Optimizing Energy with Machine Learning Grey-Box Models

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Abstract

Model Predictive Control (MPC) has demonstrated great potential to improve the energy efficiency of buildings. However, using MPC traditionally requires a comprehensive knowledge of building construction to create dynamic models of buildings' zones and energy systems. This research presents a hybrid modeling approach as an alternative method. To this end, two and a half months' worth of data collected in a living lab test cell was used to develop black-box and grey-box models to characterize zone-level thermal response and optimize its temperature setpoints. The simulation results emphasized the necessity of considering flexible schedules and temperature setpoints based on occupancy, weather, and zone-level thermal response over a prediction window rather than standard fixed schedules and temperature setpoints. Moreover, the proposed hybrid modeling approach can be used for model-based predictive control in operating existing buildings.

Keywords: Experiment; Modeling; Simulation; Artificial neural network; Genetic algorithm.

1. Introduction

In recent years, there has been a considerable movement in improving the energy efficiency of heating, ventilation and air conditioning (HVAC) systems, as a significant proportion of building energy use is because of the HVAC systems (Pérez-Lombard, Ortiz, & Pout, 2008). Advanced control systems have emerged as effective ways in this regard. For instance, model predictive controls (MPCs) have demonstrated great potential to improve building systems' performance (Prívara, Váňa, Cigler, Oldewurtel, & Komárek, 2011; Oldewurtel et al., 2012). MPC in building energy management facilitates periodic adaptation of building systems to intermittent indoor (e.g. occupancy, electric equipment) and outdoor conditions (e.g. weather). Using a prediction window, MPC tackles the time lag in buildings' responses to intermittent conditions.

Achieving the benefits of MPC requires a dynamic model of buildings' zones and energy systems that best represents thermal responses of a zone and system. The three modeling approaches that can be used are white-box, grey-box, and black-box models (Li & Wen, 2014). White-box models (e.g. mathematical-physical models used in building performance simulation tools) are based on detailed modeling of a building and its systems. For instance, the lumped capacitance method is considered as a white-box model (Kramer, van Schijndel, & Schellen, 2012). Black-box models deal with the relationship between operational data where no knowledge about buildings' thermal properties is required (Harb, Boyanov, Hernandez, Streblow, & Müller, 2016). Grey-box models use both physical models and operational data (e.g. Jiménez, Madsen, & Andersen, 2008). Hence, implementation of white-box models in existing buildings requires a comprehensive set of as-built construction information. However, such information may not be easily available in existing buildings. In contrast, black-box and grey-box models can deal with this drawback of white-box models.

Previous research aimed at optimizing HVAC systems to reduce energy input and provide comfortable environment (Wang & Ma, 2008). MPC has been widely used to optimize HVAC system controls (Killian & Kozek, 2016). For instance, Corbin et al. (2013) incorporated a MPC environment that integrated a white-box model (using EnergyPlus) to optimize building control systems. The present research developed a hybrid model that combined grey-box with black-box modeling approaches to optimize the energy performance of a building system. Data collected over 2.5 months during the heating season in a full-scale living lab test cell was used to model thermal dynamics of the test cell as well as the HVAC system (i.e. heat pump) provided the heating demands of the test cell. Based on the developed grey-box and black-box models, the optimal control setpoints for MPC of the heat pump serving the test cell were identified to reduce heat pump's energy use while maintaining comfort conditions.

The test cell and collected data used to develop grey-box and black-box models are described in Section 2. Section 3 explains the methods of developing black-box models using artificial neural network (ANN), grey-box model, and the optimization process using multi-objective genetic algorithm (GA). Section 4 presents the simulation results and discussion of the results, followed by Section 5 which outlines the findings and limitations of the current study and necessary future work.

2. Description of the collected data

The data used for developing the black-box models were collected in an east-facing private office space in an academic building located on a dense urban campus in Toronto, Canada. The office test cell was a single faculty office adjacent to similar conditioned private offices to the north and south, and surrounded by a large student teaching space (above) and shared office (below). As the studied office was surrounded by other buildings, it received little direct solar radiation. A water-source heat pump delivered the heating and cooling demands of the office through a dedicated duct and adjacent offices on the same HVAC zone. A radiant heater also provided the heating demands to the office when the outdoor air temperature fell below 15°C in the heating season. An air handling unit delivered tempered fresh air to the office through a dedicated outdoor air system with dedicated ductwork.

A local weather station on the roof of the building recorded outdoor air temperature and relative humidity, wind speed and direction, and solar radiation. The data collected in the test cell throughout the study were: occupancy, door position, use of lights and electric equipment, air temperature of the office, discharge air temperature and flow rate of the air handling unit and heat pump vents to the office. Table 1 presents a summary of the sensors used in the test cell to measure the aforementioned variables.

Table 1: Summary of the sensors used in the test cell.

Data collected	Sensor model	Description
Indoor air temperature	OmniSense S-10 Ambient Sensors	The sensors had an accuracy of ±0.4˚C with a resolution of 0.1˚C and data collection frequency of 5-6 minutes.
HVAC input	Wind Sensor Rev P data loggers	The sensors detected the velocity of the incoming air. The accuracy of the sensors was not provided by the vendor.
	AM2302 Temperature/humidity Sensor	The sensor was installed within the HVAC ducts leading to the test cell reading the temperature (with the accuracy of ±0.5˚C) and relative humidity (with the accuracy of ±2-5%) of the incoming air.
Occupancy	Toggle switch	The occupancy and light state of the test cell were recorded as occupants used the manual toggle switches.
Lights		
Door position	Reed switch	The reed switch installed on the door frame of the test cell opened and closed a circuit based on proximity to a magnet installed on the test cell's door.
Electrical equipment	Watts up? PRO	The power consumption of electric equipment was measured by a wattmeter at the power bar. The data logger was set to collect data at every 3 minutes.

3. Modeling and simulation

In this research, black-box models were developed to characterize a full-scale test cell's response to indoor and outdoor conditions. Using the developed black-box models, the thermal response of the test cell to varying inputs from the heat pump was simulated. This section presents the methodology used to develop black-box models followed by an explanation of the MATLAB-based simulation process to optimize the heating setpoints of the test cell.

3.1 Black-box and grey-box models

Prior to data modeling, the collected data from multiple data acquisition systems (i.e. sensors and weather station) from 22 November 2017 to 7 February 2018 were cleaned and organized. Due to the heterogeneity of the data, both in terms of type and sampling frequency, pre-preocessing was required to develop a coherent dataset. The collected data were averaged across each 5-minute timestep. However, for the occupancy, lights, and door states, the obtained averaged values were rounded to have an integer for these variables at each 5-minute timestep. Figure 1 presents the probability density of the outdoor air temperature and relative humidity as well as indoor air temperature measured in the test cell (T_{in}) during the data collection period. The relative frequency of the collected data indicates a wide range of indoor and outdoor conditions in the data collection period.

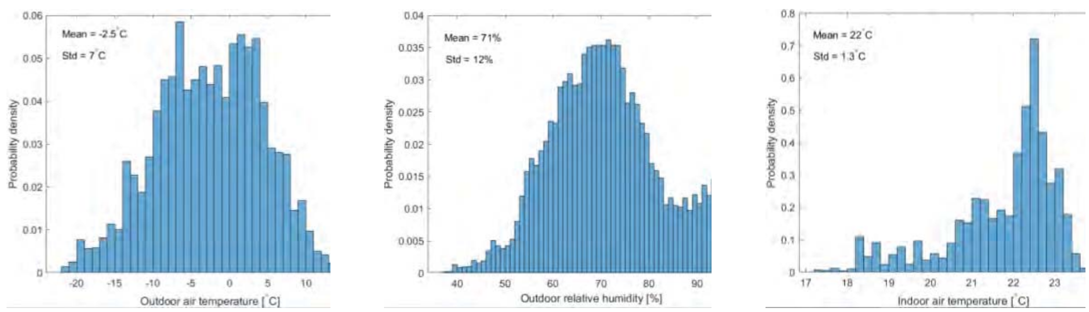

Figure 1: Probability densities of the indoor and outdoor conditions in the data collection period.

The distribution of the hourly occupied duration and the corresponding hourly occupied duration averaged across each hour on weekdays during the data collection period are shown in Figure 2. In general, the studied office had low occupied duration than standard occupancy schedules. It was occupied mostly between 9 am and 5 pm. In total, the office was occupied about 132 hours on weekdays during the data collection period. As shown in Figure 2, the test cell was mostly not occupied for the whole hour during business hours. There were a few days that the test cell was occupied for the whole hour during the data collection period.

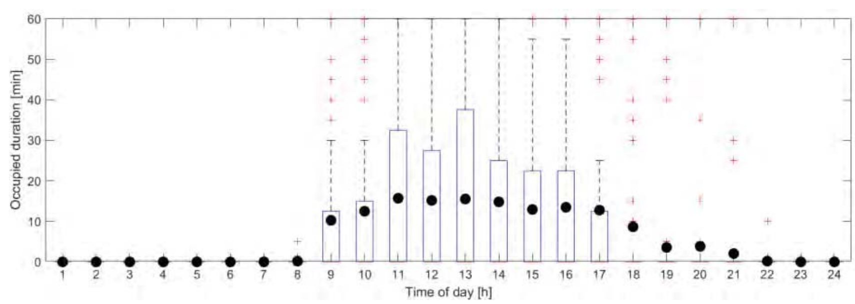

Figure 2: Distribution of hourly occupied duration (boxplot and outlier +'s) and mean hourly occupied duration (filled circles) on weekdays during the data collection period.

The collected data were used to develop black-box models to estimate the air temperature of the test cell. ANN method with one hidden layer was used to construct black-box models. The variety of the collected data facilitated training black-box models under different conditions. The input dataset and associated target outputs (i.e. indoor air temperature of the test cell) were used to train the ANN models in MATLAB. The ANN models were constructed with the 11 variables measured in the test cell, which resulted in the root mean squared error (RMSE) of about 0.6˚C in predicting the indoor air temperature. However, the input variables selected to train the ANN models were reduced afterwards. For instance, since the test cell was shaded by surrounding buildings, using solar radiation as input did not improve the accuracy of the models. Moreover, as there were relationships between occupancy and use of lights and electric equipment, adding lights and electric equipment use as input did not improve the accuracy of the models trained with the dataset included them. The input variables selected finally to train the ANN models included: outdoor air temperature, outdoor relative humidity, occupancy (i.e. number of occupants), door position, and air flow rate and temperature of the air handling unit and heat pump unit vents of the test cell. Using these variables resulted in the RMSE of about 0.6˚C.

Similar to previous research, different prediction windows were used to estimate building spaces' thermal behavior. For instance, Thomas and Soleimani-Mohseni (2007) stated that the minimum of 15-30 minutes as the prediction window in MPC in building controls is required. Mustafaraj et al.'s (2011) neural network-based models had a good performance in predicting air temperature of an open office within 30 minutes to three hours. Similarly, Ferracuti et al. (2017) showed the good performance of neural network-based models when the prediction window was shorter than three hours. In this research, to assess the performance of the ANN models, the models were constructed under varying prediction windows including 5, 30, 60, 90, 120, 150, and 180 minutes. For instance, for the prediction window of 30 minutes, an ANN model was developed using the input variables at each timestep to predict the air temperature of the test cell in the next 30 minutes.

To develop the ANN models for each of the considered prediction windows, the dataset was partitioned randomly using a stratified 10-fold cross-validation on the observations (i.e. 22464 data points). Note that as the order of the dataset was not arbitrary (it was time series), the dataset was not shuffled prior to splitting it into a training and test set. Each of the 10 partitions divided the data points into a training set and a test set. The 10-fold cross-validation partitioned the data points as 90% of the data points for training the ANN model and 10% of the data points for testing the corresponding developed ANN model. The RMSE of the indoor air temperature averaged across the 10 subsamples generated by the 10-fold cross-validation was almost identical (i.e. 0.6˚C) for the considered prediction windows. This error in short-term prediction of buildings' thermal behavior is in line with previous studies (e.g. Ferracuti et al., 2017). As an example, Figure 3 presents the measured air temperature versus the predicted air temperature of the test cell using the ANN models with the prediction window of 30 minutes for the training and test sets of the 10-fold cross-validation on the observations. The errors of the ANN models indicated the good performance of the models considering the wide range of the measured air temperature of the test cell during the data collection period.

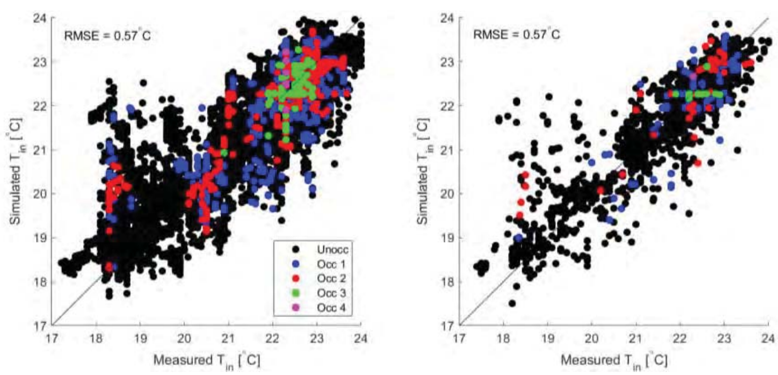

Figure 3: Five-minute time series of measured air temperature versus simulated air temperature of the test cell using the ANN model with the prediction window of 30 minutes on: (left) training set, and (right) test set.

3.2 Simulation process

This research formulated the optimal setpoint controls with two objectives: (1) reducing occupants' discomfort during occupied periods, and (2) reducing electricity energy use of the heat pump serving the test cell. This multi-objective optimization targeted the minimization of the vector of these two objectives.

In the simulation process, it was assumed that the test cell had a thermostat which was used to control the heat pump states (i.e. ON and OFF). The heating operation mode of the heat pump was set based on the test cell's temperature setpoint and air temperature. To find test cell's optimal setpoints for reducing electricity energy use of the heat pump while maintaining the test cell's temperature in the comfort zone (i.e. between 21˚C and 24˚C), various heating setpoints at varying prediction windows were tested. Table 2 presents the range of the considered heating setpoints in the optimization process. In total, the number of test cases were 14336.

Table 2: List of adjusted heating setpoints for each of the considered prediction windows (i.e. 5, 30, 60, 90, 120, 150, and 180 minutes).

Heating setpoint	Minimum [˚C]	Maximum [˚C]	Increment [˚C]
Occupied periods ($T_{sp,h,occ}$)	18	25	1
Unoccupied periods after the first arrival and before the last departure times on occupied days ($T_{sp,h,unocc,d}$)	10	25	
Unoccupied periods before the first arrival and after the last departure times on occupied days; and Unoccupied days ($T_{sp,h,unocc,n}$)	10	25	

Figure 4 presents a summary of the rule-based control strategy to find the optimal heating setpoints. For each test case of the heating setpoints, as the test cell's air temperature fell below the adjusted heating setpoint, the heat pump delivered the heating demand of the test cell; otherwise, the heat pump did not deliver any heating demands to the test cell. As shown in Figure 4, three variations of the heating setpoints were set: (1) on unoccupied days and occupied days before the first arrival time and after the last departure time ($T_{sp,h,unocc,n}$), (2) during unoccupied times after the first arrival time and last departure time on occupied days ($T_{sp,h,unocc,d}$), and (3) during occupied times on occupied days ($T_{sp,h,occ}$). In addition to the rule-based control strategy to optimize control setpoints, a baseline case was simulated. The control strategy for the baseline was on the basis of the standard practice in existing buildings. It was assumed that between 7am-7pm on weekdays, the heating setpoint was set to 21˚C. On weekends and before 7 am and after 7 pm on weekdays, the heating setpoint was set to 10˚C.

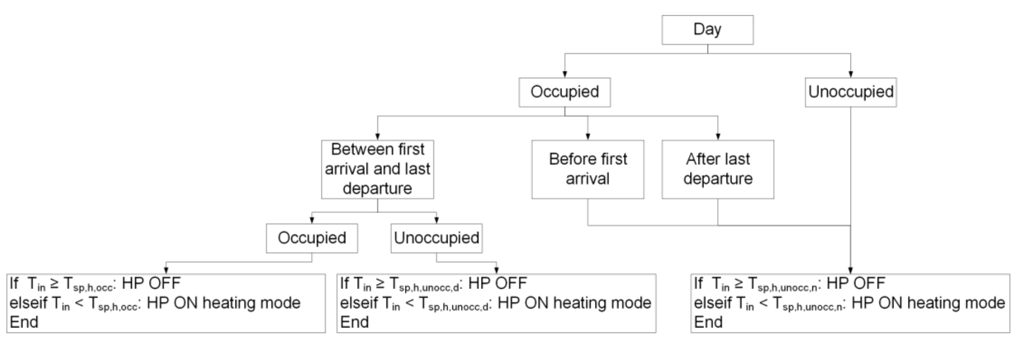

Figure 4: Rule-based control strategy to optimize temperature setpoints.

Optimizing control setpoints was based on the dataset which was used to construct the ANN models. Indoor and outdoor conditions were set to the measured data for each timestep (i.e. five minutes). However, the supply air temperature of the heat pump was calculated based on the air temperature of the test cell assuming the heat pump delivered the energy demands of the test cell at its maximum capacity and the return air vent was located in the test cell. A water-source heat pump model, which was almost identical to the one provided the heating and cooling demands of the test cell, was considered for the simulation process. The heating capacity of the considered heat pump was 5393 W, whereas its cooling capacity was 6887 W. Its energy efficiency ratio was 13.4 and the coefficient of performance was 4.4. The heat pump delivered an air flow rate of 0.3 m^3/s at the external static pressure of 0.20" (inches of water column). To avoid short cycling in the operation of the heat pump, it was assumed that it can slow down to a cruise control mode. The minimum air temperature supplied from the heat pump vent was set to be at the minimum of 10˚C lower than the air temperature of the test cell.

At each timestep, the air temperature of the test cell (T_{in}) was calculated using the black-box ANN models based on the inputs from the dataset, except for the air temperature and flow rate of the heat pump vent. Once the air temperature of the test cell was calculated, the air temperature and flow rate of the heat pump vent were calculated using the grey-box model (Figure 5) and the rule-based control strategy to optimize the control setpoints (see Figure 4). Note that the initial values of the air temperature and flow rate of the heat pump vent were assigned to be identical to the dataset. Moreover, as the heat pump delivered the energy demands of multiple rooms, the air flow rate from the heat pump vent to the test cell was calculated based on the average measured values.

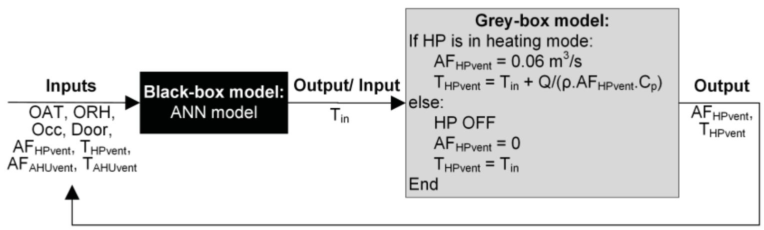

Figure 5: Inputs and outputs of black-box and grey-box models.

To find the optimal control setpoints among the considered ones, the multi-objective GA was implemented in MATLAB to find a set of points that have the relative minimal fitness function values (Pareto front) where reducing one fitness function (reducing electricity energy use) degraded another fitness function (increasing discomfort hours). The two fitness functions in the current research were to calculate: (1) the electricity energy use of the heat pump, and (2) the number of discomfort hours during occupied periods for the whole simulation time period. The multi-objective GA was set to create populations with 10 members per 10 generations. The sequence of generations was created based on the children type of mutation. Using the mutation children, single members of the population of a previous generation are randomly changed to form the population of the next generation.

4. Results and discussion

Table 3 presents the heating setpoints at Pareto front points obtained by the multi-objective GA. The obtained prediction windows for the optimal cases were 60 and 90 minutes. This prediction window means that for instance, the temperature setpoints of the test cell should be reset from the nighttime setbacks one hour before the occupant's first arrival time on an occupied day and one hour before the occupant left the office for the rest of that day. This trend is due to that the fixed temperature setpoints based on a standard occupancy schedule (between 7 am and 7 pm on weekdays) may not be applicable regarding flexible work schedules. For example, the occupancy profiles (see Figure 2) of the test cell shows that the office was in use mainly between 9 am and 5 pm during the data collection period. As such, the building spaces may be conditioned much earlier than when an occupant arrives an office or much longer than when an occupant leaves an office. Likewise, if an occupant arrives earlier than standard schedules or stays after standard schedules, the occupant will feel uncomfortable.

Determining optimal prediction window is also important in controlling HVAC system output as thermal response rates of buildings may not be as quick as what building operators assume in managing temperature setpoints. Hence, an occupant may feel uncomfortable when the occupant arrives an office. For instance, Dobbs and Hencey's (2014) study showed that controlling HVAC systems purely based on occupancy led to the reduction in energy use, however it increased occupants' discomfort upon their arrival to a space. Moreover, due to the delay in buildings' response because of their high thermal mass, it may take time to restore an office's temperature to a comfortable level once an occupant change the temperature setpoint or building operators adjust temperature setpoints following receiving occupants' complaints. However, accurate information of an existing building for developing white-box model of building thermal response may not be readily available. The current study used black-box models to predict thermal responses of the test cell to indoor and outdoor conditions without the requirement to go through detailed information of the thermal characteristics of the test cell.

In addition to the necessity of flexible schedules to reduce HVAC system output, the temperature setpoint values should also be revisited. For instance, in the current test cell, the optimal nighttime heating setpoints were 12-16˚C, rather than the commonly used temperature setbacks of 10˚C for the heating demands during weekends and nighttime on weekdays. Furthermore, the results of the studied test cell showed that on occupied days, the temperature setpoints should be adjusted during occupied and intermediate unoccupied periods, rather than determining fixed temperature setpoints (e.g. 21˚C for heating) for the whole business hours on weekdays. For instance, in this study, the optimization simulations yielded the optimal heating setpoint during occupied periods as 18-20˚C, whereas the optimal heating setpoint during unoccupied periods was 13-18˚C on the days that the occupant was present.

Table 3: Comparing Pareto front points with baseline.

Output \ Case		Optimal cases			Baseline
		1	2	3	
Prediction window [min]		60	60	90	5
Heating setpoint [˚C]	Occupied periods ($T_{sp,h,occ}$)	20	19	18	21
	Unoccupied periods after the first arrival and before the last departure times on occupied days ($T_{sp,h,unocc,d}$)	13	18	15	21
	Unoccupied periods before the first arrival and after the last departure times on occupied days; and Unoccupied days ($T_{sp,h,unocc,n}$)	16	13	12	10
Discomfort hours during occupied hours [h]		36	37	76	96
Electricity energy use [MJ]		824	221	21	2660

Figure 6 presents the average hourly air temperature of the test cell where the temperature setpoint was controlled based on the heating setpoints of the second optimal case compared to the baseline where the heating setpoints were adjusted based on the standard operating practice. These profiles show the hourly air temperature averaged across each hour during occupied periods, intermediate unoccupied periods, and unoccupied periods excluding intermediate unoccupied periods. Using the optimal heating setpoints, the average air temperature of the test cell was generally above 21˚C during occupied periods, whereas it was below 21˚C during occupied periods when the heating setpoint was controlled based on the standard practice in existing buildings. The simulation results showed that the fraction of occupied periods when the heat pump was on while the indoor temperature was below 21˚C reduced by 89% during occupied periods with the second optimal case compared to the baseline.

The mean hourly heating setpoints and occupied fraction on weekdays are displayed in Figure 7. As shown in this figure, the range of the average heating setpoint on the basis of the optimal heating setpoints of the second optimal case (see Table 3) was from 13˚C to 15˚C, while the fixed standard heating setpoints are 10˚C and 21˚C. During standard hours for resetting from setbacks, the average heating setpoint based on the optimal heating setpoints was lower than the fixed standard heating setpoint, whereas it was higher than the fixed standard heating setpoint during nighttime. This trend indicates that on average, using the optimal heating setpoints, the heating system provided more output during nighttime, whereas it provided less output during daytime compared to the fixed standard heating setpoints. Despite this trend, the heat pump electricity energy use and discomfort duration were lower with the optimal heating setpoints than the baseline (see Table 3).

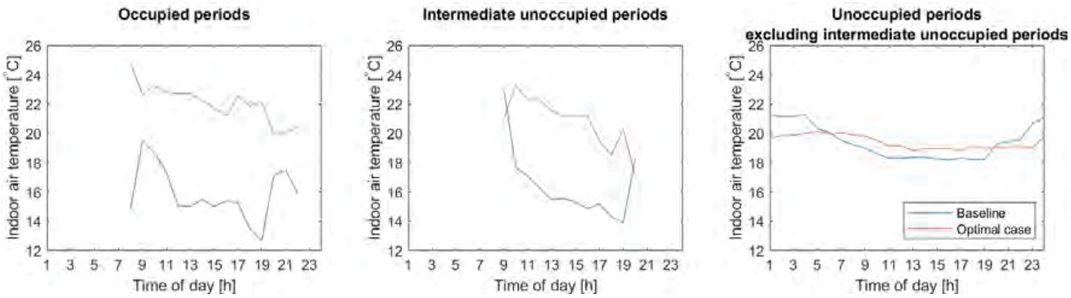

Figure 6: Mean hourly indoor air temperature of the optimal case #2 (see Table 3) and the baseline.

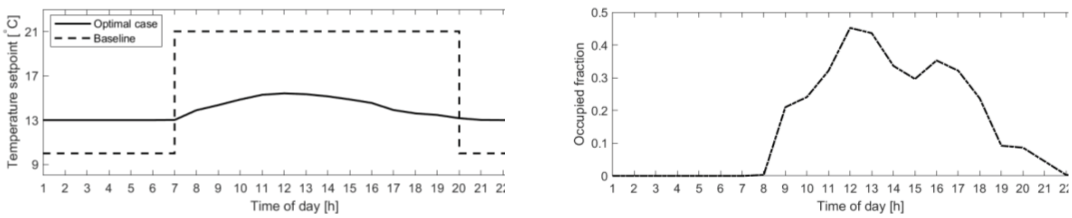

Figure 7: Comparing optimal case #2 (see Table 3) with baseline on weekdays: (left) simulated mean hourly heating temperature setback for the optimal case and baseline, (right) measured mean hourly occupied fraction.

This study showed that while fixed temperature setpoint schedules is a common practice in controlling HVAC systems, using a model predictive control and dynamic temperature setpoint control system based on occupancy, weather, and thermal response of the test cell can reduce energy use while keeping the air temperature of the test cell in the comfort zone. However, accurate prediction of occupancy, weather, and thermal responses of a building zone are necessary to control temperature setpoints properly. Moreover, the effectiveness of the proposed control system requires future real world data and testing in a living lab where full HVAC system control is possible.

5. Conclusions

This research combined black-box and grey-box models to develop a hybrid model to characterize thermal responses of a full-scale test cell without a requirement for a comprehensive knowledge of the physical characteristics of the test cell. Using the hybrid model, the temperature setpoints of the test cell for MPC of the heat pump delivered the heating demands of the test cell were optimized. The simulation results showed that flexible schedules and temperature setpoints based on occupancy, weather, and zone-level thermal response using MPC reduced energy use of the test cell compared to the standard practice in defining fixed schedules and temperature setpoints.

The method developed in the present research is an efficient method that can be applied in existing buildings where accurate as-built characteristics of a building space may not be readily available. Such black/grey-box model-based predictive control using real-time data can be used for continuous commissioning in existing buildings. This research had limitations that require future work. While this research used data-driven models for modeling the relationship between inputs and target outputs, the presented optimal temperature setpoints and control system were assessed using simulation. Further assessment of the control system necessitates a real test case. Generalization of the optimal control setpoints requires data collection in various cases studies. Moreover, future work on developing accurate models for predicting occupancy, weather, and thermal responses of the studied test cell is necessary.

Nomenclature

$AF_{AHUvent}$	Air flow rate of AHU vent (m3/s)	Q	Full capacity of HP in heating operation mode (W)
AF_{HPvent}	Air flow rate of HP vent (m3/s)	$T_{AHUvent}$	Air temperature of AHU vent (˚C)
AHU	Air handling unit	$T_{hallway}$	Air temperature of adjacent hallway (˚C)
C_p	Specific heat capacity of air (J/kg.K)	T_{HPvent}	Air temperature of HP vent (˚C)
Door	Door position	T_{in}	Indoor air temperature (˚C)
HP	Heat pump	$T_{sp,h,occ}$	Heating temperature setpoint during occupied hours (˚C)
OAT	Outdoor air temperature (˚C)	$T_{sp,h,unocc,d}$	Heating temperature setback during unoccupied hours on occupied days (˚C)
Occ	Number of occupants	$T_{sp,h,unocc,n}$	Heating temperature setback on unoccupied days (˚C)
ORH	Outdoor relative humidity (%)	ρ	Air density (kg/m^3)

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