Optimal HVAC Building Control with Occupancy Prediction

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Abstract

Buildings account for about 41% of primary energy consumption and 75% of the electricity. Space heating, space cooling, and ventilation are the dominant end uses, accounting for 41% of all energy consumed in the buildings sector. Growing interest in sustainability has resulted in research efforts to reduce energy consumption while providing adequate comfort to users.

In this work, we present a Model Predictive Control (MPC) framework for optimal HVAC control that minimizes energy consumption while staying within the comfort bounds of the occupants. The novelty of our approach lies in the use of prediction occupancy models derived from data traces and incorporating those models within the MPC framework. We use a Blended Markov Chain (BMC) occupancy prediction model in order to predict thermal load and occupancy of each zone in the building. We test our approach in simulation and compare it with occupancy schedules and control rules currently use in our university buildings. Our preliminary results show that 15.5% savings in cooling in the summer, and 9.4% savings in heating in the winter are achievable when conditioning the building using our MPC/BMC control framework.

Categories and Subject Descriptors

I.6.5 [**Simulation and Modeling**]: Model Development; J.7 [**Computers In Other Systems**]: Command & control

General Terms

Experimentation, Measurement, Performance

Keywords

Model Predictive Control, Occupancy, HVAC

1 Introduction

In the U.S., the buildings sector accounts for about 41% of primary energy consumption and 75% of the electricity, 44% more than the transportation sector and 36% more than the industrial sector. Space heating, space cooling, and ventilation (HVAC) are the dominant end uses, accounting for 41% of all energy consumed in the buildings sector. HVAC systems are ideal candidates for applying advanced controls to reduce energy consumption. Previous work [5, 9, 6] has evaluated the potential of MPC to get energy savings for HVAC systems. [7, 3] have also explored the use of occupancy prediction models. However, none of the previous work has evaluated the use of an occupancy estimation model from building occupant data traces in a MPC framework. In our work, we used the BMC [4], which can predict occupancy counts and thermal load for each zone, and use the prediction outputs in our MPC formulation.

This work focuses on MPC of buildings' HVAC systems over a system of thermal zones. The main idea of MPC is to use a model of the plant to predict the future evolution of the system [8]. At each discrete sampling time, an open-loop optimal control problem is solved over a finite horizon. The optimal command signal is applied to the process only during the next sampling interval. At the next time step a new optimal control problem based on new measurements of the state is solved over a shifted horizon. MPC has become the standard in industry for complex constrained multivariable control problems. Its success is largely due to its ability to handle hard constraints on control inputs and states [10].

2 HVAC System Model

The HVAC system considered is a single duct variable air volume (VAV) with terminal reheat system shown in Fig. 1. There is a system wide variable speed supply fan or central air handling unit (AHU) that pushes air through a cooling coil (water-to-air heat exchanger) to cool the supply air. The AHU's fan speed determines the total supply air flowing into the system. This air gets distributed to each zone and passes through *VAV box*, which consists of a heating coil and a damper. The former changes (heat) the air temperature to its final zone supply temperature, and the latter determines the amount of flow supplied to each zone at the supplied zone temperature. From each zone, after the air is mixed with the zone's air, the air is sent back to the loop. The mixed exit air recirculates back through a return duct. In general, the return air is cooler than ambient temperature on a hot day when cooling is required, and hotter than ambient temperature on a cold day when heating is required. Hence, it is

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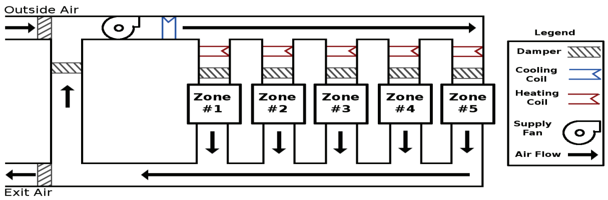

Figure 1. VAV Terminal Reheat HVAC System

more efficient to recirculate as much of this air as possible subject to some minimal outside air exchange to reduce the CO2 and other gas levels. This operation is part of the *economizer* operation, and it is controlled by 3 dampers, the exit, return and the outside air dampers.

The MPC zone temperature and HVAC model used is based on [6] with some modifications. In our model, we revised the heat transfer to include only the outside temperature applied to zones with a surface area exposed to the outside wall. This difference in temperature is significantly larger than inter-zone heat transfer when those zones are conditioned. In addition, we also included further constraints with respect to the occupancy schedules, since these are now controlled by our BMC prediction model and require different temperature settings for occupied and unoccupied zones.

Thermal Zone Model: We start by developing the thermal zone model. The heat transfer between a zone and the outside environment is

$$\begin{aligned} R &= U_{oa}A_{oa} \\ H &= R(T_{oa} - T_z) \end{aligned} \tag{1}$$

where U_{oa} is the heat transfer coefficient from outside to the zone, A_{oa} is the surface area that is exposed to the outside, T_{oa} is the outside temperature, and T_z is the zone temperature.

The continuous temperature dynamics of a zone, based on previous work [6] is given by

$$M\frac{d}{dt}T_z = -T_z(R + c_p\dot{m}_z) + \dot{Q} + T_{oa}R + c_p\dot{m}_zT_s \tag{2}$$

which includes a thermal load $\dot{Q}$, the mass air flow to the zone $\dot{m}_z$, the heat capacity of the air c_p, the thermal capacitance of a zone M, the temperature of the air supplied to the zone T_s, and the heat transfer as mentioned above.

We discretized Eq. 2 using the trapezoidal method to get

$$M\frac{T_z^+ - T_z}{\Delta t} = -\frac{T_z^+ + T_z}{2}(R + c_p\dot{m}_z) + Q + T_{oa}R + c_p\dot{m}_zT_s \tag{3}$$

where T^+ is the temperature at the next time step, and by reorganizing it we get zone temperature dynamics

$$T_z^+ = \frac{2T_zM + \left[(2T_{oa} - T_z)R + c_p\dot{m}_z(2T_s - T_z) + 2\dot{Q}\right]\Delta t}{2M + (R + c_p\dot{m}_z)\Delta t} \tag{4}$$

Cost Function: The goal is to condition the room while minimizing the cost. The system wide cost is dependent on the power used by cooling, heating, and the fan. The power to cool the air is system wide and is based on the total mass flow $\dot{m}_s$ with a cooling efficiency η_c and the amount needed to cool the mixed air as shown below:

$$P_c = \frac{c_p}{\eta_c}\dot{m}_s(T_m - T_c) \tag{5}$$

The total power consumption due to heating is based on the difference between the cooling temperature and the supplied air temperature given a heating efficiency of η_h for each zone as shown below:

$$P_h = \sum_{i=1}^{n}\frac{c_p}{\eta_h}\dot{m}_{zi}(T_{si} - T_c) \tag{6}$$

The last component is the fan power, which is approximately the total mass flow squared times fan coefficient κ.

$$P_f = \kappa\dot{m}_s^2 \tag{7}$$

Due to the price difference of electricity and gas, there are separate coefficients to turn the power into cost in dollars. The cost conversion of electricity is written as r_e and for gas is written as r_h. We assume that cold water is produced by electric chillers, and hot water by a gas-powered boiler. This is the setup we currently have in our campus. The total utility cost from time t to time $t + N\Delta t$ is

$$J = \int_t^{t+N\Delta t} r_e(P_f + P_c) + r_hP_h d\tau \tag{8}$$

At each time step this cost is being minimized while staying within the system constraints (see below). We could also have included a penalty factor for peak electricity consumption, but we have left this analysis for future work.

Occupancy and Load Prediction: Both the thermal load and comfort constraints are related to the occupancy of a zone. A BMC model is used to predict occupancy. It consists of a Markov model where the states represent the occupancy vector for all zones (e.g. state 304 means zone 1 has 3, 2 has 0, and 3 has 4 occupants). The transition probabilities are determined by the training data in hourly blocks since they change over time. A kernel function is used to smooth state transitions over the entire day. For further details see [4]. Using this BMC occupancy model we can get the predicted occupancy, Op over a fixed number of time steps creating a matrix of size N. The thermal load, $\dot{Q}$, is a vector containing the loads through each time step such that $\dot{Q} = \{q_1, q_2, ..., q_N\}$ where q is a thermal load. A thermal load vector is held for each zone. Each thermal load is created by applying a thermal coefficient, c_{occ} to the number of occupants. Hence, the load can be calculated by using the predicted occupancy as $q_i = c_{occ}.op_{ij}$, with op_{ij} being the number of occupants predicted by the BMC model for zone i at time step j.

Each zone contains a vector of predicted upper and lower temperature bounds based on occupancy. The constants $\overline{T}_{occ}$ and $\underline{T}_{occ}$ are based on the Fanger's predicted mean vote (PMV) model as stated in ASHRAE Standard 55 [2]. PMV is a method for finding the comfort level of occupants from hot at +3 to cold at -3. To comply with ASHRAE Standard 55 [2], we keep the PMV between -0.5 and 0.5. A temperature between these PMV bounds means that the occupants do not feel too hot or cold.

Constraints: Due to control restrictions and actuator limits, the system states and control inputs are subject to the following constraints:
C1: $\underline{\dot{m}}_s \leq m_s \leq \overline{\dot{m}}_s$, minimum overall ventilation requirement and maximum fan capacity.
C2: $\underline{\dot{m}}_{zi} \leq m_{zi} \leq \overline{\dot{m}}_{zi}$ $\forall i \in \{1, \cdots, n\}$, minimum ventilation

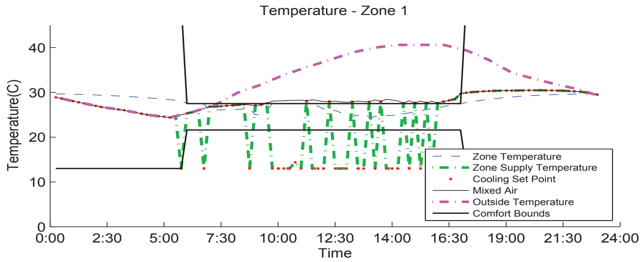

Figure 2. Baseline Conf. Room's Temperature

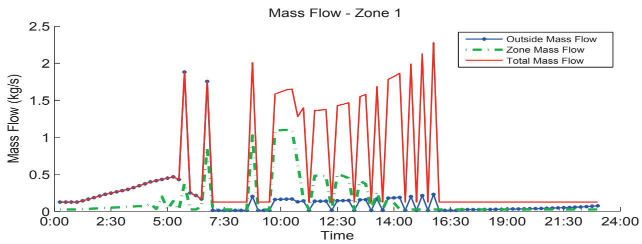

Figure 3. Baseline Conf. Room's Mass Flow

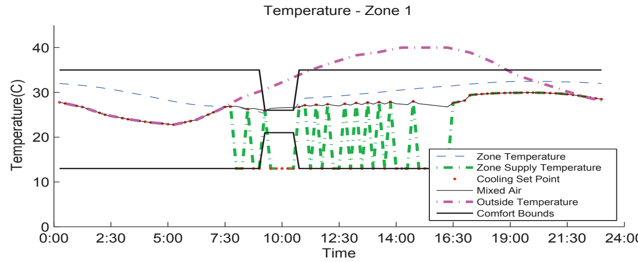

Figure 4. BMC Conf. Room Temperature

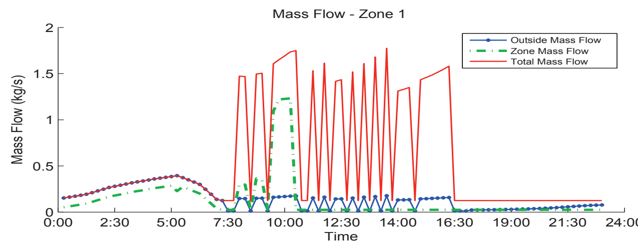

Figure 5. BMC Conf. Room Mass Flow

requirement and maximum VAV box capacity.
C3: $T_{si} \geq T_c \ \forall i \in \{1, \cdots, n\}$, heating coils can only increase temperature.
C4: $T_{si} \leq \overline{T}h \ \forall i \in \{1, \cdots, n\}$, heating coil capacity.
C5: $T_c \leq T_m$, cooling coil can only decrease temperature.
C6: $T_c \geq \underline{T_c}$, cooling coil capacity.
C7: $0 \leq d_r \leq \overline{d_r}$, minimum is no recirculation, maximum set by required fresh air for indoor air quality.

Many of the values in the PMV calculation are difficult to acquire, such as occupants' clothing coefficient and metabolic rate, so we used fixed constants. The constants used are 0.1 m/s air speed, 50% humidity, 1.2 metabolic rate, and 0.5 clothing coefficient. We assume an uniform metabolic rate per occupant and do not believe that people will have an increased metabolic rate in an office environment. We found the upper and lower temperature bounds to meet comfort constraints to be $\overline{T}_{occ} = 27.5°C$ and $\underline{T}_{occ} = 21.5°C$ in an occupied situation. For an unoccupied zone the upper and lower temperature bound is $\overline{T}_{unocc} = 36.5°C$ and $\underline{T}_{unocc} = 18.5°C$, respectively, in order for the bounds to fall within ANSI/ASHRAE/IESNA Standard 90.1-2004 [2].

$$\overline{T}_{zi} = \begin{cases} \overline{T}_{occ} : if(op_i > 0) \\ \overline{T}_{unocc} : if(op_i == 0) \end{cases} \quad (9)$$

$$\underline{T}_{zi} = \begin{cases} \underline{T}_{occ} : if(op_i > 0) \\ \underline{T}_{unocc} : if(op_i == 0) \end{cases} \quad (10)$$

C8: $\underline{T}_{zi} \leq T_{zi} \leq \overline{T}_{zi} \ \forall i \in \{1, \cdots, n\}$, comfort range.

3 Simulation Results

Simulation Setup: An occupancy schedule was set for the 5 zones. One zone was a conference room and the remaining were offices. We used several weeks of data traces for each type of zone in order to train the BMC model.

The outside temperature is based on two separate weather traces retrieved from [1] at Fresno, CA. A summer trace was collected for the entire month of June 2010 and a winter trace for the month of December 2010. Fresno is located in the central valley of California and typically has temperatures around $10°C$ in the winter and around $38°C$ in the summer. Currently we do not consider the impact due to solar gain and we will evaluate this in future work.

We run two simulations based on different occupancy knowledge. The first one (Baseline) is a baseline that assumes an occupied schedule in all zones from 6am to 6pm. This is compatible with our current campus building control policy. The second one (BMC) uses the BMC model in order to predict the occupancy of each zone for the day. With occupancy data, we can aggressively condition the room based on its current and *predicted* occupancy.

In order to simulate the building based on the control inputs provided by the MPC solution at each time step, we use the same MPC thermal model previously developed and use its state outputs to be the new state inputs into the MPC framework at the following time step.

Simulation Results: We start by discussing the specific results on the conference room zone, which is the zone that has the most potential for energy savings without sacrificing quality of comfort for users. Fig. 2 shows the different temperatures (zone, zone supply, mixed air), as well as the temperature comfort bounds the cooling set points as a function of the time of the day for an average day. We see that the system tries to maintain the zone temperature within the comfort zone over the occupancy period pre-defined from 6am to 6pm. Fig. 3 shows the zone, total building and outside mass flow of the system as a function of the time of the day. By taking a look at the zone mass flow (green dotted line), we see that zone temperature is maintained by short bursts of cool air at 7:00, 9:00, 10:00, 11:00, 12:30, and 14:00, with decreasing burst size over time. Throughout the day the supply temperature is low due to the cool air needed for other zones. Although the supply temperature is low, the conference room only includes a small amount of air to meet ventilation requirements. The total system mass flow (red solid line) is larger, since the short bursts are also used to cool down the other zones (not shown) and the aggregate flow must be larger to cover all zones' needs. The outside mass flow remain increases in the early morning before 7:30am, when the early morning cool outside temperature provides opportunities for energy savings, but afterwards it remains

Season	Zone	Type	Cool Fan (kWh)	Heat (thm)	Cost (USD)	Savings
Summer	Conf.	Base	1276	0	$174	49.4%
		BMC	647.7	0	$88	
	Office	Base	891.5	0	$121	3.3%
		BMC	861.1	0	$117	
	All	Base	4842	0	$659	15.5%
		BMC	4092	0	$557	
Winter	Conf.	Base	45.52	232.4	$264	23.9%
		BMC	41.03	175.7	$201	
	Office	Base	36.46	251.0	$289	8.0%
		BMC	36.82	235.4	$266	
	All	Base	191.4	1236	$1398	9.4%
		BMC	188.3	1117	$1266	

Table 1. Energy usage in multiple zones and seasons

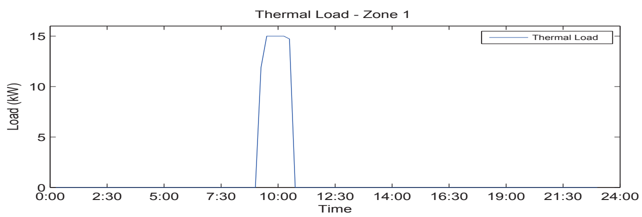

Figure 6. Conference Room's Thermal Load

closer to zero (although not completely zero since the air must be refreshed to remove CO_2 and other gases) since the outside temperature remains high during most of the day and there are few opportunities to use the economizer.

Figs. 4 and 5 show the same temperature and mass flow relationships as a function of the time of the day for a typical day and the conference room zone. In this case, we use the BMC model to predict occupancy. In this particular day, the conference room was only used from 9:15 to 10:30 with a big meeting, and the thermal load as a function of the time of the day is shown in Fig. 6. We can see that the room is properly conditioned within the comfort bounds during the meeting, but the controller then let the temperature float outside the occupied comfort temperature since the model predicts no one will use the room in the afternoon. This can be clearly seen in Fig. 5, where the zone mass flow (green dotted line), remains close to zero after 10:30. Similarly to the previous figures, the total mass flow (red solid line) still produces bursts in the afternoon to cool down the remaining zones. The outside air mass flow has a similar behavior already explained above. It is clear that with a fixed occupancy schedule used in our baseline strategy, energy is being wasted to condition a room that is not being used. Using the BMC occupancy prediction model, we can accurately condition when the room is predicted to be occupied.

We want to explore what would be the overall potential energy savings for different seasons. We run simulations for 1 month in the summer and 1 month in winter to evaluate the different control strategies with prices of $1.11 per therm and $0.136 per kWh. Table 1 summarizes our results.

For the summer, the heating cost is nearly negligible due to the heat transfer from outside hot air. Similarly, the electricity cost is much smaller in winter due to the lack of cooling required. If we compare the savings obtained by BMC in the conference room we can see a 49.4% in cost savings. Interestingly, we also see a smaller savings in the remaining zone offices (3.3%). This smaller savings in other zones can be attributed to allowing the conference room's temperature to float. By doing this, the temperature gets warmer in the conference room, increasing the mixed air temperature that is returned into the system. So although we see large savings in the conference room, there is a cost distributed to the other zones in order to cool this higher mixed temperature. The resulting savings for cooling for summer ends up being 15.5%.

During the winter months, we can see a cost decrease of 23.9% in the conference room and a decrease of 8% in the offices when comparing the Baseline to BMC strategy. However, we also notice that the electrical cost (fan and cooling) is similar for the BMC strategy. This is due to the optimizer trying to minimize the cost of heating by recirculating air from zones with high thermal loads. In the BMC the office zones are mostly occupied during the day, and are therefore constantly being conditioned, so the ventilation is increased from this area in order to benefit other rooms such as the conference room.

4 Conclusions and Future Work

In this paper, we introduce a MPC framework for optimal HVAC control that uses occupancy prediction models derived from occupancy data traces and minimizes energy consumption while staying within the comfort bounds of the occupants. We test our approach in simulation and compare it with occupancy schedules and control rules currently use in our university buildings. Our preliminary results show that 15.5% savings in cooling in the summer, and 9.4% savings in heating in the winter are achievable when conditioning the building using our MPC/BMC control framework.

The long term plan is to deploy the MPC framework in a real building, using occupancy sensors and users' comfort feedback, and define the model constants using system identification techniques. We also plan to introduce stochastic model predictive control techniques that can take advantage of our model uncertainty estimates in the control process to increase performance.

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