Applying data-driven thermal modeling techniques to provide office occupants with time-to-setpoint estimates

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Abstract

While satisfaction with the ability to adjust personal thermostats offers significant benefits to peoples' productivity, health, and satisfaction in the workplace, surveys have shown that current office workers have low levels of perceived control over their thermal environment. Meanwhile, using building sensors to develop data-driven thermal models for advanced building control has become increasingly popular. Currently, there are no known examples of presenting insights from these models to office building occupants to further engage them with their heating and cooling systems. In this study, three months of heating season operational data from 25 offices of an academic building was used to develop a grey box model of the offices. This model was used to provide occupants with estimates for time to reach the setpoint temperature. When tested on the same months of the following year, the time-to-setpoint estimations had a mean absolute error of 20, 42, and 65 minutes for 30, 60, 120 minute prediction horizons, respectively. This model was implemented into the building controller, with the predictions displayed to occupants through wall-mounted thermostats.

Introduction

Several surveys have shown that satisfaction with the ability to control the thermal environment is low in commercial office buildings (Boerstra & Beuker, 2011; Huizenga et al., 2006; Karjalainen, 2009; Tamas et al., 2020). This lack of perceived control has been shown to affect thermal comfort, impacting the productivity, health, and wellbeing of office occupants (Boerstra & Beuker, 2011; Wagner et al., 2007; Wyon, 2000). Interestingly Karjalainen (2009) found a direct correlation between user's reported understanding of their heating and cooling system and their perceived sense of control. As such, complex heating and cooling systems with slow thermal response times have been identified as a reason for a low sense of control. While in residential applications, products exist, such as the Nest learning thermostat, which provides estimates for the time expected to reach the setpoint, there are no known such examples of providing this information to office occupants.

Meanwhile, the usefulness of data-driven models has been demonstrated for the purposes of advanced control strategies and energy monitoring (Gunay et al., 2019; Shaikh et al., 2014). As an example, optimal start algorithms which use the historical building data to estimate time to recover from setback temperatures have existed since the early seventies (Birtles & John, 1985). Some recent applications include next day heating/cooling load estimation for better operation of heating plants and model predictive control to reduce energy demand from the heating and cooling system (Bursill et al., 2019; Zhou et al., 2008).

Broadly, the two categories of data-based modeling are hybrid or grey box and black box (Amasyali & El-gohary, 2018). Grey box modeling uses prior knowledge of the input parameters to create representative models, often represented as electrical analogous resistance capacitance (RC) circuits. Depending on the application and implementation, these models can perform better than black box models, as they better represent the building physics. Black box models, on the other hand, are purely data-driven and can be developed without knowledge of the source data. For this reason, they can be applied to building data without knowledge of the building dynamics or sensor locations, making them more versatile.

While many examples exist of using data-driven models for control, few applications have provided this information to occupants. This paper describes the model development, training, and implementation of a model used to estimate time-to-setpoint in a commercial building. This fits under a larger project aimed at communicating HVAC operational information to occupants to improve perceived control and thermal comfort in office buildings. Because this time-to-setpoint estimate will be displayed on the thermostat, the model developed needs to provide robust, predictable, and consistent estimations.

Gunay et al. (2016) provided a comparative analysis of various electrical analogous room models and had several key findings. By training various models with real building data, they found that increasing parameters without increasing the number of sensors decreases the model predictive accuracy. Also, they found the simplest model that provided satisfactory predictive accuracy included the parameters indoor and outdoor temperature, indoor light intensity, motion sensors, and heating system status, using 15-minute timesteps. The model formulated in this paper is based on the methods developed in this study.

This paper describes the model development, training, and implementation, of an electrical analogous grey box room model, trained using multiple linear models (MLR), used to provide occupants with an estimate of the time it will take for their room to reach the setpoint. The grey box model was developed to represent outdoor weather conditions, heating system operation, and occupancy. The implementation occurred during the heating season and aims to display real-time time-to-setpoint estimations during morning warm up periods and setpoint increases.

Methodology

Building information

The model development, training, and implementation was all performed on 25 offices in a commercial building located in Ottawa, Ontario. These rooms are near-identical single occupancy offices with a north-east orientation. During the period of the study, all of the offices were in use, and the data was collected directly from the building automation system (BAS). Measurements are collected and stored directly from the BAS system, at 5-minute intervals. With the appropriate ethics clearance, this data was collected in a non-intrusive way without the occupant's knowledge, meaning that the Hawthorne effect is not a concern. A layout of the office and some key sensors are shown in Figure 1.

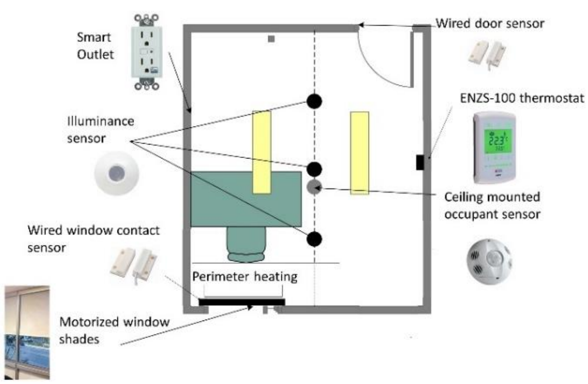

Figure 1: Room layout and key sensors.

Each office is equipped with a thermostat and, during the heating season, is heated by two systems: (1) a hydronic radiator, located at the base of the window, and (2) a variable air volume (VAV) system with a reheat coil. The two systems operate on a proportional integral (PI) controller to control the office to the setpoint requested by the occupant.

Each room is equipped with a radiator which operates using an on/off basis with activation determined by the PI algorithm. The VAV is shared between 2-4 offices and provides both ventilation and heating. When the reheat coil is inactive, the VAV supplies 18°C air at a minimum airflow, an operation designed to provide the required ventilation and offset solar and internal gains. The reheat coil is activated whenever one of the rooms in the zone requires heating. By design, the airflow is intended to increase from its minimum ventilation based on the PI controller; however, due to an error in the code, the VAV operated at minimum airflow during all non-setback periods. This contributes to slower than intended warmup and setpoint response times in this building.

While heating, typically, both the radiator and VAV operates at full capacity until the temperature is at least within 0.5°C. While this threshold is not fixed and depends on the PI control algorithm, it will be used as the prediction threshold in this paper.

The building has scheduled setbacks that operated outside of what was considered "occupied hours," between 6:30 am to 5:30 pm Monday to Friday. During this time, the VAVs are inactive, and the radiators are only used to keep the office above 18°C. The early start likely aims to warm up the building before occupancy; however, partly due to the issues with the VAV airflow, the requested setpoint temperature is often not reached until the late morning or, in some cases, the early afternoon.

The room thermostats had displays which were comparatively flexible to other commercial thermostats and were programmed via the BAS system. As such, they could be re-programmed to display the time-to-setpoint temperature. Since they are directly connected to the BAS they can display real-time estimates based on the HVAC system operation.

Time-to-setpoint estimation

The primary goal of the time-to-setpoint readings is to display a time estimation directly to the occupants on the thermostat in their office. The purpose is to inform users of the time-to-setpoint under two key situations, (1) when the user increases their setpoint, and (2) during the morning warm-up time. While these are the primary targets, there may be other times throughout the day that this information is relevant. For example, if a window is open and the room cools down, the occupant may be interested in how long it will take after the window is closed for the room to heat back up.

Time-to-setpoint estimations will be displayed as the time it will take from the current temperature until the time the indoor air temperature will reach within 0.5°C of the setpoint. This information will only appear when the temperature is less than 0.5°C than the setpoint and the heating system is active. The reasons for this threshold are mentioned in the building description; the heating system reduces its heating input based on the PI controller, and so the actual setpoint may never be reached. This threshold avoids cases where the thermostat displays the same estimate for long periods of time as the temperature remains just below the setpoint. Since this range was selected based on the limitations of the heating systems capacity, the implication of this threshold on comfort was not explored in detail.

Model formulation and training

To build the data driven grey box model of the room, each room was modeled using an electrical analogous thermal network model. Parameters considered the effects of outdoor air temperature, thermal gains, radiator and VAV operation, occupancy, and internal gains. The room model and inputs are shown in Figure 2. The list parameters collected from the BAS system are listed in Table 1.

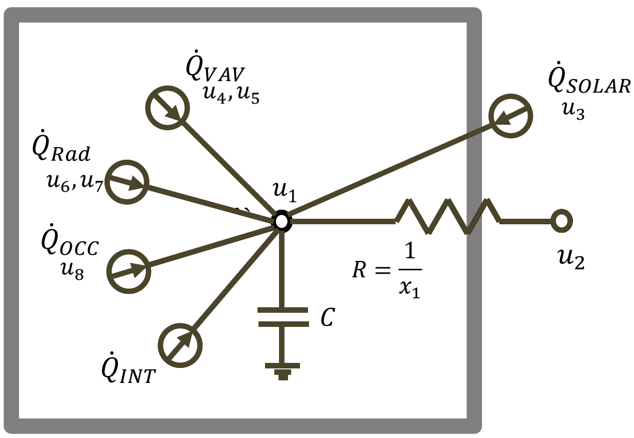

Figure 2: Electrical analogous room model.

Table 1: List of parameters used in the model formulation.

Inputs	Description of measured parameter	Unit
u_1	Indoor air temperature	°C
u_2	Outdoor air temperature	°C
u_3	Indoor Illuminance	Lux
u_4	VAV flow	L/s
u_5	VAV supply air temperature	°C
u_6	Radiator Valve	open/closed
u_7	Radiator supply water temperature	°C
u_8	Occupancy	yes/no

The heat losses due to the outdoor air temperature ($\dot{Q}_{OAT}$) is shown in equation (1) and is modeled as a thermal resistor between the indoor and outdoor air temperature. The indoor and outdoor air temperature is measured directly by the building automation system. The conductance incorporates the combined conductance of the window and wall assemblies, as well as the convective coefficients on the inside and outside of the building. This resistance is represented in the model as ($R = 1/x_1$).

$$\dot{Q}_{OAT} = x_1(u_1 - u_2) \tag{1}$$

The solar gains ($\dot{Q}_{SOLAR}$) are shown in equation (2) and are inferred by using an average of three illuminance sensors at three depths within the room. This model assumes that there is a linear correlation between the measured illuminance and the solar gains of the room, represented as the parameter (x_2). While this assumption has limitations, it provides some insight related to the effect of solar gains. In one study, Bursill et al. (2019) performed an analysis of this assumption on an office room and found a 0.42 linear correlation between the illuminance sensor and the expected solar irradiation at the office.

$$\dot{Q}_{SOLAR} = x_2 u_3 \tag{2}$$

VAV heat input ($\dot{Q}_{VAV}$) is shown in equations (3) and is captured using basic thermodynamic principles with the heat input modeled as mass transfer from the incoming air ($\dot{m}C_v\Delta T$). It is assumed that flow provided through the VAV is equivalent to the flow return through the return vent. It is also assumed that the return air temperature is equivalent to the indoor office temperature. This can be represented in the following equation, where the trained parameter (x_4) is representative of the heat capacity and density of the incoming air.

$$\dot{Q}_{VAV} = x_3 u_4(u_5 - u_1) \tag{3}$$

Heat input due to the radiator ($\dot{Q}_{RAD}$) is shown in equation (4) and is captured by measuring the radiator supply water temperature and valve position. During operation, the valve actuates to maintain a temperature difference of 3°C between the water temperature of the inlet and outlet of the radiator. For the purposes of this model, it is assumed that during operation, if the radiator valve is open (u_6=1), the radiator surface temperature is the same as the water temperature, and if the valve position is closed, the surface temperature is the same as room temperature (no heat transfer occurs). This assumption has limitations, as some heat loss occurs between the water and the metal of the radiator, and the radiator takes some time to cool down after the valve is turned off. Additionally, heat transfer will occur both through both convection, and through radiation to the room surfaces, however, radiator heat input is only modeled as convection. The trained parameter x_4, therefore, is representative of the convective heat transfer coefficient and area of the radiator associated with that convective heat transfer.

$$\dot{Q}_{RAD} = x_4 u_6(u_7 - u_1) \tag{4}$$

Finally, internal gains are represented using x_5 and x_6, where x_5 represents the gains associated with occupancy ($\dot{Q}_{OCC}$), and x_6 represents the internal gains from other equipment in the room ($\dot{Q}_{INT}$). Occupancy was inferred using two PIR sensors, one located on the thermostat panel, and one on the ceiling above the occupant's desk. Occupancy was assumed for 60-minutes after the most recent motion detected. Reducing occupancy to a binary variable likely fails to capture the complexity of how occupant behavior effects the gains in this office, however, these simplifications are necessary given the available data.

The heat inputs are applied to the room temperature node of the RC grey-box model. The thermal capacitance, represented by C, characterized the thermal response time of the room. Heat flow through the capacitor is defined by equation (5).

$$\dot{Q} = C\left(\frac{dT}{dt}\right) \quad \text{(eq 5)}$$

This thermal capacitance includes both the capacitance of the air, the solid objects in the room, and the thermal mass of the envelope. While the response time between these would be different, it is assumed they can be represented by a single thermal capacitance. This simplification is based on the finding from Gunay et al. (2016) that increasing the number of parameters without increasing the number of sensor inputs can decrease the predictive power of the model. Since there is only one temperature measurement in the room, a single capacitance was deemed most appropriate.

Applying Kirchhoff's law, that heat flow into a node is equal heat flow out of that same node. Therefore, the heat flow through of the thermal capacitor is equal to the sum of all the other heat flows associated with the temperature node. The heat flow through the capacitor can be written as equation (6).

$$C\frac{dT}{dt} = x_1(u_1 - u_2) + x_2(u_3) + x_3u_4(u_5 - u_1) + x_4u_6(u_7 - u_1) + x_5u_8 + x_6 \quad (6)$$

Since the capacitance (C) is assumed constant, it can be incorporated into the trained parameters. Additionally, the room data is discrete timestep data, therefore (dT/dt) is estimated as $(\Delta T/\Delta t)$. These final simplifications are represented in equation (7).

$$\frac{\Delta T}{\Delta t} = x_1(u_1 - u_2) + x_2(u_3) + x_3u_4(u_5 - u_1) + x_4u_6(u_7 - u_1) + x_5u_8 + x_6 \quad (7)$$

Time-to-setpoint estimation

Once trained, predictions of the temperature of the next time step (T_{i+1}) is found by adding the calculated change in temperature to the temperature of the current time step (T_i) as shown in equation (7).

$$T_{i+1} = T_i + \Delta T \quad (8)$$

Time-to-setpoint is determined by repeating this process (marching forward in time) until the predicted temperature reaches within the threshold of 0.5°C of the setpoint. The number of timesteps required provides an estimate of the amount of time it will take to reach the setpoint. If the prediction exceeds the threshold temperature, linear interpolation between the current and previous timestep is used to determine a precise estimate. For each timestep the input parameters ($\boldsymbol{u}$) may be updated based on predicted parameters. For this application, outdoor conditions and HVAC operations will be assumed constant for the duration of the prediction horizon. However, indoor air temperature is updated based on the prediction.

Results

Training and validation data

The parameters of the electrical analogous room models were trained based on three months of data from mid-October 2018 to mid-January 2019. The training was performed using MLR on three months of data, from mid-October 2018 to mid-January 2019. Setback periods (evening and weekends) were removed from the training data. Since these offices are equipped with window sensors, times that the window was open was also removed from the training data, as the room dynamics would change significantly during this time. Aside from these exclusions all other operation data was used to train the parameters. The choice to use all data, rather than focusing on warmup and setpoint changes was made to ensure room models were robust regardless of how often morning warmups and setpoint changes occurred. The performance of these models was assessed based on the ability to predict time-to-setpoint on a validation set.

The validation set is made up of the same three-month period in the following year, from mid-October 2019 to mid-January 2020. model performance, the time-to-setpoint of each warmup and setpoint change is calculated. An example of a morning warmup time is visualized in Figure 3.

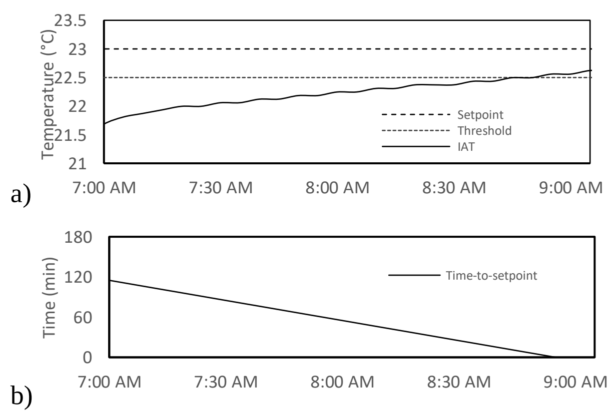

Figure 3: Example of validation data for a morning warmup. Figure 3(a) shows indoor air temperature (IAT), and the threshold for the estimation. Figure 3(b) plots the corresponding measured time-to-setpoint.

Model performance is assessed based on the mean absolute error (MAE) of the trained parameters to estimate time-to-setpoint when the validation data is heating and is 30, 60, and 120 minutes from the setpoint threshold. 848, 717, and 406 examples of 30, 60, and 120 time-to-setpoint horizons have been collected from the validation data. For the assessment of model performance, MAE between predicted and measured data is calculated for each room, and an average MAE between the rooms is used to determine the overall performance.

Five rooms were removed from the validation set. Three of these rooms were removed as they had fewer than 10 cases where the indoor air temperature was lower than the setpoint threshold for more than 30 minutes. The other two were removed due to erratic heating behavior that was unrepresentative of the rest of the offices.

Training time step determination

Determination of the room model training timestep was performed by comparing the measured data from the validation set with the time-to-setpoint estimates of the electrical analogous room model. The room model was trained using 5, 15, 30, and 60-minute time steps. When the resulting predictions from these room models were compared to the validation set, for all (30, 60, 120 minute) prediction horizons, increasing the timestep increased the MAE, however, the effect was small (<15%). Only a small difference was observed between the 5 and 15-minute timestep (<3%), and therefore a 15-minute timestep was used as this information is more likely available in other buildings. In general, this strategy would work for increased timesteps, and should typically be selected based on the minimum BAS collection frequency.

Forward selection of parameters

To investigate the effect of each parameter on predicting time-to-setpoint, a forward selection process was used. The inputs from outdoor air temperature (OAT), solar gains (SOLAR), radiator system inputs (RAD), VAV system inputs (VAV), and occupancy (OCC) were all tested individually. For each model, internal gains were included and can be considered the unexplained portion of the model. Next, combinations of each input type were combined in order of best predictors. The results are shown in Figure 4. The grey lines represent the maximum and minimum MAE for each room, while the black line represents the averages for all the rooms. This process was done for 30, 60, and 120-minute prediction horizons; however, the trend was the same for all horizons, so only the results from the 60-minute predictions are shown in Figure 4.

Unsurprisingly occupancy and outdoor conditions alone are poor predictors of time-to-setpoint. As individual parameters, radiator and VAV operational data are the best performing predictors, with the combination of the two being the best performing model. Interestingly adding other parameters to the model increased, rather than decreased MAE of the time-to-setpoint predictions. As a result of this analysis, only VAV and RAD inputs were included in the final implementation of the room models.

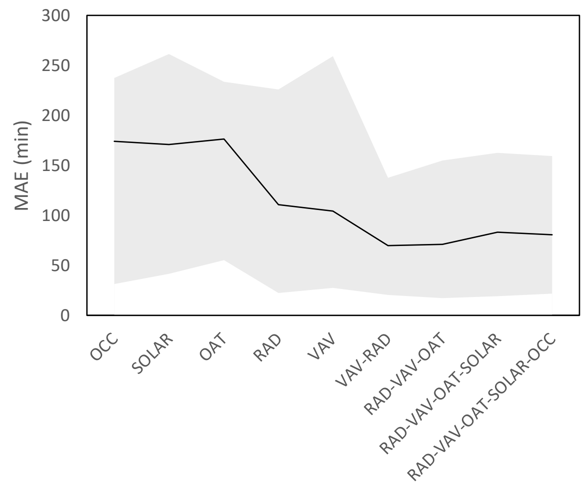

Figure 4: Average MAE (black) and maximum and minimum MAE (grey) for 60-minute predictions in 20 of the 25 rooms during the forward selection of parameters.

Room models

The impact of each input on room temperature is shown in Figure 5. The figure represents the estimated maximum and minimum effect of each input parameter on room temperature over the next hour. The trained parameters ($\boldsymbol{x}$) are compared to the full range of input parameters. The full model can be seen in Figure 5a while the radiator VAV only model can be observed in Figure 5b. These graphs were made for each room, with only a representative room shown here.

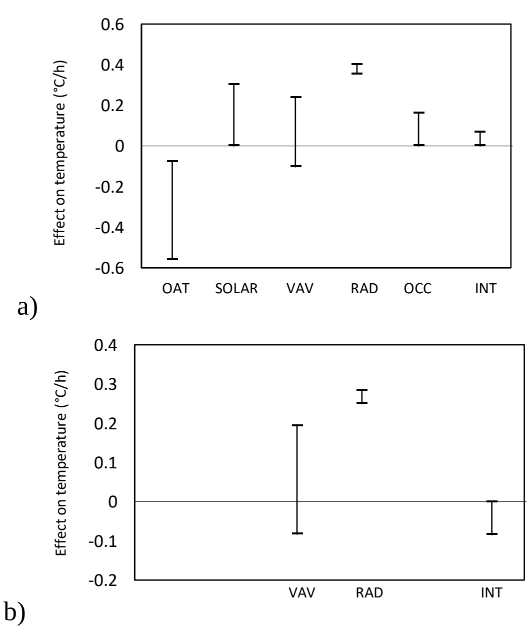

Figure 5: Impact of inputs on room temperature in 1 hour for one office. a) is the model trained with all inputs, while b) is only including RAD and VAV inputs.

Initial inspection of estimations

The initial results from using only the VAV and radiator inputs were inspected on a room-by-room basis. A key observation is that the predictions were highly sensitive to VAV supply air temperature. In the example shown Figure 6, the heating system is switched on in the morning to recover from the setback temperature, however, the VAV takes about 10 minutes to reach its operating temperature. As a result, the prediction for the first 10 minutes predicts nearly twice the time actually required for the room to warm up. Similarly changes to the state of the radiator valve, and fluctuations of the radiator flow caused large fluctuations in temperature predictions.

To address these concerns the radiator and VAV input variables were held constant, to represent typical heating operation. The chosen constant numbers were based on average operating conditions during heating. An example of the original VAV-RAD model performance and constant heating input performance is shown in Figure 6.

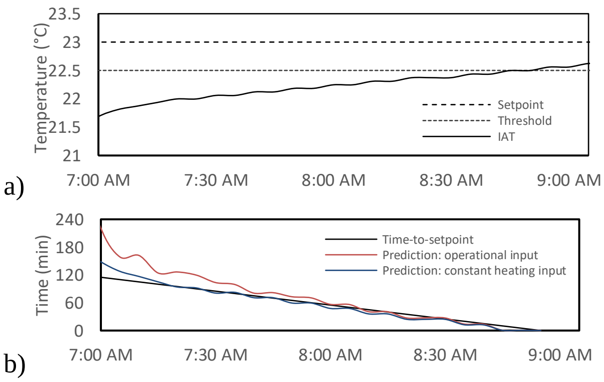

Figure 6: Example of time-to-setpoint predictions comparing operational heating inputs, constant heating inputs, and measured data. Figure 6(a) shows indoor air temperature (IAT), and the threshold for the estimation. Figure 6(b) plots the measured and predicted time-to-setpoint.

While prediction results between the two methods are similar after approximately half an hour, by assuming constant inputs the initial estimate is both more accurate and more stable. This is particularly important when considering usability as the user may be more likely to observe the time estimate immediately after a setpoint change.

Input parameter tuning

To ensure the success of the study, the model predictions of each room were inspected manually. Since the predictions are displayed directly to the offices users, large issues with any model may lead to complaints or dissatisfaction. To further reduce the remaining performance variance between rooms, some of the trained parameters ($\boldsymbol{x}$) were manually adjusted for the lowest performing rooms. The tuning process was done using a combination of considering the room level MAE and inspecting a visualization of the estimates. This manual selection of parameters was also performed based on rooms that were excluded from the validation set. The final MAE of the tuned constant heating input model is shown in Figure 7.

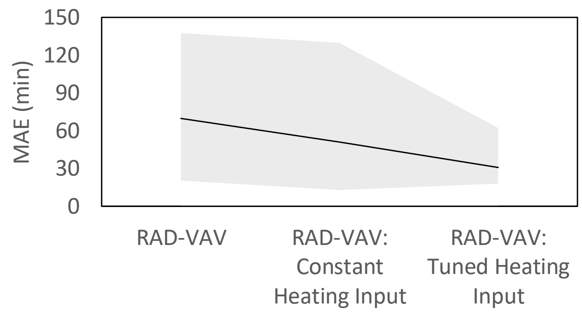

Figure 7: Comparison of MAE of 3 models, using operational data, constant heating inputs, and tuned heating inputs.

Implementation

The time-to-setpoint model was deployed in the 25 rooms to display on the thermostats. The thermostats display the time-to-setpoint estimate any time the indoor temperature is less than 0.5°C than the setpoint with estimates are rounded to the nearest half hour. The implementation is shown in Figure 8. During adjustment of the setpoint, the setpoint temperature appears on the line where the time-to-setpoint is currently shown. After 10 seconds, the time estimate appears and remains there until the temperature reaches the threshold temperature.

Figure 8: Time-to-setpoint implementation on the room thermostats. The thermostat shows indoor air temperature and the time-to-setpoint estimate.

Discussion and conclusion

This paper describes the training, tuning, and implementation of a grey box model which estimates time-to-setpoint. The final tuned models had a final MAE of 20, 42, and 65 minutes for 30, 60, 120 minute prediction horizons respectively. Ultimately final validation on the accuracy of the model was done visually, with judgment made as to what the users would see.

A linear model was chosen to model offices in this building for two reasons: (1) it could be easily coded into the building automation system with low computational power, and (2) it performs satisfactorily for the task at hand. This approach, however, had significant limitations in implementation, and the prediction accuracy was held back by the lack of linear behavior of the indoor air temperature.

The room models showed that future temperature was heavily impacted by outdoor conditions. Despite this impact, including these parameters in the time-to-setpoint estimation decreased overall performance. The likely cause of this is that these parameters change throughout the prediction horizon. Solar gains would vary significantly throughout the morning warmup period. In future work, predictions of the outdoor air temperature and lux measurements will be added into the model to test if this improves time-to-setpoint estimates.

In the final step of this process, visualizations of the predictions where then inspected and further manual adjustments of the parameters was done when required. This step was performed to ensure estimates were behaving in a way that would be satisfactory to occupants, however, this step is time-consuming and acts as a barrier to large scale implementation of this method.

Working from real building data presented several key challenges. First, this building has a slow response time to respond to a user setpoint and as a result, the prediction horizon for this model was quite long, often extending beyond four hours. The heating response was frequently non-linear, posing an issue for using a linear model to predict. This is likely a result of both non-linearity in the relation between the measured variables and room temperature, and as well as unmeasured inputs into the room. Occupant behavior likely plays a key role. While occupancy is measured as a binary variable, heat generation due to occupancy is unknown. As an extreme case, some occupants may be using space heaters to adjust their thermal comfort.

An observed advantage to data-driven modeling, is that unexpected or faulty equipment can be captured in the model. For example, one of the generated room models deviated from the rest, as the modeled internal gain deviated significantly from the other rooms. Upon further investigation, it was discovered that the radiator valve was allowing flow through the radiator even when the radiator valve was switch off by the BAS. This was automatically compensated for by the model, by increasing the internal gain trained parameters.

For this application the described method was considered to be the most accurate approach that could be simply programmed into the building controllers; however, future work will include a comparison of other data-driven models including autoregressive and long short-term memory artificial recurrent neural network approaches. It is expected that these models could provide more accurate and versatile time-to-setpoint predictions.

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