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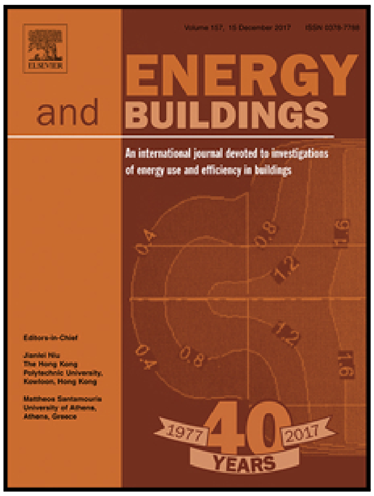

Sensitivity Analysis and Optimization of Building Operations

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HIGHLIGHTS

- Key operational parameters of 14 office buildings were reviewed.
- Over 60% of the air handling units were not turned off outside normal occupied hours.
- Most of the reviewed buildings did not have an economizer cycle program.
- A sensitivity analysis was conducted with the reviewed operational parameters.
- A mixed-integer genetic algorithm was applied to identify the optimal operational parameters.

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Sensitivity Analysis and Optimization of Building Operations

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Abstract

Operator decisions regarding daily and seasonal scheduling of systems' availability and setpoints play an important role in building performance. This paper reviews the key operational parameters of 14 office buildings in Ottawa, Canada. The results revealed that over 60% of the air handling units (AHUs) were not turned off outside of normal occupied hours, and most of them did not have an economizer cycle. The indoor temperature setpoints were between 20 and 24°C. Based on these insights, a building performance simulation (BPS)-based sensitivity analysis was conducted to better understand the energy and comfort performance implications of common operator decisions. Eight operational parameters were studied: AHU start and stop times, seasonal switchover to heating and cooling times, heating and cooling season temperature setpoints, and ventilation rate and mode (i.e., constant or occupancy-based). The results revealed that the AHU start and stop times and the ventilation rate are the most critical operational parameters examined in terms of affecting the energy and comfort performance of the buildings investigated. Subsequently, a mixed-integer genetic algorithm was applied to identify the optimal operational parameters among the set of eight operational parameters investigated for four different heating dominated climate zones, nine different occupancy and three different envelope scenarios. The relationships between the variables of these scenarios and the optimal operational parameters were examined.

Keywords: Operation; Sensitivity analysis; Optimization; Building performance simulation

1. Introduction

Operational decisions such as default temperature setpoints, hours-of-operation for the AHUs, ventilation rates, and seasonal switchover to heating and cooling times play an important role in a building's energy and comfort performance [1]. Mainly as a consequence of these decisions, energy use in buildings designed to attain similar levels of energy performance can vary by a factor of two or more [1, 2]. Occupant comfort and satisfaction indicators such as thermal complaints, sick days, and absenteeism are greatly influenced by indoor environmental quality – and in turn by operational practices [3, 4].

Despite the importance of operational variables in building performance, operators and controls service providers often make such operational decisions without having access to information regarding building occupancy, occupant comfort preferences, building envelope, and heating, ventilation, and air-conditioning (HVAC) equipment characteristics. Absence of analytical tools that can guide operational decisions often leads to conservative setpoint and scheduling choices [5]. Common examples of such conservative decisions are overventilation [6], HVAC operation extending well-beyond occupancy hours [7], and temperature setpoints that are too high in the winter and too low in the summer [8].

Although building management systems that can leverage the data in building automation systems (BASs) to tune a building's operation to its occupancy, HVAC, and envelope characteristics increased in popularity, penetration of these technologies in existing commercial buildings is still low and engineering cost remains a tangible barrier [9]. The energy and comfort penalties of suboptimal operational decisions have yet to be recognized by the stakeholders.

The objectives of this study are to (1) better understand the sensitivity of energy and comfort performance to system-level operational variables; (2) demonstrate a BPS-based metaheuristic optimization method to evaluate many operational decisions; (3) examine the variations in optimal operational decisions in different climate, envelope, and occupancy scenarios; and (4) consolidate the optimization results to a set of operational rules that can be easily understood by operators.

To this end, the building automation system data gathered from 14 government office buildings in Ottawa, Canada are reviewed to understand which key variables operators adjust, and the typical diversity of values. Subsequently, the following operational parameters are examined through a simulation-based investigation: seasonal switchover to heating and cooling times, ventilation rate and mode, zone temperature setpoints, and AHU fan start and stop times on weekdays. A nine-zone EnergyPlus model is developed representing an intermediate floor of an office building. In the study, 108 variants of this office model are created on the basis of: four different Canadian cities, with three different envelope and nine different occupancy characteristics. The sensitivity of the energy and comfort performance to the operational parameters is studied. A mixed-integer genetic algorithm is applied to identify the optimal set of operational parameters minimizing the HVAC energy use, the occupant-hours above 1000 ppm of CO_2, and ASHRAE 55.1 [10]'s predicted percentage dissatisfied (PPD) thermal comfort metric. The scope of this study is limited to office buildings in cold climates – i.e., ASHRAE 90.1 [11] climate zones 4 to 7.

First, the paper presents a review of the literature on BPS-based sensitivity analysis and optimization of building operations. Secondly, it presents the results from the survey of the system-level operational parameters of the 14 buildings. Thirdly, the methodology section presents an overview of the EnergyPlus model, simulation scenarios and optimization parameters. Subsequently, the sensitivity analysis and optimization results are presented, limitations of the methodology and the results are discussed, and future work recommendations are developed.

2. Literature review

In general, retro-commissioning involves improving building operation by making changes to system-level operational parameters such as changing AHU schedules, applying temperature setbacks, tuning the ventilation rates, as well as fixing hardware malfunctions [12]. For example, Bynum et al. [13] reports that 68% of the deficiencies identified during retro-commissioning are related to controls and operation. Hence, the retro-commissioning literature could offer insights into the sensitivity of building performance to operational parameters [14]. For example, Mills et al. [12] analyzed the commissioning results from 224 buildings in the United States. Later, the analysis was expanded with data from over 600 buildings [15]. In both cases, the median of the energy savings estimated from these case studies was about 15% [15]. However, as energy efficiency measures (many operational changes and other upgrades regarding sensing, equipment, envelope) are implemented concurrently (not one at a time), it is hard to isolate the impact of each operational change on the overall performance. Further, often the metering and data archiving infrastructure lack the resolution to support the measurement and verification of the sensitivity of performance to changes in individual operational parameters. Simply put, because it is challenging to vary operational variables systematically and collect sufficiently long-term data for the measurement and verification of the impact of operational changes in real buildings, researchers often resort to BPS for such analysis.

A BPS-based sensitivity analysis in building operations is intended to reveal the most important operational decisions in terms of their impact on building performance [16]. For example, Macdonald and Strachan [17] and Hopfe and Hensen [18] carried out sensitivity analyses to study the impact of the uncertainty in operational variables such as the heat gains from people, lighting, and equipment as well as the uncertainties from the thermophysical properties of the envelope materials and climatic conditions. Aside from sensitivity analysis papers that aim to capture all aspects of building performance uncertainty (e.g., envelope, climate, occupancy), several researchers studied different sources of uncertainty individually. For example, Wang et al. [19] studied the influence of occupancy variables on building energy performance predictions. This study concluded that the occupancy variable does not account for a substantial uncertainty on mean energy use predictions, when the relationship between occupancy levels and ventilation, lighting, and plug loads is neglected. Many researchers have assessed the uncertainty propagated from occupants' interactions with lighting, blinds, operable windows, and thermostats to building performance predictions and BPS-based design decisions [20-22].

Several papers conducted simulation-based sensitivity analyses of building performance to system-level operator (or controls technician) decisions [1, 23-25]. Through a simulation-based investigation, Yan et al. [24] studied the impact of uncertainty in parameters involved in the outdoor airflow control, and identified that such uncertainty can lead to a 17% variation in cooling and a 43% variation in heating energy use. Eisenhower et al. [23] studied uncertainty propagation from over 1000 parameters – including envelope, HVAC, lighting, equipment, and occupancy-related parameters. Some of the most influential parameters identified were common operator assumptions such as: the heating and cooling availability sequences, the minimum outdoor airflow rate, the supply air temperature setpoint, and the zone temperature setpoint. Wang et al. [1] employed the BPS tool EnergyPlus with the medium-sized office building archetype model, and examined uncertainties introduced to the energy consumption due to common operator decisions such as the HVAC equipment operation schedules, room temperature setpoints, terminal units' minimum airflow setpoint, economizer programming scheme, nighttime temperature setback setpoints, and supply air temperature control scheme. Three different operational scenarios were modelled in four different climatic conditions in the United States. The results of this simulation-based investigation indicate that these common operator decisions can affect the energy performance by as much as 80%. The focus of the reviewed papers on the sensitivity analysis of building operation was primarily on the energy performance – indoor air quality and thermal comfort indices were rarely included in these studies [18].

Optimization of building operations, beyond studying the energy and comfort impact of top operational decisions, represents a mathematical framework to find the best operational parameters. Particularly within the model-based predictive controls (MPC) domain, optimization of building operations is a popular research topic [26]. An MPC algorithm employs an optimization method together with a model of the controlled system to dynamically determine the optimal control sequence over a receding time horizon – typically less than 24 h. After executing the control decision for a single timestep, the MPC calls for the optimization algorithm again and re-evaluates its next move iteratively. In the reviewed literature, different forms of MPC have been applied for the control of zone, system, and plant-level equipment – e.g., chillers and boilers, AHUs, variable air volume (VAV) terminal units, perimeter heaters, radiant floor heaters, and automated shades [27-29]. Commonly used optimization algorithms in MPC include quadratic programming, dynamic programming, integer programming, genetic algorithms, and particle swarm optimization [30, 31].

Despite case studies demonstrating the potential of MPC in building operation, there are several barriers to its widespread use in real life [32]. First, although self-adaptive models that rely on state and parameter estimation algorithms, such as Extended and Unscented Kalman Filters, can alleviate this problem [33, 34], there is still a considerable engineering cost associated with model development and configuration [31]. Secondly, beyond obtaining a model that can be used by the optimization algorithm, an MPC needs forecasts for the disturbances over the prediction horizon – e.g., occupant-driven thermal loads, solar heat gains, infiltration and envelope losses. The need for accurate short-term disturbance forecasts in MPC led to a number of research activities – e.g., short-term weather forecasts [35], Bayesian filtering techniques to filter out the effect of disturbances [33], and pattern detection for occupant-driven thermal loads [36]. Thirdly, the BASs in many existing buildings offer only a limited computational power for the deployment of these algorithms inside controllers, and sometimes a network cannot reliably accommodate the data traffic from a server dedicated for an MPC. Lastly, as highlighted in a recent review article [31], a non-technical barrier to the widespread use of MPC in building operations is the industry's reluctance to adopt innovation. Many building operators may not wish to hand over the read and write authority to a supervisory control system – especially if it is one which they do not fully understand.

Given the aforementioned challenges, a gap in the reviewed literature on optimization in building operations is the need for practical intermediate solutions. For example, in lieu of employing a full-fledged optimization algorithm for the real-time control of building systems, near-optimal control rules / policies can be derived by using a (physics-based or data-driven) building model and an optimization algorithm. However, only a few researchers (e.g., [37, 38]) examined the viability of extracting such control rules / policies – which can be easily interpreted by the building operators and implemented in most BASs without any additional hardware and software costs. A few research questions that remain unanswered can be listed as follows: How do the derived optimal control rules vary from one climate to another or with envelope performance and occupancy characteristics? Can we generalize operational rules such as seasonal switchover to heating / cooling times, AHU on / off schedules, and default temperature setpoints for heating / cooling seasons depending on variables such as building envelope and occupancy characteristics, and the local climate? The relationship between the optimal operational strategies and a building's design and use conditions has not been studied in a systematic way using optimization.

3. Review of building operations

To complement the findings of the literature survey, the building energy management system (BEMS) databases of 14 government buildings in Ottawa, Canada were queried regarding their high-level operational characteristics. The BASs in each of these buildings were programmed by different controls vendors. The buildings were used mostly by government employees, and they tended to have similar occupancy characteristics. The floor area of the studied buildings varied from 4,000 to 61,000 m^2. They were constructed between 1847 and 1979. Over their lifetime, the buildings underwent several envelope and HVAC retrofits, and today they all have a typical VAV-AHU HVAC configuration. Each building is served by a single central heating and cooling plant – circulating steam and chilled water year-round. In total, there were three central plants that served these buildings.

From the BEMS databases of these buildings, archived data records pertaining to zone temperature setpoints and AHU supply and return fan operating schedules were extracted. The outdoor air intake at the AHUs was not monitored in any of the buildings. The outdoor airflow was sustained simply by keeping the outdoor air intake damper open at a minimum position. The amount of outdoor air in the supply air, which varies depending on the return and supply fans' actuation, and exhaust, outdoor, and mixed air dampers' position, could not be extracted. Data records for the AHU outdoor air intake damper positions and the CO_2 concentrations were extracted from BEMS databases. Lastly, the AHU supply air temperature setpoint values were extracted. The original data records were sampled at 5 to 15-min intervals. For ease of analysis, all data records were interpolated linearly to obtain data records at 15-min intervals with common timestamps. Table 1 presents an overview of the data records.

In total, data records for 490 indoor temperature setpoints, 191 AHU fan schedules, 47 AHU outdoor air intake damper positions, 72 AHU return air CO_2 concentration sensors, and 100 AHU supply air temperature setpoints were downloaded for the timespans covering both heating and cooling seasons in Ottawa (see Table 1). Note that it is likely that there are many relevant data records other than the ones listed in Table 1. However, they may not be found due to inconsistencies in data labeling. In addition, some data records were discarded as they contained gaps due to missing and erroneous data. Further, some buildings had more points than others. Consequently, the data extracted may disproportionately represent a subset of the 14 buildings, and readers should be cautious about generalizing these operational characteristics to other buildings. The sole intent in analyzing the BEMS data of these buildings was to form a reasonable basis for the range of operational parameters used in the sensitivity analysis and optimization.

Table 1: An overview of the data records extracted from the BEMS of the fourteen government buildings.

Type	**Number of BAS points**	**Units**	**Start date**	**End date**
Room temperature setpoint	131	°C	Nov 9, 2017	May 31, 2018
	181		Dec 16, 2017	May 31, 2018
	178		May 4, 2017	May 31, 2018
AHU fan schedule	191	0 or 1	Feb 11, 2018	May 31, 2018
Outdoor air intake damper position	37	0 to 100%	Nov 16, 2017	Aug 31, 2018

	10		Mar 16, 2018	Aug 31, 2018
CO_2 concentration	72	ppm	Feb 10, 2018	May 31, 2018
Supply air temperature setpoint	100	°C	Nov 15, 2017	May 31, 2018

Figure 1 presents the mean weekday zone temperature setpoint profiles computed from individual data records. The shaded areas indicate the 10^{th} and 90^{th} percentile range, and the black solid lines indicate the ensemble average for the mean weekday zone temperature setpoint profiles. The results indicate that the zone temperature setpoints did not change between the heating and the cooling seasons. The mean temperature setpoint was ~22°C during both seasons. This can be interpreted as demonstrating that a seasonal temperature setback was not applied in these buildings. The 10^{th} to 90^{th} percentile range was between ~20°C and ~24°C. Further, the weekday temperature setpoint profiles in any of the 490 zones did not change during the day; meaning that an overnight temperature setback strategy was not applied in both seasons. Note that in Figures 1 to 4, the data collected from November to March were treated as the heating season data, whereas the data collected from May to September were treated as the cooling season data. Similar to Figure 1, Figure 2 presents the mean weekday AHU supply air temperature setpoint profiles. The mean supply air temperature setpoint was about 18°C for both heating and cooling seasons – which is considered quite high for these forced air VAV AHU systems during the cooling season. However, it is observed that many of the AHU supply air temperature setpoints were not programmed to change from one season to another. The 10^{th} to 90^{th} percentile range for the supply air temperature setpoint profiles was observed between ~15°C and ~22°C. Furthermore, only small variations were observed in the daytime mean weekday supply air temperatures. Note that the perimeter zones in these buildings were typically equipped with other heating systems such as radiant panels, reheat coils, and induction units.

Figure 3.a presents the ensemble average for the availability schedules of the AHU supply and return fans (a schedule value of one means that AHU fans are on and zero means that AHU fans are off). The results indicate that over 60% of the 191 AHU fans remained operational overnight during both the heating and cooling seasons. Simply put, the majority of the AHUs did not appear to have an on-off schedule. The ones that have a daily on-off schedule tend to start operating between 5 am and 8 am, and they tend to stop operating between 4 pm and 6 pm. Figure 3.b presents the ensemble averages for the AHU outdoor air intake damper positions. The results did not reveal any difference between the damper positions during the heating and the cooling seasons. This is likely because an air-side economizer was not programmed in these buildings. The average overnight damper position appears to be about 10% during both the heating and cooling seasons. This may have severely affected the heating energy use given that many of the AHU fans remain operational overnight during the heating season.

Recall that the AHU outdoor airflow rate was not monitored in any of the studied buildings. Alternatively, to gain insight into potential over- or under-ventilation issues, the AHU return air CO_2 concentration data from 72 sensors were examined (see Figure 4). It should be noted that the authors did not install, upgrade, or recalibrate these CO_2 sensors; we used the sensor data extracted from the BEMS as is. The results indicate that the CO_2 concentrations do not exhibit a noticeable variation between the heating and the cooling seasons. This is in line with the observation that the outdoor damper operation does not change between seasons (see Figure 3.b). If there had been an air-side economizer, we would have observed a lower CO_2 concentration during the cooling season than the heating season. In addition, the mean weekday CO_2 concentration profiles that the CO_2 concentrations were spread across a wide range of values with many spaces over-ventilated and some under-ventilated. The insights from this data analysis and the literature survey will serve as a basis for the range of the operational parameters of the simulation-based sensitivity analysis and optimization presented in the following sections.

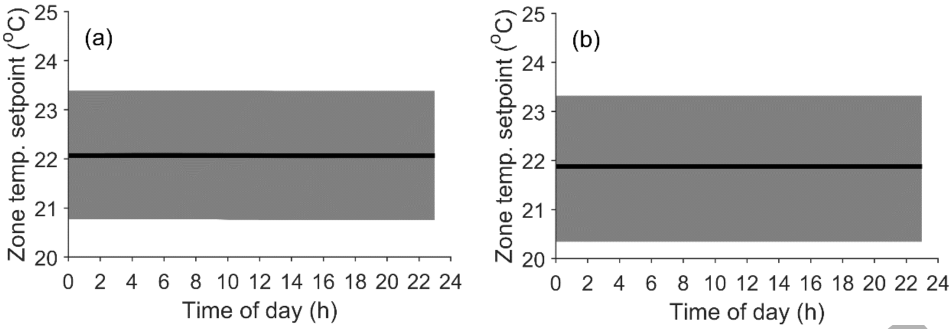

Figure 1: Mean weekday zone temperature setpoint profiles for (a) the heating and (b) the cooling seasons. The black solid lines indicate the mean and the shaded areas indicate the 10th and 90th percentiles of the mean weekday zone temperature setpoint profiles.

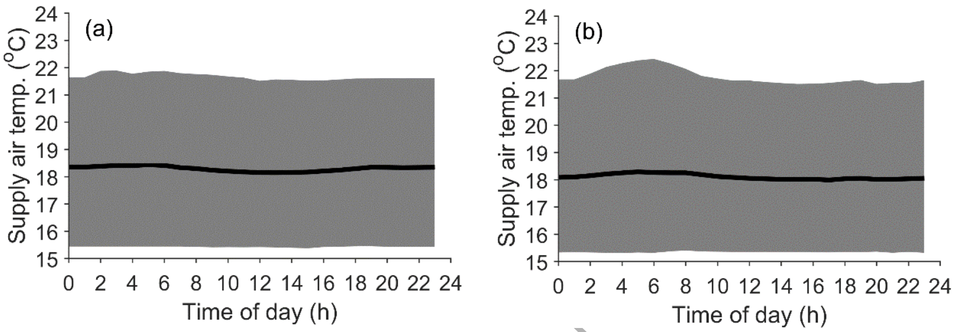

Figure 2: Mean weekday AHU supply air temperature setpoint profiles for (a) the heating and (b) the cooling seasons. The black solid lines indicate the mean and the shaded areas indicate the 10th and 90th percentiles of the mean weekday AHU supply air temperature setpoint profiles.

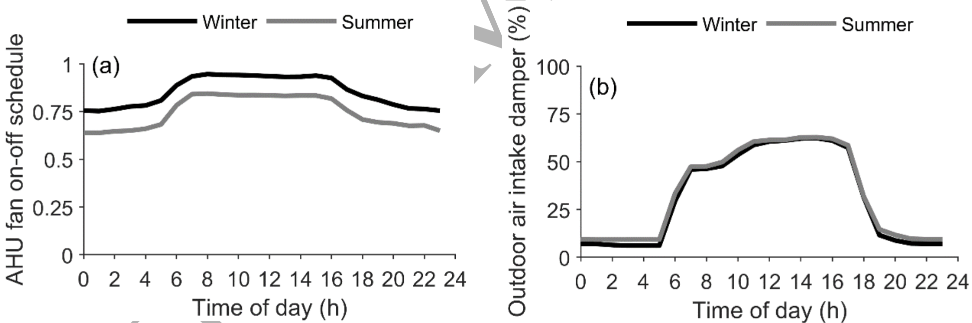

Figure 3: Mean weekday (a) AHU fan availability and (b) AHU outdoor air intake damper position profiles. A schedule value of one means that all AHU fans are on and zero means that all AHU fans are off. A damper position of 100% means that all dampers are open and 0% means that all dampers are closed.

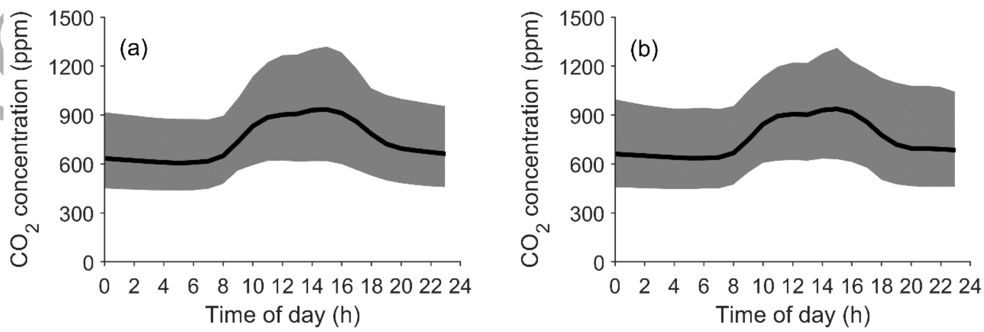

Figure 4: Mean weekday AHU return air CO_2 concentration profiles for (a) the heating and (b) the cooling seasons. The black solid lines indicate the mean and the shaded areas indicate the 10^{th} and 90^{th} percentiles of the mean weekday AHU return air CO_2 concentration profiles.

4. Methodology for simulation-based investigation

The operational parameters used in the sensitivity analysis and the optimization problem are listed in Figure 5. These parameters are the start and stop times for the AHU, the temperature setpoints during the heating and the cooling seasons, the seasonal switchover to heating and cooling times, and the ventilation rates and mode. The first parameter determines the availability schedule for the AHU on weekdays. In all scenarios, it was assumed that the AHUs remain off during the weekends. The AHU heating coil and VAV reheat coils were set to be available from *the seasonal switchover to heating* time to *the seasonal switchover to cooling* time. During the heating season, the heating season temperature setpoints were applied. Analogously, the AHU cooling coil was set to be available *from the seasonal switchover to cooling* time to *the seasonal switchover to heating* time. During the cooling season, the cooling season temperature setpoints were applied. The final operational parameters were the ventilation rate (i.e., minimum outdoor airflow rate for indoor air quality) and the ventilation mode (i.e., constant and occupancy-based minimum outdoor airflow). The *constant* ventilation mode does not vary the ventilation rate prescribed by the *ventilation rate* parameter. With this ventilation mode, a constant minimum outdoor airflow is provided as long as the AHU operates. The *occupancy-based* ventilation mode multiplies the *ventilation rate* with the occupancy profile (see Figure 6). Note that the real life implementation of the occupancy-based ventilation mode requires a sensing technology dedicated for occupancy count estimation (e.g., WiFi-based, camera-based [39-42]). Determining an appropriate constant ventilation rate in real life requires information on peak occupancy levels.

For the sensitivity analysis and optimization, the BPS tool EnergyPlus v8.9 was used to build an energy model of an intermediate floor of a multi-storey office building. For simplicity, the 27 m by 27 m floor is divided into nine equal thermal zones (eight perimeter zones and one core zone). We should acknowledge that the impact of this zoning decision on the optimization results was not studied. This is because our focus was on the optimization of operational decisions given a design form. It was assumed that the floor is between two identical floors, thus the heat exchange through the floor and the ceiling is neglected (i.e., adiabatic boundaries). The window-to-wall ratio (WWR) is 33% on all cardinal directions. The heating and cooling to each thermal zone was supplied through a VAV terminal unit with a reheat coil. The minimum airflow fraction of the VAVs was assumed to be 20%. A packaged AHU which contained heating and cooling coils was modelled to serve the nine zones. The gross rated coefficient of performance of the cooling equipment was assumed to be 3. Note that EnergyPlus defines rated conditions for coefficient of performance for cooling as air entering the cooling coil at 26.7°C drybulb and 19.4°C wetbulb temperatures, and air entering the outdoor condenser coil at 35°C. The input electricity used in coefficient of performance calculations includes the power demand for compressor and condenser fans but does not include the power consumption of the supply air fan. The natural gas-based heating equipment was assumed to operate at 80% efficiency. A differential dry-bulb airside economizer was assumed to increase the outdoor airflow rate to reduce the cooling load when the outdoor temperature is less than return air temperature but more than 10°C. We determined this 10°C value through trial and error to ensure that the cooling needs of core spaces at outdoor temperatures lower than the threshold value can mostly be met via the redistribution of air returned from both perimeter and core zones and via the minimum outdoor airflow for ventilation. Note that differential drybulb is a built-in economizer type in EnergyPlus. It is set to increase outdoor airflow rate when there is a cooling load and the outdoor temperature is below the zone exhaust air temperature. The default NECB [43] lighting and plug load density and schedule values were assumed. At full occupancy, the occupant density was assumed to be 0.05 person/m^2 [43]. An overview of the characteristics of the building model is shown in Figure 5.

Subsequently, 108 variants of this base building model were generated to cover three envelope scenarios, four different cities, and nine occupancy scenarios. As shown in Figure 5, the envelope scenarios are generated by varying the common envelope performance metrics systematically – e.g., incrementally decreasing the window U-factor, increasing the wall R-value, and increasing the airtightness. Four different Canadian cities were selected from four different NECB climate zones – i.e., Zone 4 Vancouver, Zone 5 Toronto, Zone 6 Ottawa, Zone 7 Edmonton. The standard NECB occupancy schedules were varied by multiplying its values by 1.0, 0.8, and 0.6 – representing three plausible occupancy levels. From this point on, we will refer to these three occupancy levels as high, medium, and low occupancy, respectively. The occupancy schedules were also varied by shifting it by one-hour earlier or one-hour later than its default NECB values. Hence, the nine occupancy scenarios shown in Figure 6 were generated: high early, high, high late, medium early, medium, medium late, low early, low, and low late.

For each of the 108 scenarios, the solution space for the eight operational parameters listed in Figure 5 is searched. The set of eight operational parameters that minimize a cost function was selected by the genetic algorithm. Aside from the HVAC energy use intensity, the cost function incorporated two discomfort metrics: (a) a thermal discomfort metric derived from ASHRAE Standard 55 [10]'s predicted percentage dissatisfied (PPD) metric and (b) the percentage of occupied hours spent above 1000 ppm of CO_2. For the calculation of PPD, a clothing insulation level of 0.5 clo was assumed from May to October, and 1.0 clo from November to April [10]. The metabolic heat generation rate and human surface area were assumed to be 120 W (for sedentary office work) and 1.8 m^2, respectively [10]. The room air velocity was assumed to be 0.1 m/s. Equation 1 presents the calculation of the thermal discomfort metric:

$$I_{TC} = \frac{\sum_{i=1}^{9}(\sum_{t=1}^{8760} \mathrm{PPD}(t,i) People(t,i))}{\sum_{i=1}^{9}(\sum_{t=1}^{8760} People(t,i))} x100 \quad (1)$$

where PPD is the ratio of people predicted to be dissatisfied based on Fanger's thermal comfort model, *People* is the number of people in a zone, *i* is the thermal zone index, and *t* (h) is the timestep index for the annual simulations. The indoor air quality (IAQ) metric I_{IAQ} is computed as follows:

$$I_{IAQ} = \frac{\sum_{i=1}^{9}\left(\sum_{t=1}^{8760} B_{co_2}(t,i) People(t,i)\right)}{\sum_{i=1}^{9}(\sum_{t=1}^{8760} People(t,i))} x100 \quad (2)$$

where B_{CO_2} is a binary indicator for high CO_2 (ppm) concentration. It takes the value "*1*" when the CO_2 concentration exceeds 1000 ppm in zone *i* at timestep *t*; otherwise, it takes the value "0". The CO_2 generation rate was assumed to be 16.5 L/h-person [44]. The cost function *J* is heuristically formulated as follows:

$$J = EUI_{HVAC} + (I_{TC})^2 + (I_{IAQ})^2 \quad (3)$$

where EUI_{HVAC} (MJ/m^2-yr) is the HVAC energy use intensity. Based on a preliminary inspection, it was identified that EUI_{HVAC} is expected to take values between 100 and 500 MJ/m^2-yr. The thermal and indoor air quality discomfort metrics can take values between 0 and 100. To penalize deviations from ideal comfort conditions (i.e., I_{TC} = 0 and I_{IAQ} = 0), a quadratic relationship is proposed between them and the cost function. These artificial penalties for discomfort (${I_{TC}}^2$ and ${I_{IAQ}}^2$) are also known as the penalty functions in the optimization literature. They enable us to convert a constrained optimization problem (i.e., minimize energy use without violating occupant comfort) to an unconstrained form. As such, Eqn. 3 combines multiple objectives by using a weighted distance metric from the ideal solution (i.e., EUI_{HVAC} = 0; I_{TC} = 0; I_{IAQ} = 0). However, in this paper, the relative weight of these two penalty functions was determined heuristically – based on preliminary trials with a few of the 108 scenarios to assess the sensitivity of optimal solutions to the cost function form. The relative importance of energy use, thermal comfort, and indoor air quality can be different for each building operator. Regardless, future research should investigate the sensitivity of optimal operational rules to different cost function configurations.

It is worth noting that we idealized the operational parameters as discrete quantities instead of treating them as continuous. The eight operational parameters were assumed independent, and we permitted them to attain one of each of the 9 AHU start and 9 AHU stop times, 12 seasonal switchover to cooling and 12 seasonal switchover to heating times, 5 setpoints during heating season and 5 setpoints during cooling season, 11 ventilation rates, and 2 ventilation modes. For each of the 108 scenarios, the brute force search of the best set of operational parameters would have resulted in about 6.5 million EnergyPlus simulation runs (9 x 9 x 12 x 12 x 5 x 5 x 11 x 2). Given the computational burden of doing so, a mixed-integer optimization problem is solved by using a genetic algorithm. The process of creating the 108 scenarios and finding the optimal set of operational parameters was carried out through a custom Matlab script that read / write from the base EnergyPlus model. Matlab's genetic algorithm function *ga* was used in searching the optimal set of operational parameters. The crossover fraction was set to 0.5 whereby the crossover is a process of mixing multiple candidate solutions to generate a new solution. The number of elite individuals to pass to the next generation were set to two. The population size in each generation was 75; and the algorithm continued searching for the optimal solution for up to 8 generations unless there were 5 consecutive generations with no improvements in the objective function (i.e., 5 stall generations). Note that the input parameters of the genetic algorithm were determined through a preliminary sensitivity analysis to assess the stability of the solution at each run. Further information regarding the theory and application of genetic algorithms can be found elsewhere [45, 46].

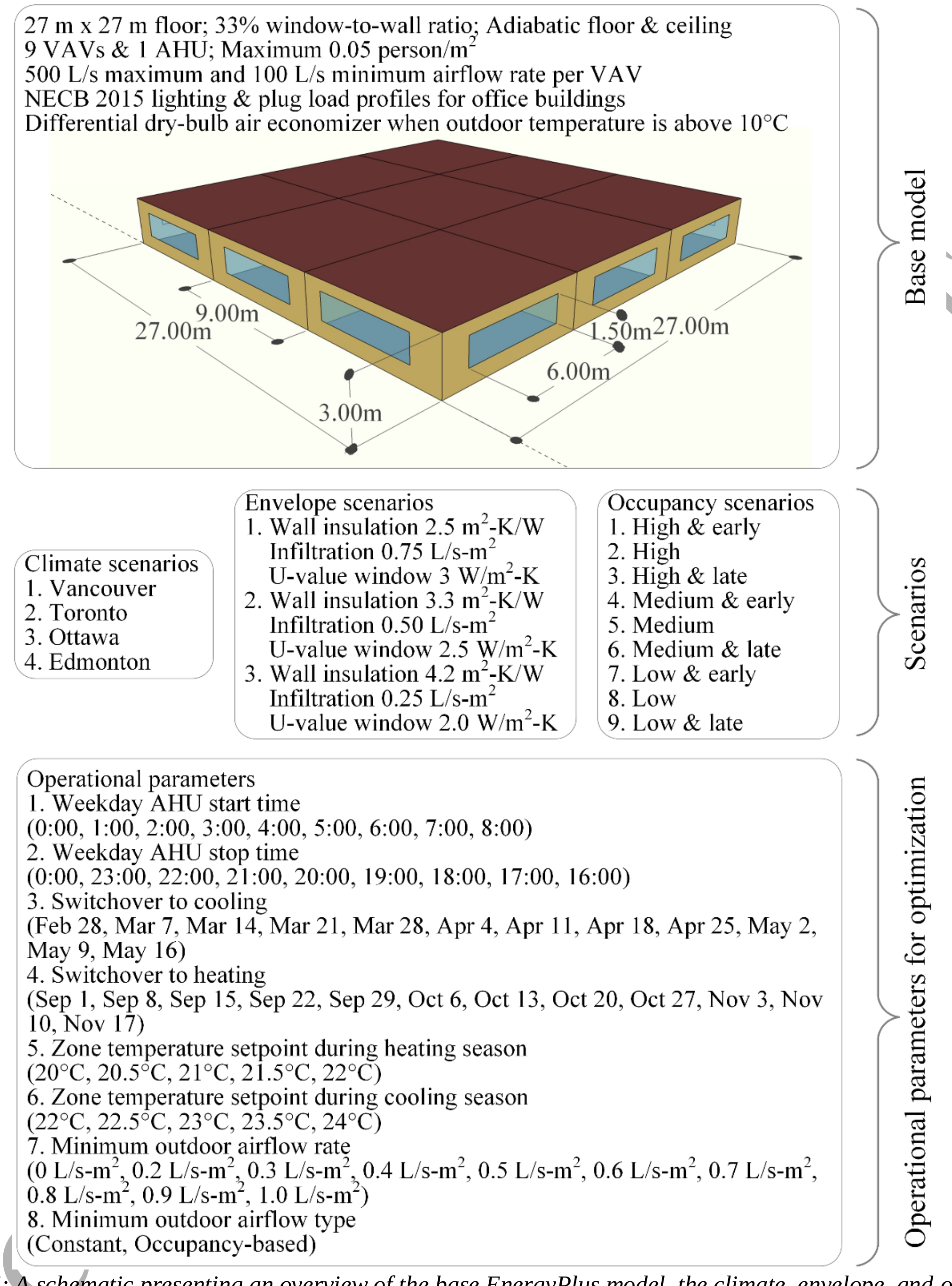

Figure 5: A schematic presenting an overview of the base EnergyPlus model, the climate, envelope, and occupancy scenarios, and the operational parameters of the sensitivity analysis and optimization.

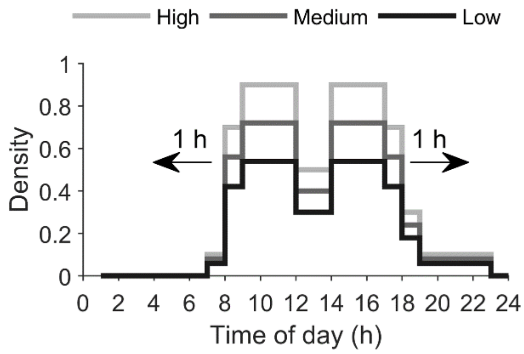

Figure 6: Nine occupancy scenarios: high early, high late, high, medium early, medium late, medium, low early, low late, and low. The "early" occupancy scenarios were generated by shifting the occupancy profiles by one-hour earlier in the day, and the "late" occupancy scenarios were generated by shifting occupancy profiles by one-hour later in the day.

5. Sensitivity analysis results

Figure 7 presents the results of a sensitivity analysis for one of the scenarios listed in Figure 5 (i.e., climate scenario 2, envelope scenario 3, and occupancy scenario 2 in Figure 5). The operational parameters were varied individually from the following case: AHU start time: Nov 3, setpoint during the heating season: 21°C, setpoint during the cooling season: 24°C, ventilation rate: 0.5 L/s-m^2, and ventilation mode: constant. AHU operating schedule was the most influential parameter affecting the HVAC energy use. The results indicate that applying a daily on-off schedule on weekdays can drastically reduce the HVAC energy use. The HVAC energy use was estimated to decrease by ~4% for each hour the AHU start time is delayed or for each hour the AHU stop time is moved to an earlier time in the day. Considering that more than half of the surveyed 191 AHU fans in Section 3 did not have daily on-off schedules, applying simple daily AHU schedules can be one of the most cost-effective ways to achieve significant energy savings. Beyond its impact on the energy performance, over the studied range AHU start and stop times account for a ~30% variation in the thermal comfort metric I_{TC}.

A degree Celsius increase in the cooling season temperature setpoint was estimated to decrease the HVAC EUI by ~2%, and a degree Celsius decrease in the heating season temperature setpoint was estimated to decrease the HVAC EUI by ~6%. Finding setpoints that exploit the seasonal variations in the comfort temperatures, due to factors such as changing clothing insulation levels across seasons, can be another simple energy saving opportunity. Recall that the surveyed temperature setpoints in Section 3 did not exhibit any noticeable variations between the heating and the cooling seasons. They had a mean value of 22°C for both seasons. Varying the temperature setpoints over the studied range caused a 10 to 15% variation in the thermal comfort metric I_{TC}. It is worth noting that the clothing insulation levels used in this paper (which were based on ASHRAE Standard 55 [10]) neglected the inter-occupant diversity – i.e., assuming that all occupants have a clothing insulation level of 1.0 clo during the winter and 0.5 clo during the summer. Further, typical winter and summer clothing insulation assemblies tend to vary in different climate zones [47] – this variation was also neglected. Clothing insulation models that capture inter-occupant and inter-climate diversities may have affected the heating and cooling temperature setpoints determined through this optimization exercise.

The studied range of the seasonal switchover to heating and cooling times account for a ~5% variation in the HVAC EUI and a ~10% variation in the thermal comfort metric I_{TC}. Therefore, selecting appropriate seasonal switchover to heating and cooling times can make modest improvements in the overall energy and comfort performance. Note that Figure 7 presents cases with a constant ventilation rate of 0.5 L/s-m^2 only. Hence, the CO_2 concentrations shown in the figure did not exceed the 1000 ppm threshold. The sensitivity analysis results for ventilation rate are shown in Figure 8.

The results shown in Figure 8 present the sensitivity analysis results for the ventilation rate and mode for high, medium, and low occupancy levels. With the constant ventilation mode, the studied ventilation rate range accounts for a ~40% variation in the HVAC energy use for all three occupancy levels. With the occupancy-based ventilation mode, the studied ventilation rate range accounts for a ~20% variation with the high occupant density scenario, a ~16% variation with the medium occupant density scenario, a ~12% variation with the low occupant density scenario. With both ventilation modes, the lowest ventilation rates that can maintain the IAQ metric I_{IAQ} at 0% were 0.3, 0.2, and 0.1 L/s-m^2 with high, medium, and low occupant densities, respectively. At these ventilation rates, the HVAC EUI with the occupancy-based ventilation mode was estimated to be 3 to 6% less than the HVAC EUI with the constant ventilation mode. These results indicate that information regarding the shape of the occupancy profile is of practical use in lowering the energy implications of over-ventilation; whereas, the information regarding the peak occupancy levels is needed to determine a reasonable ventilation rate. It is worth noting that with the VAV-AHU HVAC configuration the air returned from individual zones is mixed with the outdoor air, conditioned, and redistributed to the zones to primarily meet their space heating and cooling needs. As a result, supply air cannot be perfectly divided proportional to the intrazonal ventilation needs. Hence, some over-ventilation is often inevitable with this common HVAC configuration, which nullifies the need for perfect real-time occupancy information. HVAC configurations that separate the space heating / cooling functionalities from ventilation (e.g., dedicated outdoor air system) will better benefit from the occupancy-based ventilation mode.

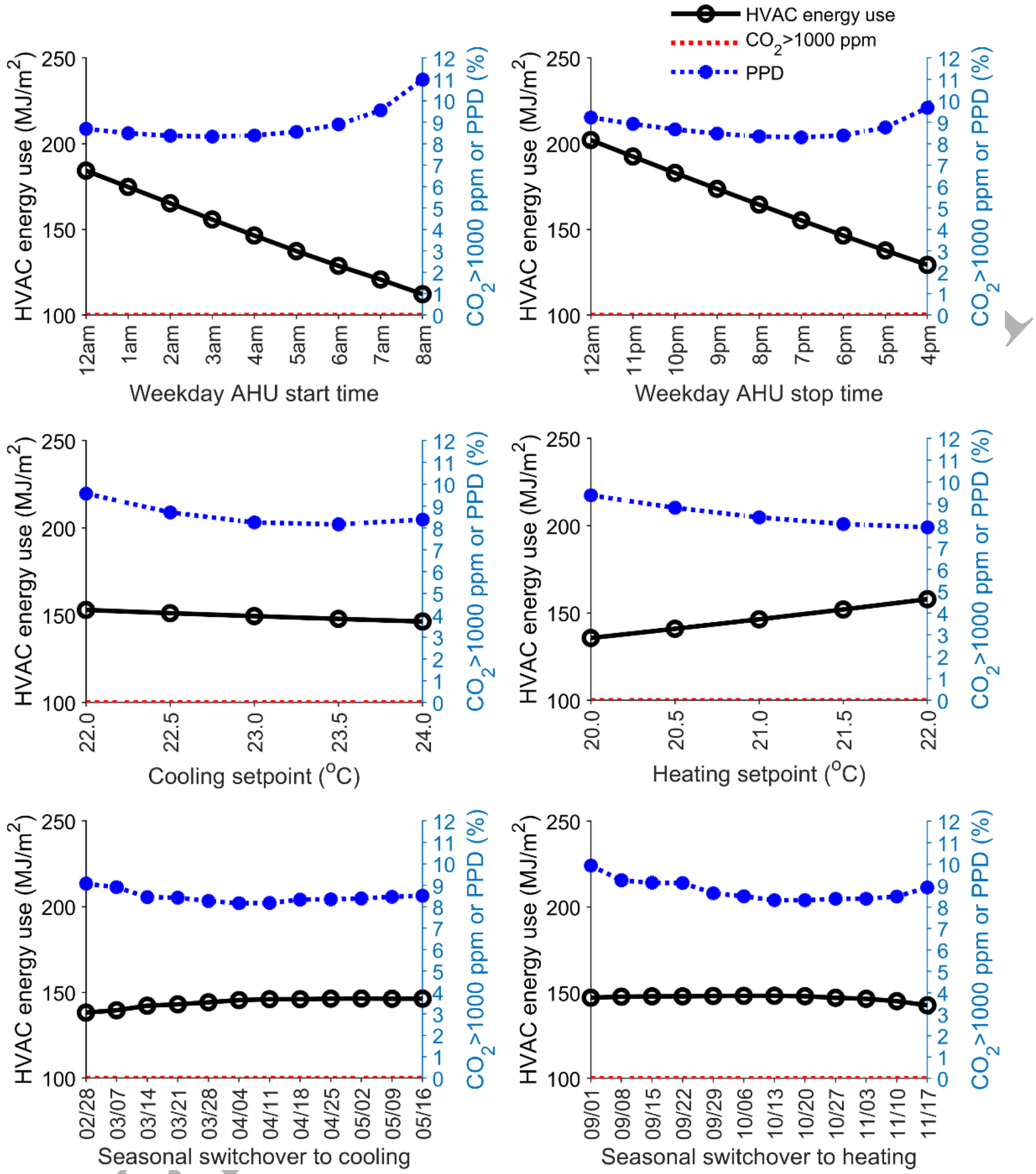

Figure 7: The sensitivity of the HVAC EUI and the comfort metrics I_{TC} and I_{IAQ} to the operational parameters for climate scenario 2, envelope scenario 3, and occupancy scenario 2 listed in Figure 5. The sensitivity analysis was carried out by systematically varying the individual operational parameters from the following case: AHU start time: 5 am, AHU stop time: 6 pm, switchover to cooling: May 2, switchover to heating: Nov 3, setpoint during the heating season: 21°C, setpoint during the cooling season: 24°C, ventilation rate: 0.5 L/s-m^2, and ventilation mode: constant.

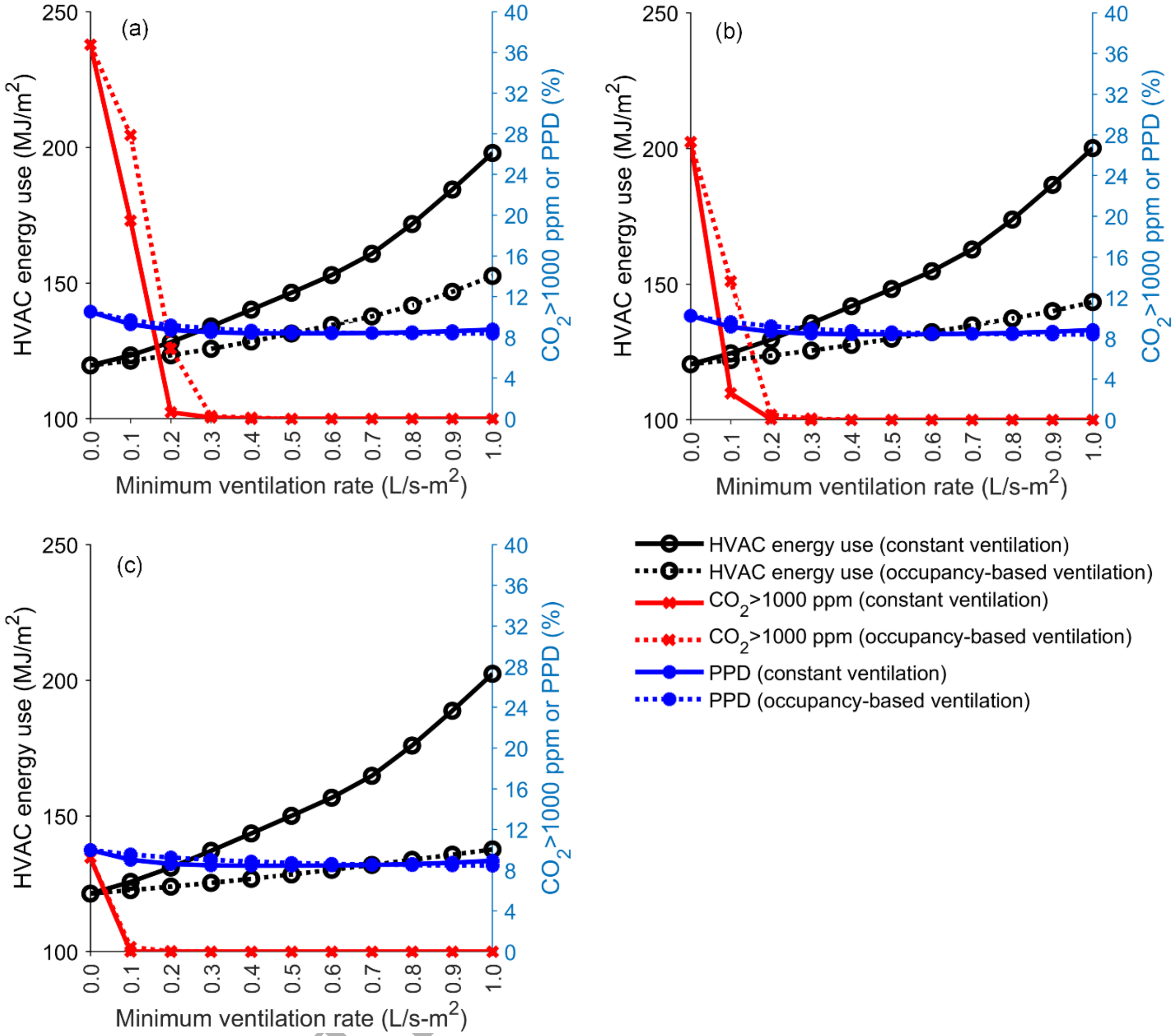

Figure 8: The sensitivity of the HVAC EUI and the comfort metrics I_{TC} and I_{IAQ} to the ventilation rate and mode parameters for climate scenario 2, envelope scenario 3, and ***(a)*** *occupancy scenario 2,* ***(b)*** *occupancy scenario 5,* ***(c)*** *occupancy scenario 8 listed in Figure 5. The sensitivity analysis was carried out by systematically varying the ventilation rate for the two ventilation modes while the AHU start and stop times were 5 am and 6 pm, the seasonal switchover to cooling and heating were May 2 and Nov 3, the setpoint during the heating and cooling seasons were 21°C and 24°C, respectively.*

6. Optimization results

For each of the 108 scenarios listed in Figure 5, the eight operational parameters that minimize the cost function (see Eqn. 3) were determined by using the genetic algorithm. The repeatability of the results was assessed by repeating the optimization process for a few of the scenarios, while the random seed was systematically varied. Figure 9 illustrates the evolution of the cost function for one of the 108 scenarios – which was the same scenario used in the sensitivity analysis presented in Figure 7. Recall that each generation consists of 75 EnergyPlus simulations with different operational parameters. The genetic algorithm by selectively sampling the operational parameters reduces the median cost J (see Eqn. 3) of each generation. Note that the whiskers enclose 1.5 times the interquartile range, and those that fall outside this region were highlighted as outliers. There were no outliers in the lower half of the population in each generation; whereas, there were several outliers in the upper half. Simply put, there are exceptionally bad operational parameters; whereas the optimal operational parameters do not result in a substantially better operational performance than the near-optimal operational parameters. In the example presented in Figure 9, the cost *J* of the best operational scenario (i.e., the lower whisker) did not change significantly beyond the third generation. In this example, the median continued improving until the 7^{th} generation. However, even after seven generations, the outliers were not completely eliminated due to crossover and mutation. Figure 9 also tabulates the optimal operational parameters determined for this scenario.

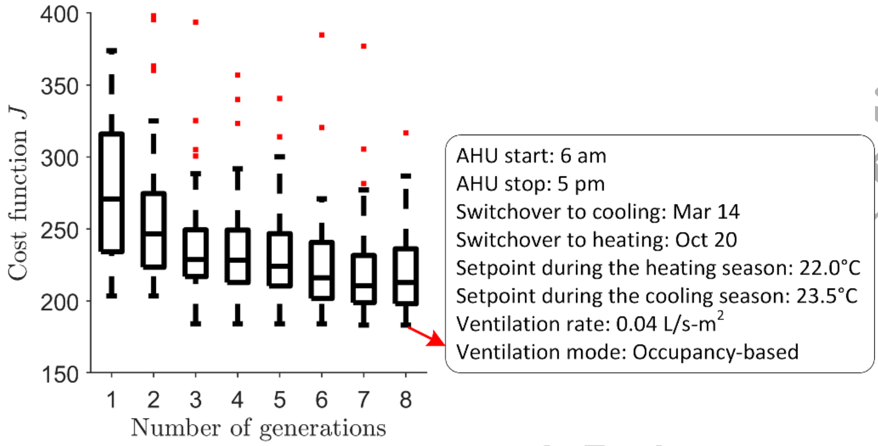

Figure 9: An example illustrating the evolution of the cost function for one of the 108 scenarios. Each boxplot consists of 75 EnergyPlus simulations with different operational parameters. The scenario used in this illustrative example is the same as the one used in the sensitivity analysis presented in Figure 7 (i.e., climate scenario 2, envelope scenario 3, and occupancy scenario 2 listed in Figure 5). The figure also tabulates the optimal operational parameters determined for this scenario.

After computing the set of eight operational parameters for each of the 108 scenarios, a fundamental challenge was to consolidate and visualize this information. To concisely present the relationship between the scenarios and the optimal operational parameters, the decision trees shown in Figure 10 were generated by using Matlab's *fitctree* algorithm. As the objective of this exercise was merely to present the optimal operational parameters, no stopping criterion was applied to the algorithm, meaning that the trees were permitted to grow until all decision paths end up with nearly pure leaf nodes (e.g., branch out until all those scenarios remaining in the leaf node are from the same class). If the optimal value of an operational parameter does not change with respect to a variable (i.e., climate, envelope, occupancy characteristics), the variable will not appear in any of the decision splits.

The optimal AHU start time was 8 am in Vancouver (climate zone 4), 6 am in Toronto (climate zone 5), and 5 am in Ottawa and Edmonton (climate zone 6 and 7). These results indicate that the length of the heating season setback-to-setpoint periods is the primary factor influencing the optimal AHU start time in cold climates. Although it is outside the scope of this paper, these results underline the importance of predictive control algorithms that adapt the AHU start time every morning based on the outdoor temperature in cold climates.

The optimal AHU stop times were mainly influenced by the timing of occupancy. The optimal stop time was 4 pm with the *early* occupancy scenarios and 5 pm with the *normal* and *late* occupancy scenarios. Recall that over 60% of the surveyed AHUs operated year-around without a daily on-off schedule and shifting the AHU stop time by one-hour earlier yields ~4% reduction in HVAC energy use. This situation highlights the conservativeness in common operational practices and its energy implications.

Note that the terms *poor, medium,* and *good envelope* in Figure 10 correspond to the envelope scenarios 1, 2, and 3 in Figure 5, respectively. The optimal ventilation rate was estimated to be 0.2 L/s-m^2 for buildings with infiltration rates higher than 0.5 L/s per m^2 of above-grade exterior surface area (i.e., envelope scenarios 1 and 2). This infiltration rate is twice as much as the amount suggested by NECB

[43]. For buildings that comply with NECB [43]'s infiltration assumption (i.e., envelope scenario 3), the optimal ventilation rate was estimated to be 0.3 L/s-m^2 if the occupant density is low and 0.4 L/s-m^2 if the occupant density is medium or high. The occupancy-based ventilation mode, instead of the constant ventilation mode, was selected in all 108 scenarios.

The optimal switchover to cooling time with envelope scenario 1 was about two months after it was with envelope scenario 3. For envelope scenario 2, the optimal switchover to cooling time was in March 28 for Toronto, Ottawa, and Edmonton (climate zones 5 to 7) and March 16 for Vancouver (climate zone 4). Similarly, the envelope performance level was the most influential parameter for the switchover to heating parameter. The optimal switchover time to heating was estimated to be as early as September 1 for a building with low density occupancy in Ottawa and Edmonton. It was as late as November 3 for envelope scenario 2 and 3 in Vancouver.

Lastly, for all 108 scenarios, the optimal heating season temperature setpoint was 22°C and the optimal cooling season temperature setpoint was 23.5°C. Recall that the mean temperature setpoints in the surveyed buildings were ~22°C for both heating and cooling seasons. Further, through the sensitivity analysis, it was estimated that a degree Celsius increase in the cooling season temperature setpoints decreases the HVAC energy use by ~2%. Therefore, simply applying a default cooling season temperature setpoint of 23.5°C instead of 22°C has the potential to reduce HVAC energy use by ~3%.

Beyond the specific optimization results shown in Figure 10, the methodology can be applied in deriving operational rules: (1) for a specific building by using its calibrated energy model and (2) for different building archetypes in different climate zones. Considering that calibrated energy models are becoming an integral part of a detailed energy audit, employing optimization techniques with these models can lead to better operational decisions. Further, the process of optimizing the operational parameters of archetype energy models in different climates and consolidating these optimization results to generic operational rules through data mining techniques (e.g., decision trees) can yield results useful for energy codes and standards. For example, the building energy codes and standards can provide guidance for default AHU start and stop times or seasonal switchover to heating and cooling times.

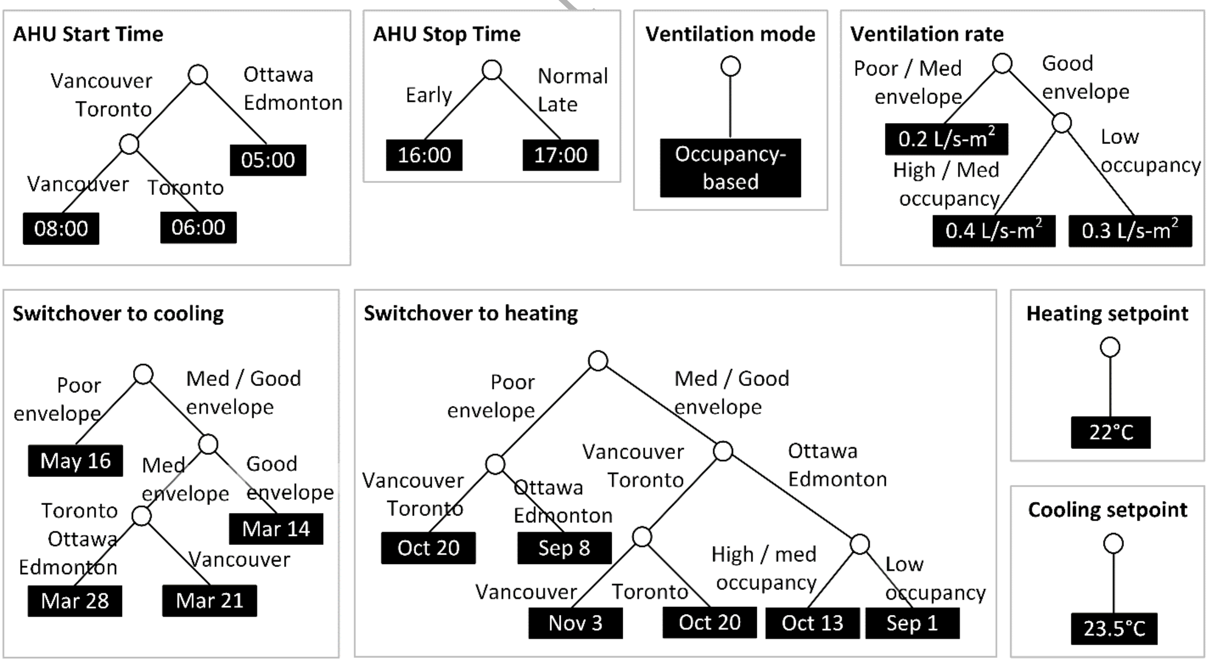

Figure 10: The eight optimal operational parameters for the 108 scenarios listed in Figure 5. The relationship between the scenarios and the optimal operational parameters is presented as eight decision trees.

7. Unresolved issues

The methodology and results presented in this paper have several gaps which are left for future work.

First, the sensitivity analysis and optimization were conducted on a base model with a specific HVAC configuration, envelope geometry, thermal mass, and casual heat gains. Future research should investigate the effect of these variables on optimal operational decisions. Further, generic assumptions were made in modelling occupant comfort (e.g., clothing level, metabolic rate, air speed, CO_2 generation amount, CO_2 threshold for discomfort). Sensitivity of optimal operational decisions to these assumptions needs to be studied. In addition, we used a typical meteorological year dataset [48] during the EnergyPlus simulations. The sensitivity of optimal operational decisions to different climate datasets should also be investigated.

Secondly, the cost function used in the optimization problem incorporated three elements representing the HVAC energy use, thermal comfort, and indoor air quality. The relative weight of these three elements in this cost function was determined heuristically. The cost function did not incorporate elements to penalize peak electricity demand or time of use pricing. Further, different performance metrics could be used in the assessment of thermal comfort and indoor air quality. For example, we used a CO_2 concentration threshold of 1000 ppm for the calculation of the indoor air quality metric used in the cost function. The assumptions regarding the definition of these metrics may have affected the results of this simulation-based investigation. In addition, the parameters of the genetic algorithm (population size, generations, crossover) were selected based on a preliminary analysis assessing the stability of the optimal solution. Future research should investigate the sensitivity of optimal operational rules to different cost function and optimization algorithm configurations.

Thirdly, the sensitivity analysis and optimization of operational parameters were presented through a case study with eight parameters. Evidently, there are many other operational parameters, including terminal box minimum flow set points, static pressure resets, economizer control, cold deck supply temperature resets, chiller and boiler plant optimization settings, optimization of pumping systems, etc. In addition, among the parameters investigated, instead of having a single weekday AHU start time, different AHU start times could be determined for different months. Increasing the number of operational parameters to optimize is expected to provide performance improvements (which are quantified by the reductions in a cost function). The relationship between the number of operational parameters to optimize and the incremental performance benefits should be studied in detail.

The methodology presented in this paper was not demonstrated on a real building. As future work, the building operation optimization should be employed with a calibrated energy model of an existing building. The optimal operational parameters should then be implemented in the building, and the energy and comfort performance improvements should be analyzed.

8. Conclusions

A building simulation-based methodology was presented to examine the sensitivity of a building's energy and comfort performance to common operator decisions and to identify the optimal set of operational parameters.

First, the building energy management systems of 14 office buildings were queried to identify their key operational parameters. The results of this analysis revealed many operational deficiencies. For example, it was identified that over 60% of the AHUs did not have daily on-off schedules; and most of them did not have an economizer cycle. The mean indoor temperature setpoints were 22°C year-around, and there were no daily or seasonal temperature setback strategies in any of the buildings. The CO_2 concentration of the return air indicated that most spaces were over-ventilated, while some were under-ventilated.

Following from these insights from the survey of building energy management systems, a BPS-based sensitivity analysis was conducted to better understand the energy and comfort performance implications of common operator decisions. Eight operational parameters were studied: AHU start and stop times, seasonal switchover to heating and cooling times, heating and cooling season temperature setpoints, and ventilation rate and mode (i.e., constant or occupancy-based). The results revealed that the AHU start and stop times and ventilation rate are the most critical of the eight operational parameters examined in terms of affecting energy and comfort performance for buildings investigated. A one-hour change in AHU start or stop times is estimated to affect the HVAC energy performance by about 4%. The studied ventilation rate range (i.e., 0 to 1 L/s per square meter of floor area) accounts for a ~40% variation in the HVAC energy use with the constant ventilation mode and a 12 to 20% variation with the occupancy-based ventilation mode. It is concluded that the information regarding the shape of the daily occupancy profile is of use in lowering the energy implications of over-ventilation; whereas, the information regarding the peak occupancy levels is needed to determine a reasonable ventilation rate.

Subsequently, the genetic algorithm was employed for an integer programming problem to identify the optimal operational parameters for four different climate zones, nine different occupancy, and three different envelope scenarios. The relationships between these scenarios and the optimal operational parameters were consolidated by training a decision tree for each operational parameter. Akin to deriving rules, the decision trees can provide guidance for high-level operational parameters. For example, the optimal operational decision for AHU start time was 8 am in Vancouver (climate zone 4), 6 am in Toronto (climate zone 5), and 5 am in Ottawa and Edmonton (climate zone 6 and 7). The optimal stop time was 4 pm with an occupancy profile one hour earlier than the default NECB schedule, and 5 pm otherwise.

Beyond the optimization results presented in this study, the methodology can be applied in deriving operational rules for a specific building by using its calibrated energy model and for different building archetypes in different climate zones to develop operational guidelines and standards. Future work is planned to demonstrate this simulation-based building operation optimization technique on an existing building.

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Conflicts of interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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