Optimizing occupant-centric building controls given stochastic occupant behaviour

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Abstract. Occupant-centric control (OCC) strategies represent a novel approach for indoor climate control in which occupancy patterns and occupant preferences are embedded within control sequences. They aim to improve both occupant comfort and energy efficiency by learning and predicting occupant behaviour, then optimizing building operations accordingly. Previous studies estimate that OCC can increase energy savings by up to 60% while improving occupant comfort. However, their performance is subjected to several factors, including uncertainty due to occupant behaviour, OCC configurational settings, as well as building design parameters. To this end, testing OCCs and adjusting their configurational settings are critical to ensure optimal performance. Furthermore, identifying building design alternatives that can optimize such performance given different occupant preferences is an important step that cannot be investigated during field implementations of OCC due to logistical constraints. This paper presents a framework to optimize OCC performance in a simulation environment, which entails coupling synthetic occupant behaviour models with OCCs that learn their preferences. The genetic algorithm for optimization is then used to identify the configurational settings and design parameters that minimize energy consumption under three different occupant scenarios. To demonstrate the proposed framework, three OCCs were implemented in the building simulation program, EnergyPlus, and executed through a Python package, EPPY to optimize OCC configurational settings and design parameters. Results revealed significant improvement of OCC performance under the identified optimal configurational settings and design parameters for each of the investigated occupant scenarios. This approach would improve OCC performance in actual buildings and avoid discomfort issues that arise during the initial implementation phases.

1. Introduction

Occupants have been identified as a driving factor in building energy consumption in recent studies. They can affect building design and building operation by behaviours that impact building energy performance and HVAC systems [1]. However, building automation systems typically control the indoor climate using constant setpoints and schedules without considering real-time occupancy and occupant preferences. Control engineers consider these setpoints and schedules at the design or early operation phase, and they must make conservative assumptions due to lack of information about occupancy and 'occupants' preferences. These conservative views lead to operating schedules that exceed occupied hours, as well as temperature setpoints that result in cold complaints in the summer and hot complaints in the winter [2]. In addition, there is always a big dilemma to satisfy the needs of
decreasing building energy usage while promoting comfort in the indoor environment. The primary objective of these control systems is to minimize the energy consumption in the buildings. However, considering occupants’ perception toward comfort is equally or even more critical for such control systems. [3]

Given the recent developments in information and communication technology, Occupant-Centric building Control (OCC) strategies have been introduced in which a control system acquires various data from occupants, the indoor environment, and the outdoor climate. The occupant-related information is gained directly or indirectly through a variety of sensors, occupant feedback from control interfaces, mobile or wearable devices. The derived information is then used for building controls, e.g., room occupancy patterns and adaptive setpoints to improve energy efficiency on the one hand, as well as occupant comfort on the other hand[4, 5]. As such, OCCs offer the potential of balancing between these two objectives (e.g., by minimizing wasteful energy use when it is not needed). Recent studies showed the success of OCC applications in buildings. For example, Nagy et al. [3] proposed an adaptive control method for lighting in office buildings. The setpoints for light switches on and off were collected dynamically from the analysis of data derived from the interaction of occupants with lighting sensors. The results of the six-week case study for 10 offices showed 37% improvement in energy saving. In another study, a reinforcement learning (RL) based OCC for thermostat was developed [6]. The agent learned occupant behaviour and indoor environment while monitoring indoor air temperature, occupancy and thermal comfort and determined the thermostat setpoint to reach a balance between energy consumption and occupant comfort.

Although previous studies showed that energy efficiency and occupant comfort improved by performing OCC, the actual performance of OCCs has a significant potential for further investigation to improve. OCCs performance can change while interacting with different types of occupants and building design parameters. Therefore, fine-tuning OCC configurations for different design alternatives and various types of 'occupants' preferences is a crucial milestone in developing their performance. Regulating OCCs with these optimal solutions will enhance control of the indoor environment which results in improving energy efficiency as well as occupant comfort. To this end, this paper aims to propose a simulation framework to estimate optimal OCC configurations while working with various kinds of occupants with different tendencies before the real-world implementation phase. The proposed optimization framework integrates stochastic occupant behaviour models as well as OCCs which learn from 'occupants' interaction with the building and then control building operations. An evolutionary genetic algorithm is used to determine the optimal OCC configurations which have the most compatibility with building design alternatives in terms of minimizing annual energy consumption for each occupant's type. To provide a proof-of-concept of the framework, a single office was modelled with different design parameters to represent the capability of the proposed framework to investigate different 'OCCs’ performance and identify their optimal configurations.

2. Method
An overview of the proposed framework to optimize OCC performance using a simulation approach is shown in Figure 1. In this approach, occupant behavior models and OCC algorithms were implemented in EnergyManagementSystem (EMS) using custom scripts in EnergyPlus. In addition, a number of PYTHON packages such as EPPY and GEOMEPPY were used as an interface to modify (EMS) 'object's scripts in EnergyPlus. In the following, the stochastic occupant behavior models which were used in this study are described. In the next step, OCC models implemented in (EMS) to learn occupant preference and their configurations are expressed. This is followed by describing a single office building model as a proof-of-concept of the proposed framework. Finally, more details about the applied optimization algorithm using PYTHON packages are provided.

2.1. Implementation of stochastic occupant behaviour
In this study, four Occupant behaviour models were implemented in EMS object of EnergyPlus to simulate stochastic occupant behaviour. In this section, a summary of these four models, including occupancy, lighting, heating and cooling setpoints, and blinds are described.

Figure 1: overview of proposed method

A probabilistic model to predict occupancy in a single office was implemented in EMS based on the model proposed by [7]. At the beginning of each day, five event times, including arrival, two coffee breaks, lunch break and departure were sampled randomly from a pre-defined normal distribution. The duration of coffee breaks and lunch breaks were calculated through an exponential probability distribution with the time constant of 15 mins for a coffee break and 1 hr for a lunch break. Office status was considered vacant during weekends and holidays. Light switch behaviour was simulated using an approach that builds on 'Reinhart's light witch model [8]. A probabilistic logistic regression model was used to predict the probability of switching lights on based on indoor illuminance upon arrival and during the presence of the occupant. The probability of light switching off upon departure was calculated based on the length of absence (Figure 2). The coefficients of the logistic regression model were modified in this study to investigate three types of occupants, namely sensitive, moderate, and tolerant. Under the same condition, the sensitive occupant had a higher probability of switching lights on in comparison with moderate and tolerant occupants.

Figure 2: Probability of light switch on at arrival and switch off at departure for a sensitive, moderate, and tolerant occupant.

Similarly, a logistic regression model was used to predict the probability of increasing and decreasing the setpoint by occupant based on the indoor temperature in each time step based on the work presented by [9]. For the same indoor temperature, the sensitive occupant had a higher probability of adjusting thermostat setpoints than the moderate or tolerant occupants, respectively.

'Occupants' interaction with blinds was predicted using the model presented by [10]. Either lowering or raising blind action was predicted based on indoor illuminance and the current unshaded fraction. If an action was predicted, the probability of fully opening or closing the blind was calculated based on solar radiation. Alternatively, if a partial lowering or closing action was predicted, the related
counterpart was drawn from the Weibull distribution. In this study, if the predicted partial for closing was more than 0.5, it was assumed that the blind is fully closed. Likewise, if it was predicted less than 0.5, the blind was assumed to be fully open.

2.2. OCC
In this study, three OCCs for controlling lights, heating and cooling setpoints were investigated. The first implemented OCC (lighting OCC #1) works with a threshold for light switching off [11]. This OCC switches the light off either when the indoor illuminance exceeds this threshold or in the absence of the occupant. This threshold decreased gradually until an occupant light switching on action is observed, at which point the threshold slightly increased (with the learning rate of 0.001 from occupant behaviour). In Gunay et al. 2017, this threshold can only decrease to 200 lux and increase to 500 lux in which becomes constant afterward. In this study, the boundaries of (0, 300) and (300, 700) were considered for minimum and maximum limits for threshold, respectively, to identify the optimized constraints for OCC configuration.

The second implemented OCC (lighting OCC #2) for lighting works with a threshold for light switching on and off [5]. The switching on threshold is derived dynamically based on the average of indoor illuminance when the occupant turns on the light. This average was taken every one month in original configurations. The light switching off threshold is calculated by adding the illuminance light provides in the room at night to the threshold for light switching on. In this study, the boundaries of (1, 120) days are considered for the duration which the average take over to investigate different duration from one day to almost one season.

The implemented thermostat OCC works with heating setpoint in the winter and cooling setpoint in the summer [12]. The heating setpoints decreased gradually till it was interrupted by occupant thermostat keypress action, after which it increased slightly. Similarly, the cooling setpoint increased gradually as long as no interaction with thermostat keypress by occupant observed. Once the occupant pressed the thermostat key, the cooling setpoint decreased slightly. The rate of increasing or decreasing setpoints gradually relied on a quadratic deviation formula explained in [12]. The configuration of this OCC has the conservative boundaries of [20, 22] °C for heating setpoint and [22, 25] °C for cooling setpoint. In other words, if the setpoints exceed these boundaries, it becomes constant at boundaries' point till it backs to the defined range. In this study, a range of [15, 20] for the lower boundary of the heating setpoint and [22, 30] for the upper boundary of the heating setpoint were considered. Likewise, a range of [15, 20] for the lower boundary and [25, 30] for the upper boundary of the cooling setpoint were considered to estimate the optimal boundaries.

It is worth mentioning that the OCCs simulated in this study were all previously peer-reviewed, and validated using real-world data in previous publications.

2.3. Office building model
To provide a proof-of-concept of the proposed workflow, a single office with a floor area of 16 m² and a height of 3 m was created in EnergyPlus. EnergyPlus weather data file (EPW) for Montreal was used for simulation. Internal heat gains from occupant were set to 130 W per person, which is based on the activity level of an occupant in the office. It is assumed that the office is occupied by one person. For the initial design, 35% WWR was installed on the south side of the building. The other three walls of the building and the roof and floor of the building were assumed to be adiabatic (i.e., attached to spaces with the same thermal condition). An interior shading device was defined as a blind which works with occupant action towards closing or opening the blind. The daylight reference point was located at the height of 0.8 m which is almost equivalent to desk height. The initial selected design parameters were derived from previous studies and they meet the requirement specified by NECB 2017 (Table 1).

| Design parameters         | Values | Unit |
|---------------------------|--------|------|
| Window glazing U-Factor   | 1.6    | W/(m²K) |
| Window glazing VT         | 0.6    | -    |
3. Optimization

In this study, a genetic algorithm (GA) is used to find the optimal solution to minimize energy use intensity (EUI). EUI is expressed as annual energy consumption per square meter. GA parameters, including the maximum number of generations, population size, mutation probability, crossover probability, and elite ratio are considered 50, 15, 0.35, 0.7 and 0.05, respectively. These parameters were selected based on a practical approach by evaluating the optimum result improvement and the computational time. The objective function for every member of a generation was evaluated by optimizing the result improvement and the computational cost. The best combinations were selected and rated for the next generation. These steps were repeated until the stop criteria were met. For this study, the maximum number of iterations (50) is considered for termination criteria. The solution space was defined based on variables boundaries for each OCC model as well as building design parameters. These ranges of design parameters were selected in a way that meets the requirements by NECB 2017. Table 2 indicates the variables and their range for thermostat OCC and both lighting OCC configurations. Table 3 indicated the solution space of design variables for lighting OCCs and thermostat OCC, respectively. Overall, solution spaces of $1.30 \times 10^{16}$ for the combination of thermostat OCC and light #1 OCC, and $7.46 \times 10^{16}$ for the combination of thermostat OCC and light #2 OCC were defined.

### Table 2: Range of OCC configuration variables

| Variables                                      | OCC  | Min  | Max  | Unit  | Increment |
|-----------------------------------------------|------|------|------|-------|-----------|
| Upper boundary for heating setpoint            | Thermostat | 22   | 30   | °C    | 0.5       |
| Lower boundary for heating setpoint            | Thermostat | 15   | 20   | °C    | 0.5       |
| Upper boundary for cooling setpoint            | Thermostat | 12   | 30   | °C    | 0.5       |
| Lower boundary for cooling setpoint            | Thermostat | 15   | 20   | °C    | 0.5       |
| Upper boundary for light switches off threshold| Lighting #1 | 150  | 700  | Lux   | 20        |
| Lower boundary for light switches off threshold| Lighting #1 | 0    | 300  | Lux   | 20        |
| Period of updating the threshold               | Lighting #2 | 1    | 120  | Day   | 1         |
| Threshold for the first period                 | Lighting #2 | 0    | 300  | Lux   | 20        |

### Table 3: Range of design parameters for the three OCCs.

| Variable                  | Unit          | Min  | Max  | Increment | OCC            |
|---------------------------|---------------|------|------|-----------|----------------|
| VT (glazing)              | -             | 0.3  | 0.8  | 0.05      | Lighting       |
| Wall visible reflectance  | -             | 0    | 1    | 0.1       | Lighting       |
| Roof visible reflectance  | -             | 0    | 1    | 0.1       | Lighting       |
| Floor visible reflectance | -             | 0    | 1    | 0.1       | Lighting       |
| North axis                | Degree        | 0    | 270  | 90        | Lighting, Thermostat |
| Blinds visible transmittance | -        | 0.05 | 0.2  | 0.05      | Lighting       |
| WWR                       | -             | 1.4  | 2.2  | 0.1       | Thermostat     |
| U-Factor (glazing)        | W/m2K         | 1.4  | 2.2  | 0.1       | Thermostat     |
| SHGC                      | -             | 0.3  | 0.6  | 0.05      | Thermostat     |
| WWR                       | -             | 20   | 70   | 5         | Thermostat     |
| Blind solar transmittance | -             | 0.05 | 0.2  | 0.05      | Thermostat     |
| Wall R-value              | $m^2K/W$      | 4    | 11   | 1         | Thermostat     |

As the simulation relied on stochastic models, electricity consumption after each run with a set of identical variables was different. Therefore, simulations had to be repeated multiple times to get an average EUI. To this end, the initial model was run 200 times and the expanding mean was calculated.
It was found that after 32 runs, the changes in expanding mean for EUI reduced to less than 0.25%. In other words, to calculate the objective function for each set of candidate parameters, the model was executed 32 times.

Optimization was conducted for a total of 6 cases, as shown in Table 4. Baseline scenarios are introduced for cases 1 to 6 when the simulation was conducted for original OCC configurations explained in section 2.2, and initial design parameters are indicated in Table 3.

Table 4: The list of investigated cases

| Case #  | Thermostat and lighting #1 OCC | Thermostat and lighting #2 OCC |
|---------|--------------------------------|--------------------------------|
|         | Sensitive                      | Moderate                       |
|         | Tolerant                       | Sensitive                      |
|         |                                 | Moderate                       |
|         |                                 | Tolerant                       |

4. Results and discussion

In this section, the results of simulating OCC performance in the developed single office model with initial configurations as a baseline are presented (Table 5). This is followed by presenting optimization results to minimize annual electricity consumption.

Comparing the performance of lighting #1 and lighting #2 OCCs when they were working with their original configurations and in a single office with the same building designs, the results revealed that lighting OCC #2 showed a better performance in terms of reducing light electricity consumption. The annual electricity consumption for lighting OCC #1 was more than twice that of lighting OCC #2 for all three occupant types (Table 5).

Table 5: Simulation results with initial configurations and initial design parameters.

| Case #  | 1  | 2  | 3  | 4  | 5  | 6  |
|---------|----|----|----|----|----|----|
| Average light electricity use (kW/m2) | 20.31 | 19.01 | 21.5 | 8.54 | 8.18 | 7.54 |
| Average annual number of light switches on | 1601 | 1298 | 1232 | 1122 | 1075 | 1046 |
| Average annual number of Light switch off | 516 | 413 | 325 | 419 | 400 | 366 |
| Average of EUI (kWh/m2/yr) | 92.02 | 82.72 | 81.77 | 83.92 | 75.12 | 74.20 |

The evolutionary process of GA in minimizing EUI after running for 50 generations is shown in Figure 3 for three types of occupants.

![Figure 3: The evolutionary process of GA in minimizing average EUI for 50 generations.](image)

The results of optimization are indicated in Table 6. Generally, the optimization algorithm was able to reduce EUI to a great extent for all 6 cases. The average EUI reductions were 21.4% and 11% for the combination of thermostat with lighting #1 OCC and thermostat with lighting #2 OCC, respectively. For each combination, GA could minimize EUI for sensitive occupant scenarios more than moderate and tolerant occupant types.

Table 6: Optimal OCC configurations value and design parameters for all cases.

| Case number# | 1    | 2    | 3    | 4    | 5    | 6    |
|--------------|------|------|------|------|------|------|
| Maximum threshold heating | 28   | 26   | 23   | 26.5 | 28   | 23   |
| Minimum threshold heating  | 19.5 | 15   | 20   | 19   | 20   | 16.5 |
| Maximum threshold cooling  | 27.5 | 27.5 | 27   | 25.5 | 29.5 | 28   |
| Minimum threshold cooling  | 16.5 | 15   | 18.5 | 16.5 | 15.5 | 20   |
### 4. Results

| Glazing U-Factor (W/m²K) | 1.4 | 1.5 | 1.4 | 1.4 | 1.4 | 1.4 |
|--------------------------|-----|-----|-----|-----|-----|-----|
| SHGC                    | 0.5 | 0.4 | 0.6 | 0.55| 0.6 | 0.55|
| Building axis            | South | South | South | South | South | South |
| Blind solar transmittance | 0.1 | 0.1 | 0.05| 0.05| 0.2 | 0.1 |
| WWR                     | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| Exterior wall R-value    | 10  | 11  | 11  | 10  | 10  | 9   |
| Period                   | -   | -   | -   | 6   | 101 | 29  |
| Initial Lux mean (lux)   | -   | -   | -   | 260 | 260 | 140 |
| Maximum threshold (lux)  | 580 | 500 | 700 | -   | -   | -   |
| Minimum threshold(lux)   | 20  | 20  | 20  | -   | -   | -   |
| Glazing VT               | 0.7 | 0.65| 0.8 | 0.65| 0.75| 0.75|
| Floor visible absorptance| 0   | 0.3 | 0   | 0   | 0.1 | 0.7 |
| Roof visible absorptance | 0.1 | 0.2 | 0.5 | 0.2 | 0   | 0   |
| Walls visible absorptance| 0.1 | 0   | 0   | 0.9 | 0   | 0   |
| Blind VT                 | 0.2 | 0.2 | 0.2 | 0.15| 0.05| 0.15|
| Average light Electricity consumption (kWh/m²) | 10.28 | 10.80 | 10.43 | 7.12 | 10.47 | 7.20 |
| Average annual number of light switches on | 1124 | 522 | 446 | 693 | 924 | 723 |
| Average annual number of light switches off | 326 | 407 | 403 | 377 | 516 | 405 |
| Average of EUI (kWh/m²/yr) | 72.31 | 68.87 | 64.98 | 74.6 | 67.75 | 66.84 |

Regarding OCC configurations, the frequency of updating for lighting #2 OCC threshold was identified as every week, every three months, and almost every month for the sensitive, moderate, and tolerant occupant, respectively. It can be said that this period was reduced to one week for sensitive occupants as they are naturally more vulnerable to change in indoor illuminance. As a result, OCC should update the threshold more frequently to track their reaction to illuminance changes by passing days. For lighting #1 OCC, the optimal minimum threshold for switching lights off was found to be 20 lux, which suggests the original 200 lux threshold was conservative. The significant decrease (about 50%) in the calculated electricity consumption implies that the 20-lux threshold was an acceptable range for different types of occupants. Considering the results for thermostat OCC configurations, it is found that for the sensitive occupant, the optimal threshold range for heating is [19, 26.5] °C whereas it was [16.5, 23] °C for tolerant occupant. In other words, heating setpoints should change within a higher range for the sensitive occupant to minimize energy consumption compared to the tolerant one.

With regard to design parameters, overall, some optimal points were in the same range for all cases regardless of the type of occupants. To name the main one: the south direction of the building was identified as the optimal axis to minimize EUI in both combinations of OCCs for lighting and thermostat. Since the simulation was conducted using the cold climate of the Montreal weather file, high solar heat gain in this direction causes a reduction in electricity consumption. In addition, WWR of 20% were estimated as the optimal window to wall ratio for all cases.

### 5. Conclusion

This study proposed a simulation framework to optimize various OCCs configurations under different occupant behaviours and building design alternatives. The proposed framework also provided an environment in which different OCCs can be compared under similar conditions. The results indicated that the performance of OCC can improve significantly when their configurations are fine-tuned based on specific occupant preferences. In addition, different building design parameters can be arranged with each type of OCC to improve their performance in terms of energy usage. This approach will enable building operations to perform efficiently by working in their optimal configurations for a broad range of occupants' preferences and building types. Furthermore, building designers can use this framework to identify the most compatible combination of OCC configurations with building alternatives as well
as the potential limitation of employing each OCC upon the existing buildings before the field implementation phase. For future work, the authors suggest doing a sensitivity analysis to find the relationship between the input parameters and objective function and rank them based on their importance. Multi-objective optimization is also planned to account for occupant comfort besides reducing energy consumption.

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