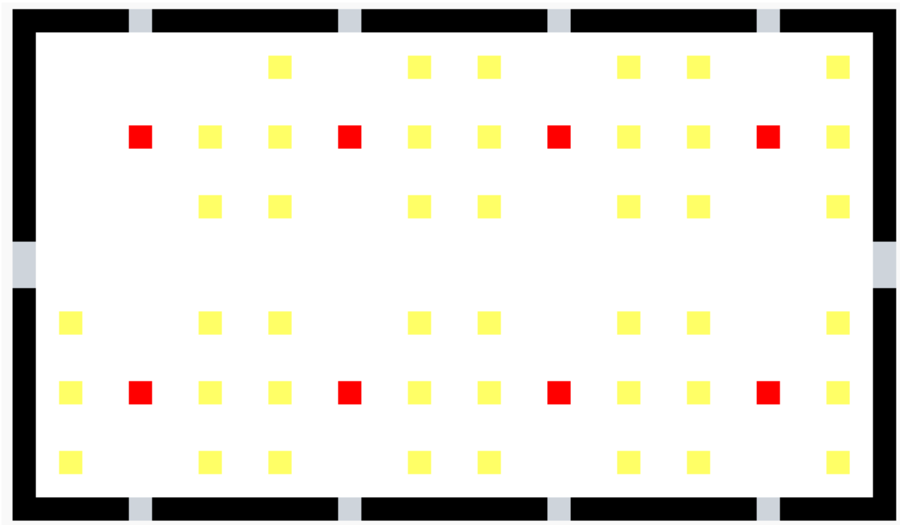

Figure 13: Experiment 1 Configuration 2 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

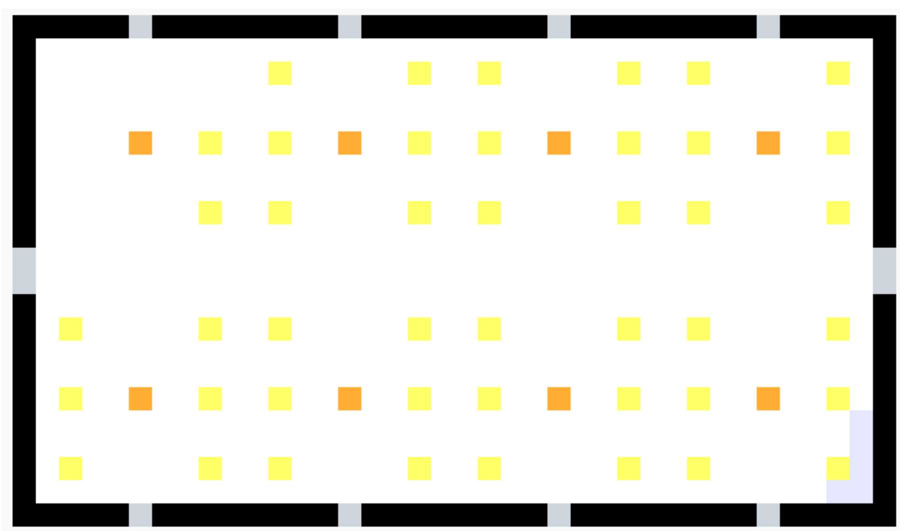

Figure 14: Experiment 1 Configuration 2 Variation 2 at $t = 95$

4.4. Experiment 2: Half Occupancy Work Day

This experiment tests an occupancy load of 24/48 employees under two occupancy configurations of two variations each:

1. Configuration 1: Scattered Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled
2. Configuration 2: Consolidated Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled

This experiment was designed to simulate an optional "work-from-home" work day of exactly half occupancy. Since exactly half of the workstations are occupied, the occupancy distribution pattern between configurations has a much more profound effect on the simulation than in Experiment 1, as does the HVAC operational mode between variations.

In Configuration 1, the scattered occupancy distribution leaves one cubicled climate zone without any occupants. In Variation 1, when the occupancy sensors are disabled, this area's heater still activates to heat the zone; however, because of the lack of occupants and their slight generative heat contributions to temperature, this zone can be seen to experience a slightly lower average temperature for most of the simulation. Other climate zones with less than full occupancy also see this effect. In Variation 2, with the occupancy sensors enabled, the unoccupied zone's climate is considerably different. As there are no occupants in this zone, the heater stationed there never engages, and therefore supplies no heat for the duration of the simulation. As such, the effects of heat dissipation are counteracted neither by the heater nor the occupant's heat generation functions, thereby making this area much colder. The effects of heat dissipation are strongest by the external windows and walls where the dissipation coefficients are highest, and the cooling effect even extends into occupied zones, causing sporadic moments of temperature discomfort for neighbouring occupants.

In Configuration 2, the consolidated occupancy distribution leaves half of the cubicled zones without occupants. In Variation 1, with occupant sensors disabled, these unoccupied zones are still heated, with many active heater time units spent in maintaining the temperature even with no occupants. In Variation 2, the occupancy sensors ensure that the heaters in these unoccupied zones do not engage. Because of this, a significant gradient is observable in the simulation: the unoccupied zones are unheated and therefore below the target temperature range, while the occupied zones are generally well heated - although occupants closest to the unoccupied zones experience occasional discomfort due to their proximity to the unheated zones. One important observation is that total active heater time units is significantly decreased, since less of the office has to be maintained.

4.4.1. Configuration 1: Scattered Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

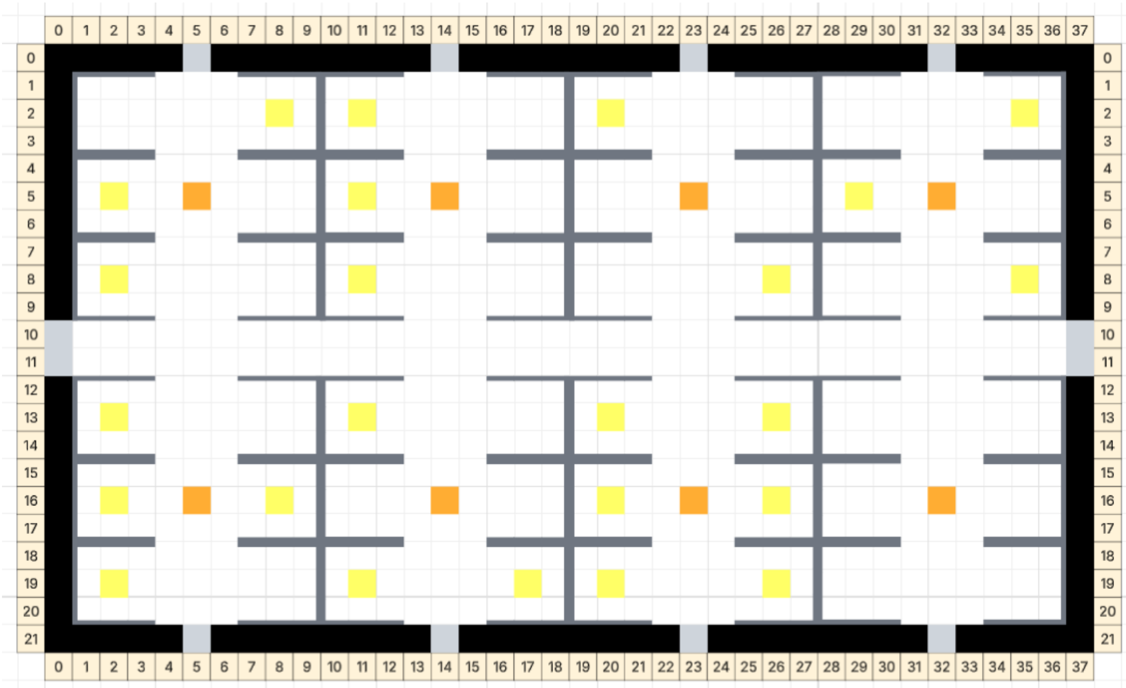

Figure 15: Experiment 2 Configuration 1 Floor Plan

4.4.1.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

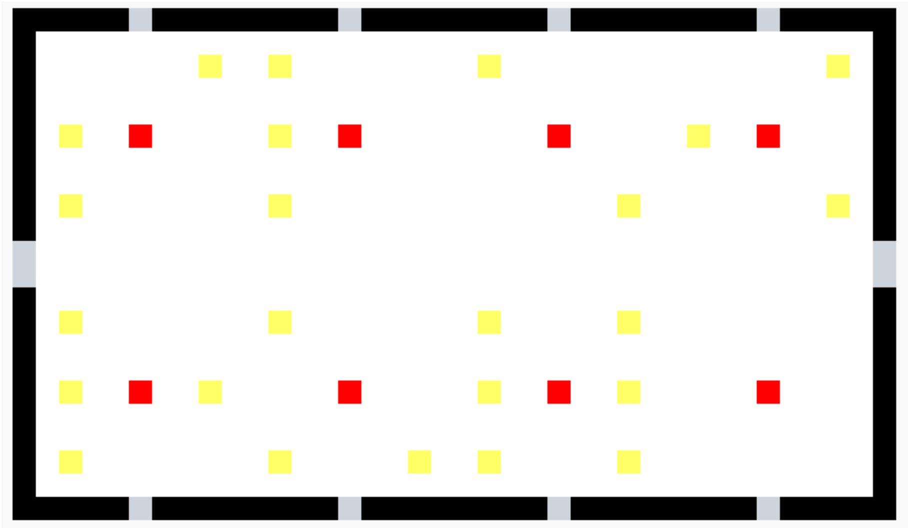

Figure 16: Experiment 2 Configuration 1 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

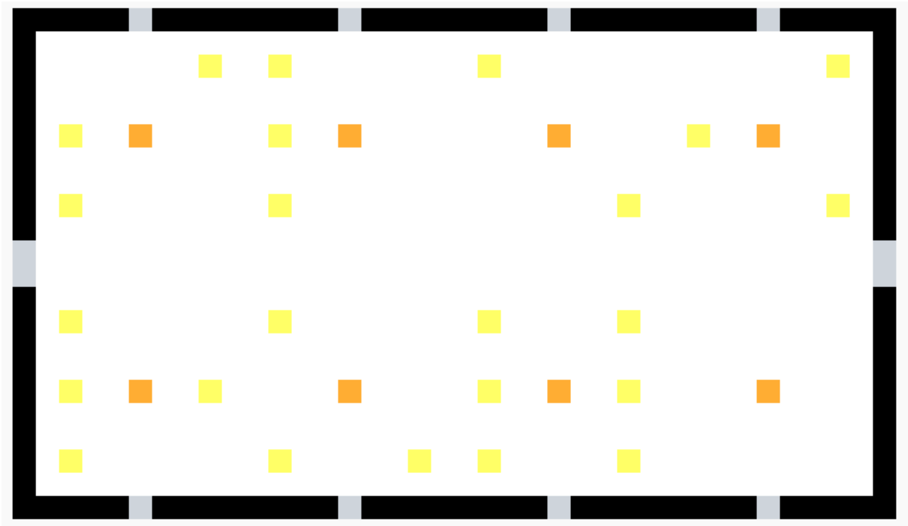

Figure 17: Experiment 2 Configuration 1 Variation 1 at $t = 95$

4.4.1.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

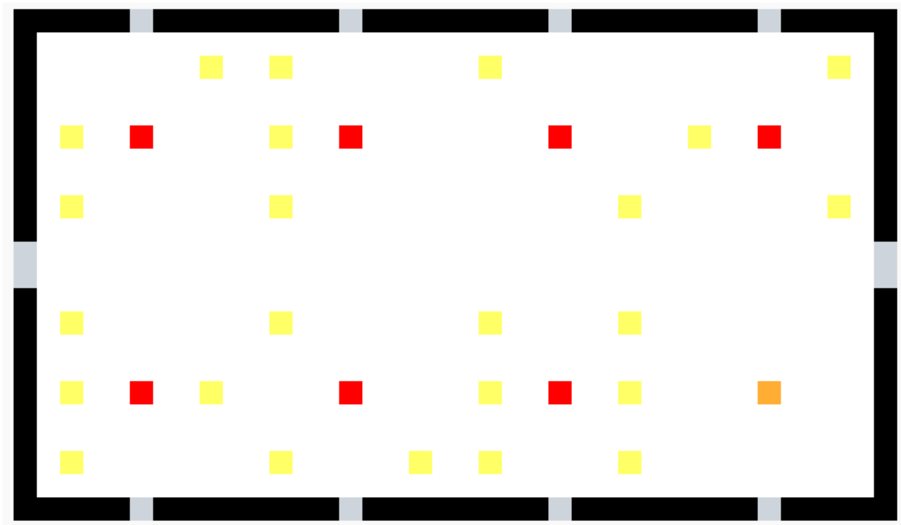

Figure 18: Experiment 2 Configuration 1 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

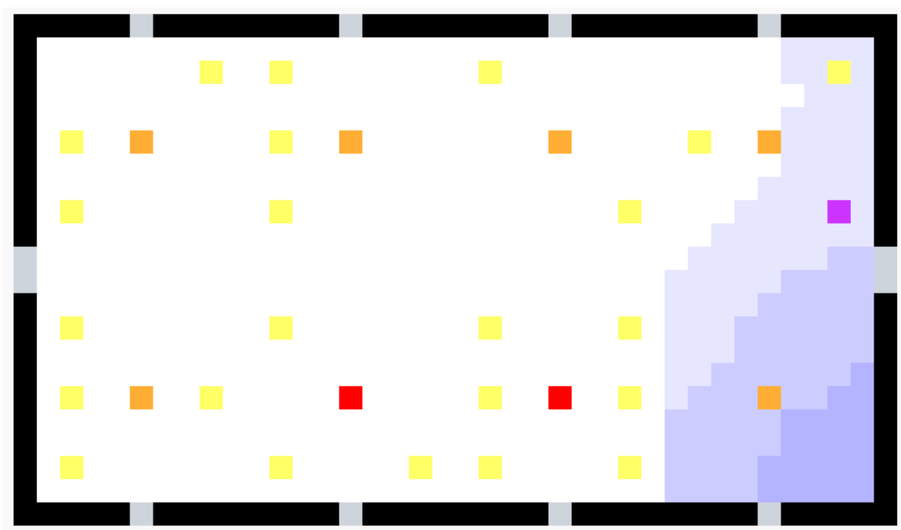

Figure 19: Experiment 2 Configuration 1 Variation 2 at $t = 95$

4.4.2. Configuration 2: Consolidated Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

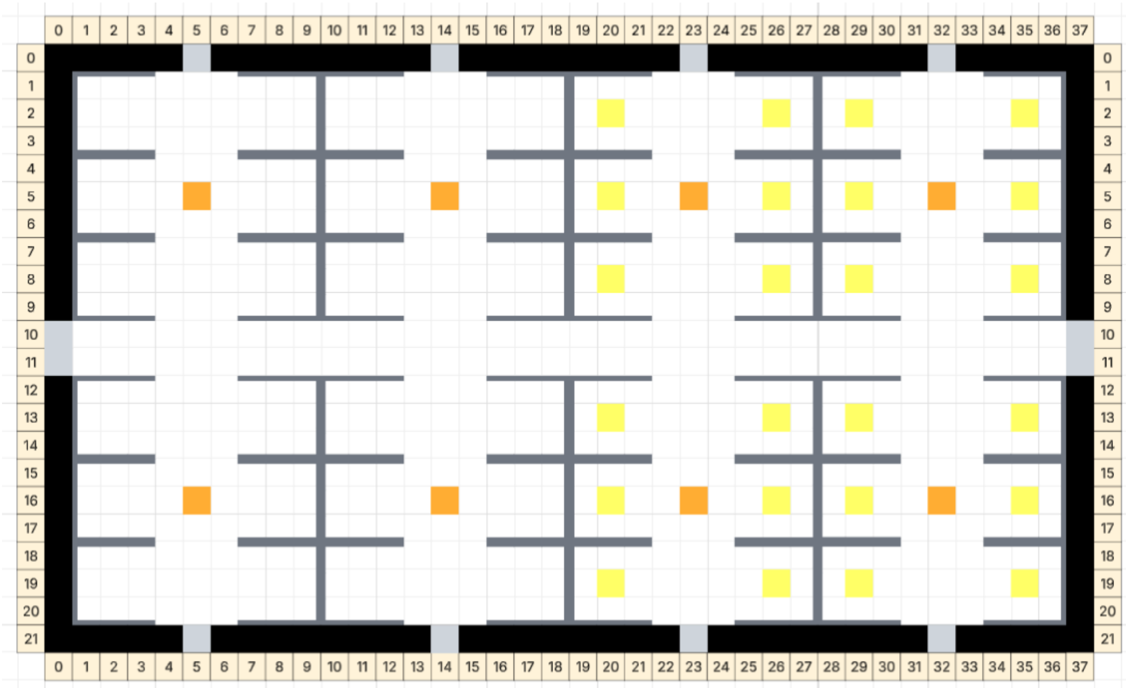

Figure 20: Experiment 2 Configuration 2 Floor Plan

4.4.2.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

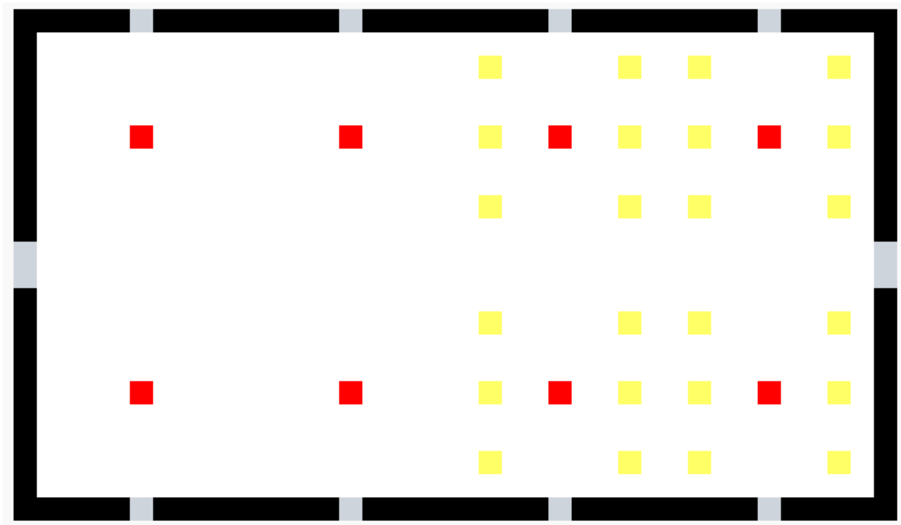

Figure 21: Experiment 2 Configuration 2 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

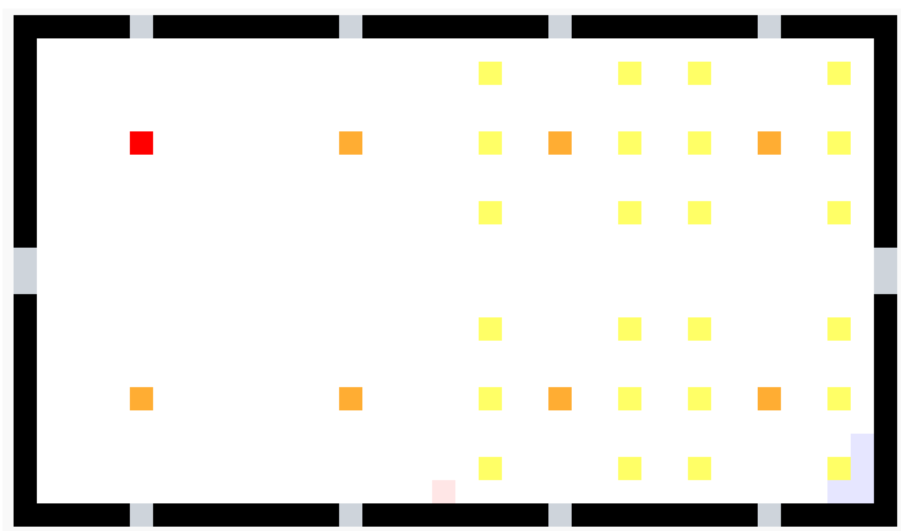

Figure 22: Experiment 2 Configuration 2 Variation 1 at $t = 95$

4.4.2.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

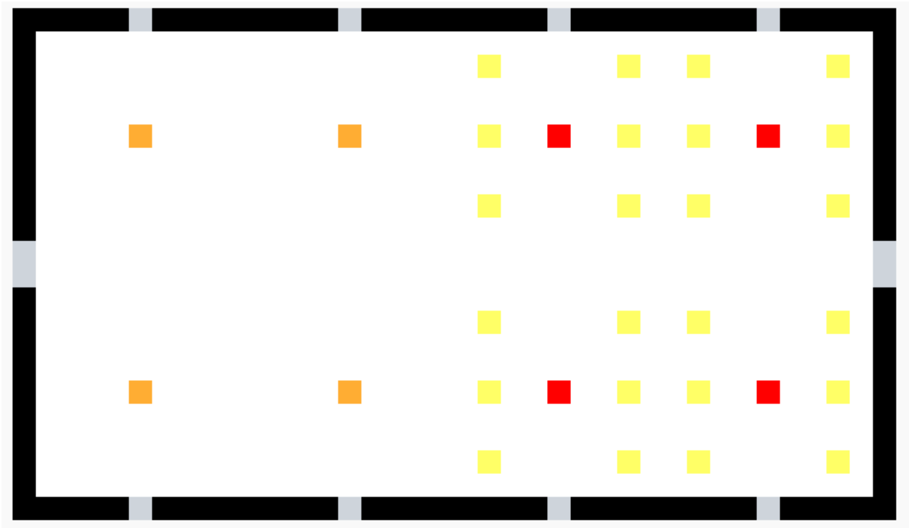

Figure 23: Experiment 2 Configuration 2 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

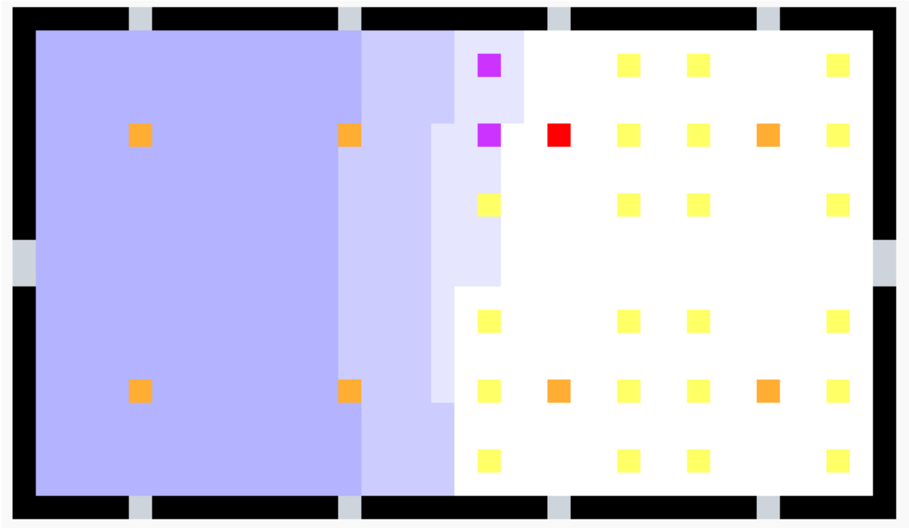

Figure 24: Experiment 2 Configuration 2 Variation 2 at $t = 95$

4.5. Experiment 3: Low Occupancy Work Day

This experiment tests an occupancy load of 8/48 employees under two occupancy configurations of two variations each:

1. Configuration 1: Scattered Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled
2. Configuration 2: Consolidated Occupancy Pattern
   (a) Variation 1: Occupancy Sensors Disabled
   (b) Variation 2: Occupancy Sensors Enabled

This experiment was designed to simulate an optional "work-from-home" work day of low occupancy. Since only eight of the workstations are occupied, the occupancy distribution pattern between configurations has a much more profound effect on the simulation than in the previous experiments, as does the HVAC operational mode between variations.

In Configuration 1, the scattered occupancy distribution leaves all cubicled climate zones with a single occupant. As such, there is little difference between Variation 1 and Variation 2, since all heaters in all zones are similarly active. Like in Experiment 2, the reduced occupancy means less generative heat from occupants, resulting in more cells falling below the target temperature from heat dissipation.

In Configuration 2, the consolidated occupancy distribution leaves all but two of the cubicled zones without occupants. In Variation 1, with occupant sensors disabled, these unoccupied zones are still heated, with many active heater time units again spent on maintaining unoccupied zones. In Variation 2, the occupancy sensors prevent heater activation in these six unoccupied zones. As in the corresponding variation of Experiment 2, this results in a significant temperature gradient, with even more of the office floor left unoccupied and therefore unmaintained. Again, occupants closest to the unoccupied and unheated zones occasionally report falling out of their climate comfort zone. As well, active heater time units are even less than in Experiment 2, as less of the office is required to be climate controlled by the demand-driven HVAC heater mode.

4.5.1. Configuration 1: Scattered Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

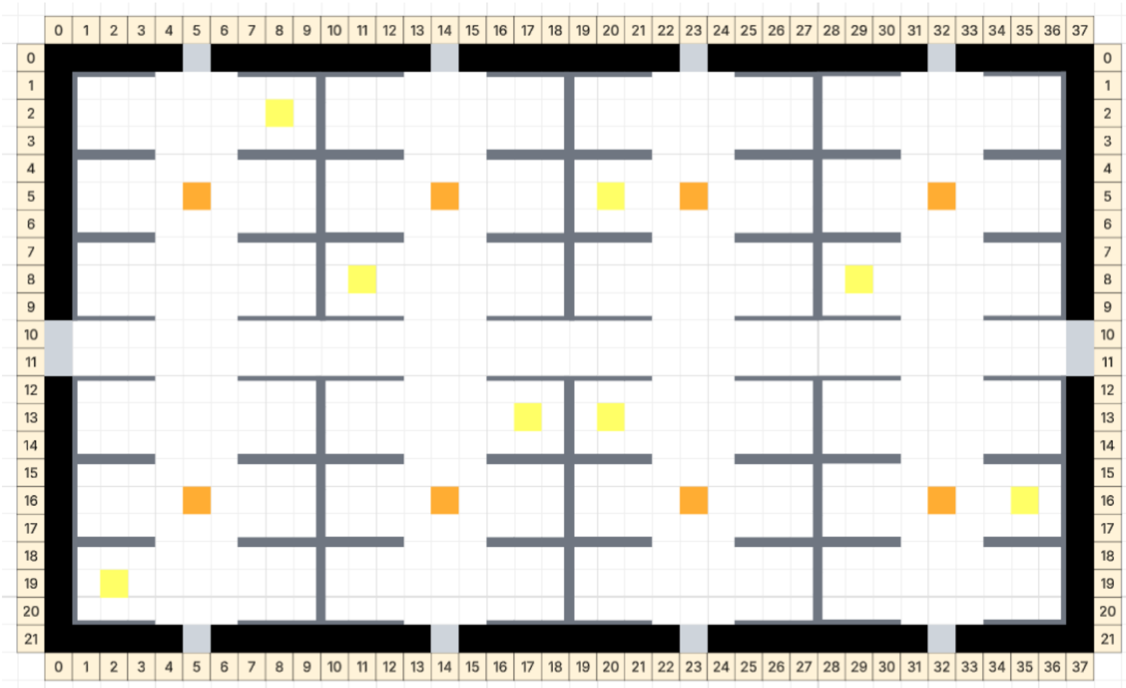

Figure 25: Experiment 3 Configuration 1 Floor Plan

4.5.1.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

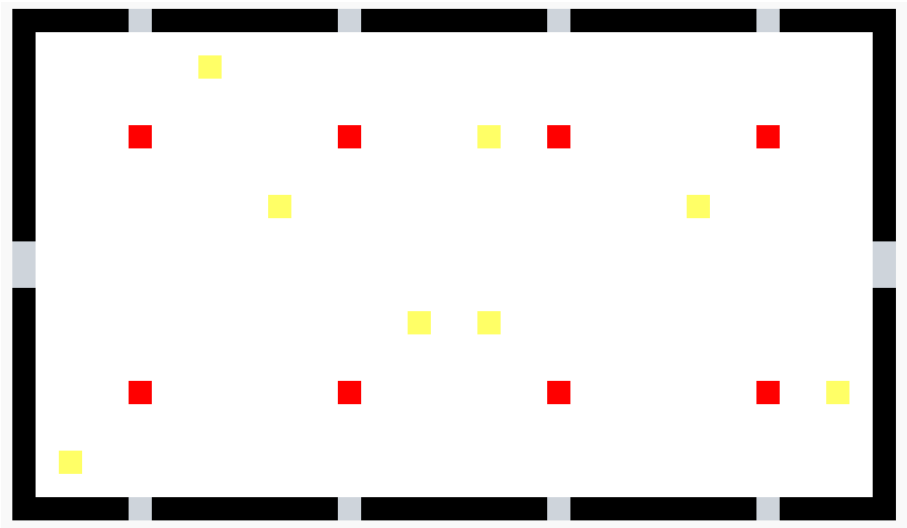

Figure 26: Experiment 3 Configuration 1 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

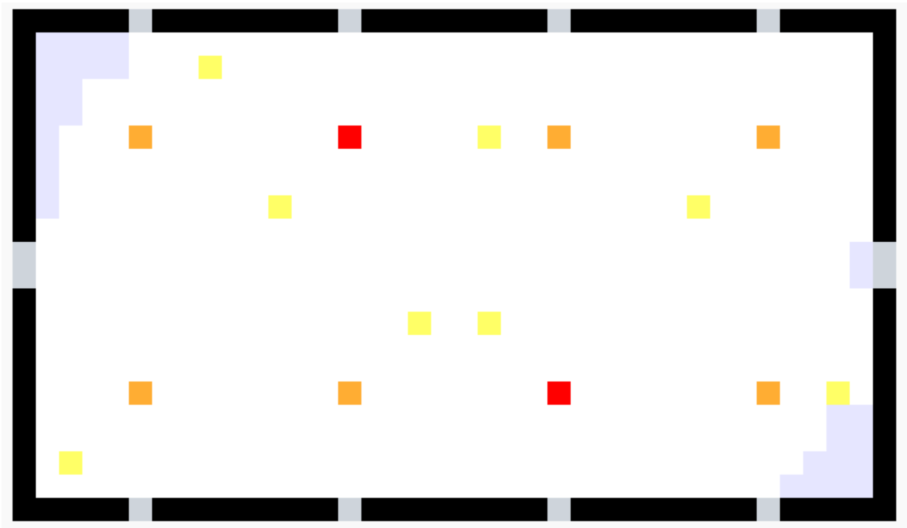

Figure 27: Experiment 3 Configuration 1 Variation 1 at $t = 95$

4.5.1.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

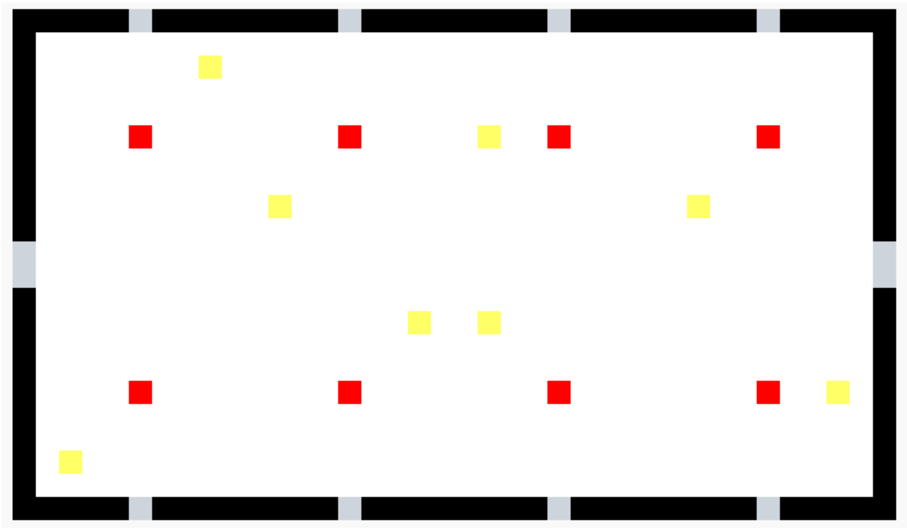

Figure 28: Experiment 3 Configuration 1 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

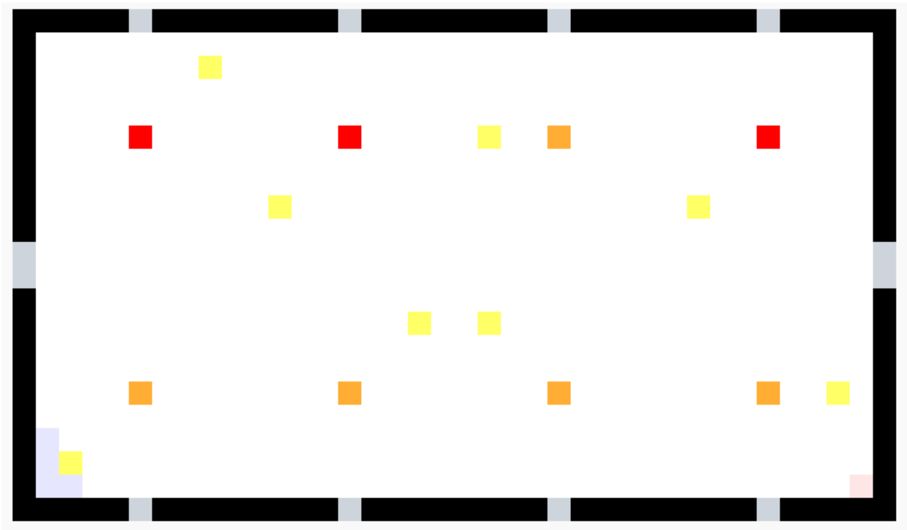

Figure 29: Experiment 3 Configuration 1 Variation 2 at $t = 95$

4.5.2. Configuration 2: Consolidated Occupancy Pattern

The floor plan used in this experimental configuration is as follows:

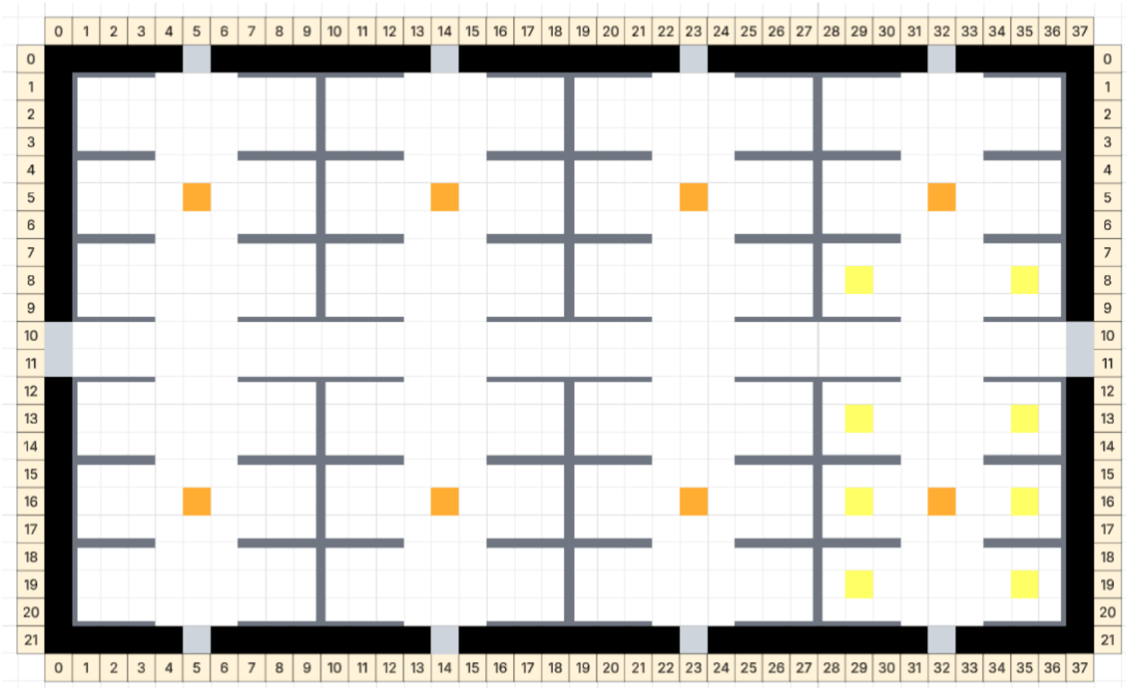

Figure 30: Experiment 3 Configuration 2 Floor Plan

4.5.2.1 Variation 1: Occupancy Sensors Disabled

The initial state of this experimental variation at $t = 0$ is as follows:

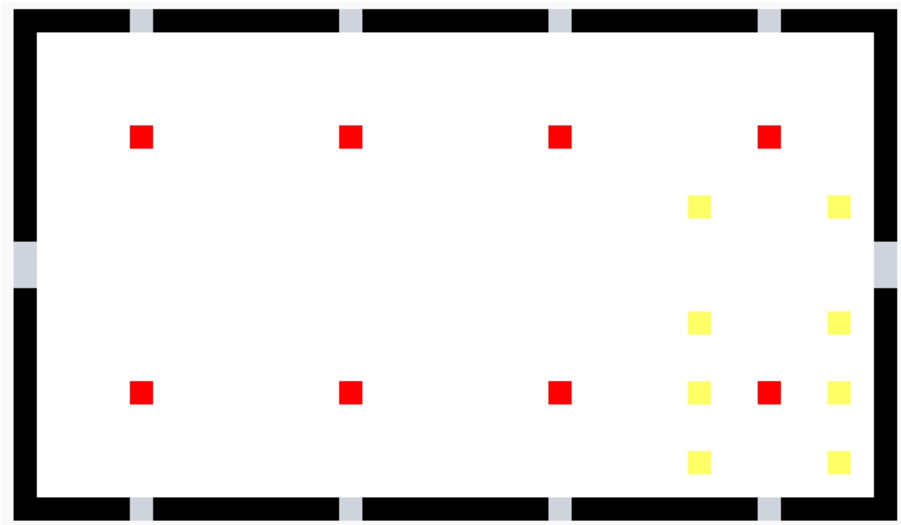

Figure 31: Experiment 3 Configuration 2 Variation 1 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

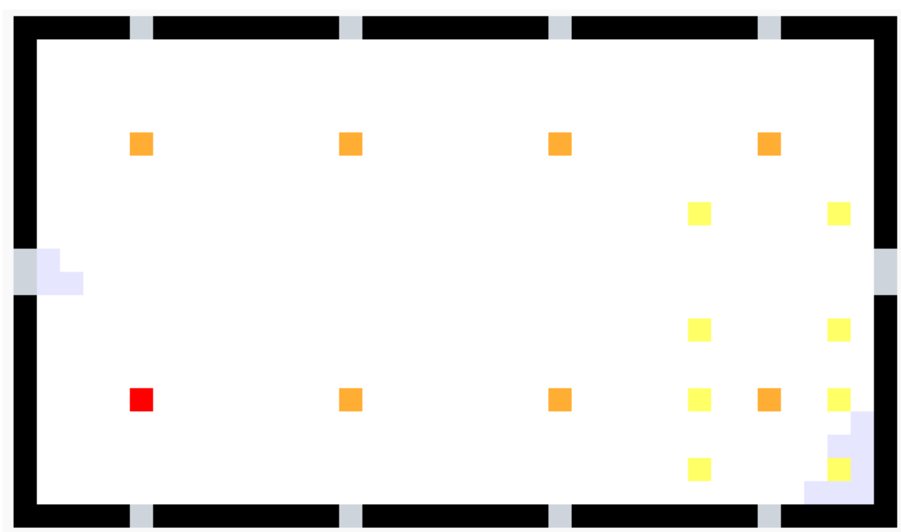

Figure 32: Experiment 3 Configuration 2 Variation 1 at $t = 95$

4.5.2.2 Variation 2: Occupancy Sensors Enabled

The initial state of this experimental variation at $t = 0$ is as follows:

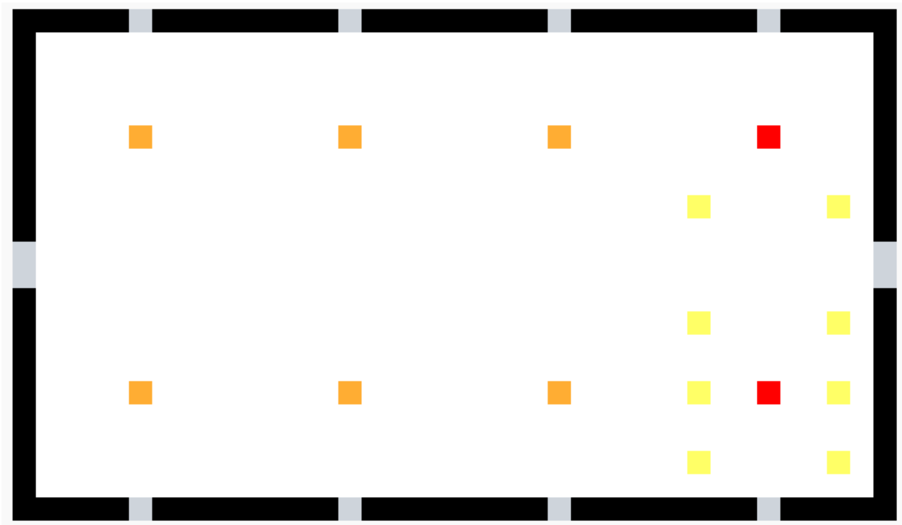

Figure 33: Experiment 3 Configuration 2 Variation 2 at $t = 0$

The initial state of this experimental variation at $t = 95$ is as follows:

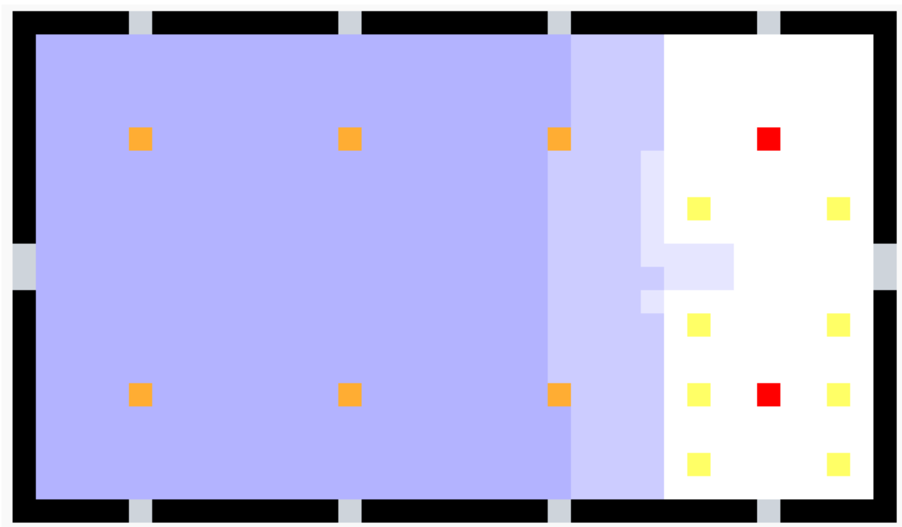

Figure 34: Experiment 3 Configuration 2 Variation 2 at $t = 95$

5. Conclusions

5.1. Analysis

Execution data was gathered from the output logs of each simulation described in Section 4 above. For each experiment, operational data was aggregated for all eight heaters in the modeled office floor, quantifying the total amount of active heater time units, and the amount of active heater time units per occupant in the simulation. The table of Fig. 35 below summarizes the experimental data for all simulations described in Section 4.

Experiment ID			Occupancy		Heaters		
Experiment	Configuration	Variation	Occupants	Distribution	Occupancy Sensors Enabled	Total Active Time Units	Active Time Units per Occupant
1	1	1	44	Scattered	NO	388	8.82
1	1	2	44	Scattered	YES	394	8.95
1	2	1	44	Consolidated	NO	392	8.91
1	2	2	44	Consolidated	YES	390	8.86
2	1	1	24	Scattered	NO	398	16.58
2	1	2	24	Scattered	YES	382	15.92
2	2	1	24	Consolidated	NO	400	16.67
2	2	2	24	Consolidated	YES	246	10.25
3	1	1	8	Scattered	NO	408	51.00
3	1	2	8	Scattered	YES	412	51.50
3	2	1	8	Consolidated	NO	410	51.25
3	2	2	8	Consolidated	YES	164	20.50

Figure 35: Experimental Data from Simulations

From this data, several important conclusions can be drawn.

In Experiment 1, simulating a high occupancy "in-office" work day, simulations reported roughly equivalent heater activation statistics. This trend suggests that the effects of occupancy distribution and HVAC operational modes are minimal when the office space is highly occupied during traditional "in-office" days.

In Experiment 2, simulating a half occupancy optional "work-from-home" work day, the effects of occupancy distribution and HVAC operational modes are more discernible. Under Configuration 1 with a scattered occupancy distribution, there was not a significant difference in active heater time units between the HVAC operational modes, although the simulation visualizations act well to show the effects on heat diffusion across occupied and unoccupied spaces. Under Configuration 2 with a consolidated occupancy distribution, the discrepancy between heater operational modes is much wider in terms of active heater time units. When operating without occupant sensors, the active heater time units per occupant was 16.67, which is significantly higher than 10.25 when operating with sensors. As such, these results indicate that consolidated occupancy distributions partnered with demand-driven HVAC operational modes may increase energy efficiency when occupancy loads are lower.

In Experiment 3, simulating a low occupancy optional "work-from-home" work day, the experimental data reveals significant differences arising from both occupancy distribution patterns and heater operational modes. Under Configuration 1 with a scattered occupancy distribution, total active heater time units were even higher than those reported in Experiment 1. This increase is largely due to effect of occupant heat generation: with less occupants, there is less active heat generation from occupants, and therefore dissipation must be compensated through increased energy expenditure of heaters. Of course, less occupants also results in a much higher energy expenditure per occupant, revealing over a 500% increase from experiment 1. Under Configuration 2 with a consolidated occupancy distribution, the discrepancy between heater operational modes is very significant in terms of energy expenditure. In Variation 1, with the occupancy sensors disabled, total and per occupant active heater time units are nearly identical to the results of both variations under the scattered distribution of Configuration 1. When the occupancy sensors are activated in Variation 2, the total active heater time units drops significantly from 410 to 164, resulting in a per occupant rate drop from 51.25 to 20.50. These results indicate that, in cases of low occupancy and consolidated occupant distribution patterns, operational modes are very significant in determining energy consumption in HVAC climate control.

5.2. Discussion

The results of this data and analysis provide useful insights that may be applied to the research questions proposed in Section 1 of this report.

1. What effects do post-pandemic work practices have on corporate building energy consumption and waste?

Post-pandemic work practices resulting in lowered occupancy of corporate office buildings have definite effects on corporate energy consumption and waste. If HVAC systems do not consider any occupancy detection in their activation algorithms and heat indiscriminately, energy expenditures are similar across all occupancy levels. With less occupants and the same heating practices, energy expenditures per occupant are necessarily higher; this inefficiency can be categorized as wasteful. As well, with less occupants comes less generative heat from those occupants, which also means that heaters must compensate for this; this compensation results in increased overall energy consumption by HVAC systems.

2. Should building systems employ different energy strategies based on work policies and occupancy patterns?

From the analysis of simulation results, different HVAC operational modes are shown to have significant effect when employed under different occupancy loads and distributions. When occupancy sensors are not used, energy expenditures from HVAC systems are roughly equivalent or even higher when occupancy loads are lower, and also when occupant distributions are more scattered. The results of simulations here suggest that, in the cases of lower occupancy loads, consolidated occupant distribution patterns and demand-driven HVAC operational modes should be combined to decrease total and per occupant energy consumption, minimizing the energy spent on maintaining unoccupied climate zones.

3. Can Cell-DEVS modeling and simulation provide guidance towards more efficient post-pandemic corporate building operational practices?

While the experiments designed as part of this study were relatively simplistic, the results of even these humble simulations demonstrate the capabilities of the Cell-DEVS methodology when applied to BIM. Valuable conclusions regarding post-pandemic building operational practices were found through the application of Cell-DEVS, and future work could be done to reveal additional guidance.

As post-pandemic work practices are likely to continue influencing corporate building energy expenditures, Cell-DEVS is a valuable methodology with much future potential in the area of BIM.

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7. Appendix A: Cell-DEVS Model Data Form

Title: Corporate Building Energy Consumption and Waste in Post-Pandemic Work Practices

Type: Cell-DEVS Model

Acronym/Short name: BimSim

Purpose for which Developed:

To apply Cell-DEVS techniques with Building Information Modeling (BIM) to study corporate office building energy consumption and waste under post-pandemic work practices.

Other Applications for which it is Suitable:

This model and simulation may inform other BIM applications of Cell-DEVS techniques.

Date Developed/Implemented: May 4, 2025.

Domain: Building Information Modeling (BIM)

Current Version: 1.0.0

URL: GitHub Repository

Description: Tool for modeling a floor of a corporate office building according to the Cell-DEVS formalism in order to study the effects of post-pandemic work practices on energy consumption and waste. Implemented in C++ using the Cadmium V2 library.

Links to Related Documents: None

Keywords: Cell-DEVS, Building Information Modeling, BIM, corporate buildings, office floor, energy consumption, energy waste, work practices

Developer:

Name: Michael De Santis	**Student Number**: 101213450
Address 1: —	**e-mail:** michaeldesantis@cmail.carleton.ca
Address 2: —	
City: Ottawa	**Province/State-Country:** Ontario, Canada
Zip: —	**Phone:** —