Building Performance Optimization for Operational Rule Extraction

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Abstract
Operational parameters regarding daily and seasonal scheduling of systems’ availability and setpoints play an important role in building performance. This paper first reviews the key operational parameters of 14 Canadian office buildings to better understand their range in practice. The results reveal that over 60% of the air handling units (AHUs) are not turned off outside of normal occupied hours, and most of them do not have an economizer cycle program. Subsequently, a mixed-integer genetic algorithm is applied to a building performance simulation model to identify its optimal operational parameters for four different climate zones, nine different occupancy and three different envelope scenarios. The effects of the variables of these scenarios and the optimal operational parameters are examined by employing a decision trees-based rule extraction method.

Introduction
Operational decisions such as temperature setpoints, hours-of-operation for AHUs, ventilation rates, and seasonal switchover to heating and cooling times play an important role in a building’s energy performance (Wang et al., 2012). 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 (Tian et al., 2018; Eisenhower et al., 2012).

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 (Granderson and Lin, 2016; Wang et al., 2005). Absence of analytical tools that can guide operational decisions often leads to conservative setpoint and scheduling choices. Common examples of such conservative decisions are overventilation, HVAC operation extending well-beyond occupancy hours, and temperature setpoints that are too warm in the winter and too cold in the summer (Bordass et al., 2001; Gunay et al., 2015, 2018).

The objective of this study is to demonstrate a BPS-based metaheuristic optimization method to identify optimal operational decisions. Further, we examine the variations in optimal operational decisions in different climate, envelope, and occupancy scenarios, and explore the viability of consolidating the optimization results to a small number of operational rules.

Literature review
Optimization of building operations requires a mathematical framework to find the best operational parameters. In the reviewed literature, the researchers have sought methods to optimize various operational parameters dynamically to execute control decisions in real-time. Particularly within the model-based predictive controls (MPC) domain, optimization of building operations is a popular research topic (Afram and Janabi-Sharifi, 2014). 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 decision 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 (Hilliard et al., 2017; Sturzenegger et al., 2016). Commonly used optimization algorithms in MPC include quadratic programming, dynamic programming, integer programming, genetic algorithms, and particle swarm optimization (Li and Wen, 2014).

Despite case studies demonstrating the potential of MPC in building operation, there are several barriers to its widespread use in real-life. First, although self-adaptive models that rely on state and parameter estimation algorithms such as Extended and Unscented Kalman Filters can alleviate this problem (Fux et al., 2014; Gunay et al., 2016), there is still a considerable engineering cost associated with model development and configuration (Gunay et al., 2019). Secondly, be-
Beyond obtaining a model that can be used by the optimization algorithm, an MPC algorithm 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, Bayesian filtering techniques to filter out the effect of disturbances, and pattern detection for occupant-driven thermal loads (Florita and Henze, 2009; Dong and Lam, 2014). 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, 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 of the BAS to a supervisory control system—especially if it is one which they do not fully understand (Killian and Kozek, 2016).

Given the aforementioned challenges, a gap in the reviewed literature on optimization for 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, overarching control rules can be derived by using a (physics-based or data-driven) building model and an optimization algorithm. However, only a few researchers have examined the viability of extracting such control rules—which can be easily interpreted by the building operators and implemented in most BASs without any additional hardware and software costs (May-Ostendorp et al., 2013, 2011). The relationship between the optimal operational strategies and a building’s design and use conditions has not been studied. The two research questions that we attempt to answer in this paper are 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?

**Review of building operations**

To complement the findings of the literature survey, the building energy management systems (BEMS) in fourteen 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 occupied mostly by government employees, and they tend to have similar occupancy characteristics. The floor area of the studied buildings varied from 4,000 to 61,000 m². They were constructed between 1847 and 1979. The buildings underwent several envelope and HVAC retrofits, and today they all have a typical VAV-AHU HVAC configuration. The heating and cooling to these buildings are provided through a central heating and cooling plant—circulating steam and chilled water year-around.

From the BEMS databases of these buildings, archived data records pertaining to zone temperature setpoints and AHU supply 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 were extracted from the BEMS databases. The original data records were sampled at 5 to 15-min intervals. For the ease of analysis, all data records were interpolated linearly to obtain data records at 15-min intervals with common timestamps.

In total, 490 indoor temperature setpoint, 191 AHU fan schedule, and 47 AHU outdoor air intake damper position data records were downloaded for the timespans ranging from 110 to 392 days—covering at least some part of the heating and cooling seasons in Ottawa. 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. Note that it is likely that there are many relevant data records other than the ones discovered in the BEMS. 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. Consequently, the data extracted may disproportionately represent a subset of the fourteen buildings. The readers should be cautious about generalizing these operational characteristics to other buildings. The sole intent to analyze the BEMS of these buildings was to form a reasonable basis for the range of operational parameters used in the optimization.

Figure 1 presents the mean weekday zone temperature setpoint profiles computed from individual data records. The shaded areas indicate the 10th and 90th 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. The 10th to 90th percentile range was between ~20°C and ~24°C. Further, the weekday temperature set-
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. All zone 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.

Figure 2.a presents the ensemble average for the binary availability schedules for the AHU supply fans during the heating and the cooling seasons. 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 2.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. 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 optimization presented in the following sections.

Methodology

The operational parameters used in the optimization problem are listed in Figure 3. 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 4). Note that the real-life implementation of the occupancy-based ventilation mode requires a sensing technology dedicated for occupancy count estimation. Determining an appropriate constant ventilation rate in real-life requires information on peak occupancy levels.

The BPS tool EnergyPlus v8.9 was used to build an energy model of an intermediate floor of a multistorey office building. The 27 m by 27 m floor is di-
Figure 3: A schematic presenting an overview of the base EnergyPlus model, the climate, envelope, and occupancy scenarios, and the operational parameters for the optimization.

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 3, 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 NECB Climate zones 4, 5, 6, and 7 represent regions with heating degree days (base temperature 18°C) of less than 3000, 3000 to 3999, 4000 to 4999, and 5000 to 5999, respectively. 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. Note that we did not study occupancy densities higher than those prescribed in NECB, as in general the literature reports much lower occupancy levels than the code (Davis III and Nutter, 2010).

For each of the 108 scenarios, the solution space for the eight operational parameters listed in Figure 3 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 provided into nine thermal zones (eight perimeter zones and one core zone). 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. The natural gas-based heating equipment was assumed to operate at 80% efficiency. A differential dry-bulb air 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. The default NECB (2015) lighting and plug load density and schedule values were assumed. At full occupancy, the occupant density was assumed to be 0.05 person/m². An overview of the characteristics of the building model is shown in Figure 3.
intensity, the cost function incorporated two discomfort metrics: (a) a thermal discomfort metric derived from ASHRAE (2017)’s predicted percentage dissatisfied (PPD) metric and (b) the percentage of occupied hours spent above 1000 ppm of CO₂. 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. The metabolic heat generation rate and human surface area were assumed to be 120 W (for sedentary office work) and 1.8 m², respectively. The room air velocity was assumed to be 0.1 m/s. Equation 1 presents the calculation of the thermal discomfort metric:

\[
I_{TC} = \frac{9 \times \left( \sum_{t=1}^{8760} PPD(t, i) \cdot People(t, i) \right)}{9 \times \left( \sum_{t=1}^{8760} People(t, i) \right)} \times 100 \quad (1)
\]

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:

\[
I_{IAQ} = \frac{9 \times \left( \sum_{t=1}^{8760} BCO2(t, i) \cdot People(t, i) \right)}{9 \times \left( \sum_{t=1}^{8760} People(t, i) \right)} \times 100 \quad (2)
\]

where \(BCO2\) is a binary indicator for high CO₂ (ppm) concentration. It takes the value “1” when the CO₂ concentration exceeds 1000 ppm in zone i at timestep t; otherwise, it takes the value “0”. The CO₂ generation rate was assumed to be 16.5 L/h-person. The cost function \(J\) is heuristically formulated as follows:

\[
J = EU_{HVAC} + (I_{TC})^2 + (I_{IAQ})^2 \quad (3)
\]

where \(EU_{HVAC}\) (MJ/m²-yr) is the HVAC energy use intensity. Based on a preliminary inspection, it was identified that \(EU_{HVAC}\) is expected to take values between 100 and 500 MJ/m²-yr. The 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 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., \(EU_{HVAC} = 0; I_{TC} = 0; I_{IAQ} = 0\)). In this paper, the relative weight of the three elements of this cost function 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.

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 \((9 \times 9 \times 12 \times 12 \times 5 \times 5 \times 11 \times 2)\). 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 / wrote 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 was 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.

**Results and discussion**

The eight operational parameters that minimize the cost function (see Eqn. 3) were determined for each of the 108 scenarios listed in Figure 3 by using the genetic algorithm. Figure 5 illustrates the evolution of the cost function for one of the 108 scenarios. Recall that each generation consists of 75 EnergyPlus simulations with different operational parameters. The genetic algorithm by selectively sampling the operational parameters of each generation reduces the cost function \(J\) defined in Eqn. 3. The whiskers shown in Figure 5 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 best set of operational parameters in each generation do not result in a substantially better op-
operational performance than a few other operational parameters. In the example presented in Figure 5, the cost \( J \) of the best operational scenario (i.e., the lower whisker) did not change significantly after the third generation. The median continued improving until the 7th generation. Figure 5 also presents 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 6 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.

Note that the terms poor, medium, and good envelope in Figure 6 correspond to the envelope scenarios 1, 2, and 3 in Figure 3, 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. This infiltration rate is twice as much as the amount suggested by NECB (2015). For buildings that comply with NECB (2015)’s infiltration assumption, 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 \( \sim 22°C \) for both heating and cooling seasons.

Beyond the specific optimization results shown in Figure 6, the methodology can be applied to derive operational rules for a specific building by using its calibrated energy model. 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 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.
Conclusions and future work

This paper introduces a methodology to derive high-level operational rules from BPS-based optimization. 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 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. The decision trees provided 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.

Note that the BPS-based operation optimization methodology was demonstrated through a simulation-based case study in which a base model with a specific HVAC configuration and envelope geometry was used. In addition, generic assumptions were made in modelling occupant comfort (e.g., clothing level, metabolic rate, air speed, CO₂ generation amount, CO₂ threshold for discomfort). Further, 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. Future work should study the sensitivity of the methodology to these assumptions.

The optimization of operational parameters was presented through a case study with eight parameters. Evidently, there are many other operational parameters. For example, 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. Future work is planned to apply this simulation-based building operation optimization technique on an existing building.

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