Predictive Setpoint Optimization of a Commercial Building Subject to a Winter Demand Penalty Affecting 12 Months of Utility Bills

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Abstract

This paper discusses the implementation of model predictive control (MPC) in a small commercial building in a heating dominated climate. The goal of this study is to investigate the potential of MPC for lowering electricity bills in commercial buildings under the typical rates applied in Québec, which include a demand charge that heavily penalizes winter peaks. Two slightly different cost functions target the minimization of the utility rate during each prediction horizon while meeting upper and lower indoor temperature constraints. A parametric study indicated that despite minor differences all studied MPC scenarios result in significant reductions in both yearly utility bills and peak power demand.

Introduction & Objectives

This paper investigates how model predictive control (MPC) can be used to lower electricity bills in commercial buildings under the typical rates applied in Québec. The goal is to evaluate the potential of MPC in buildings of common construction, without any high-tech features, technologies or systems. In Québec, Canada, where greater than 99.8% of the electric power is generated through hydroelectric plants (Hydro-Québec, 2016a), it is not unusual to find commercial buildings using electricity as their only energy source. This is a result of low electricity rates, high fuel prices and limited distribution of gas in certain regions. It is estimated that heating in the commercial and institutional building sector accounts for 9% of the province's winter peak demand (Hydro-Québec Distribution, 2012). These buildings represent a significant portion of the electric load in the province. During winter, peak loads associated with space heating impose a heavy burden on the grid. Thus, there is increasing interest in demand response strategies, especially on cold winter days.

A particular aspect of commercial customer rates in Québec is that the building's winter peak demand can affect the utility bill for an entire year. The minimum billing demand charged in the electricity bill is set at 65% of the peak power recorded during the winter (Dec 1 – Mar 31) falling within the previous 12-month period. This rule means that special attention must be given to the control strategies over the winter period.

MPC is an established control technique in other engineering fields such as chemical processing and electrical engineering (Qin & Badgwell, 2003) and is a promising strategy for improved controls in buildings. It has received increasing attention in buildings research but has yet to become a mainstream practice.

MPC is a multivariable control algorithm that uses an internal dynamic model of the system, a history of past control moves, forecasts of future disturbances (i.e. weather forecast) and an optimization cost function that is minimized over the receding prediction horizon. The basic principle of MPC in buildings is that knowledge of forecast weather and anticipated occupancy enables better control of the building energy systems, for example, by better managing thermal storage capabilities. Because of the number of variables and constraints that must be considered, optimization can become quite complex. Setting up a suitable building control model is crucial for MPC. The degree of modelling effort is difficult to assess in advance as each model is typically tailored for one specific building. MPC design requires expert knowledge on building modelling, such as good understanding on what details are appropriate to include or exclude in the control model.

Several modelling environments are suitable for MPC studies, all with their own advantages and disadvantages. This point has been addressed by Perera et al. (2016) in a paper comparing MATLAB and Modelica. However, one major aspect still incomplete in the field of MPC and building control research is an effective way to visualize the process flows, which hinders the ability to easily convey research results to a wide audience. This is a topic of ongoing research and development.

Previous studies

The potential of MPC to improve energy management in buildings has been amply demonstrated over the last decade (Cigler, Tomáško, & Široký, 2013; Donghun & Braun, 2012; Kummert, André, & Nicolas, 2001; Oldewurtel et al., 2012). MPC studies have often focused on the operation of active energy storage (ice banks, chilled water tanks, etc.), mostly for cooling applications, and typically under time-of-use rates (Touretzky & Baldea, 2014). Moroşan et al. (2010) studied a multi-zone building and compared the effectiveness of combining decentralized and centralized control structures to a distributed approach. This results in one information exchange per time step, good control performance and low computational requirements. Hou et al. (2016) also studied a variation (distributed) from the typical centralized MPC and implemented their control technique in a real case study.

Huang, Chen, & Hu, (2016) implemented robust MPC (RMPC) which incorporates knowledge on the system uncertainty to enhance the performance stability of MPC. They found that the implementation of RMPC is hindered by the additional computational burden.

Jorissen and Helsen, (2016) acknowledged the challenges of setting up the required MPC controller model for each building, and that expertise is typically required for this step. They suggest a Linear Automated Toolchain for MPC (LAT-MPC) that allows to highly automate the process of setting up a controller model and running a linear MPC.

Sturzenegger et al. (2016) show a noteworthy example of a successful MPC deployment in a real building. MPC was implemented for three summer months in an office building in Switzerland. The experimental data show that the MPC operated reliably and successfully maintained adequate comfort levels for occupants. The simulation study suggests a superior control performance compared to the original control strategy.

This paper addresses an issue that has seldom been investigated in previous MPC studies: the long-term impact of a relatively short-term optimization.

Objectives

As mentioned above, the goal of this study is to determine if the implementation of MPC can be useful for lowering electricity bills in commercial buildings under the typical rates applied in Québec.

This paper investigates, for the case of an electrically-heated building, the reduction of the annual energy bills associated with the combined effect of energy price, demand charges, and a minimum monthly billing charge based on the winter peak. While other MPC studies have used an objective function combining both an energy price and a demand charge (Braun, 1990; Cai, Braun, Kim, & Hu, 2016), our goal was to examine how an MPC algorithm with a short-term horizon can offer benefits in the long-term electricity bill.

The building introduced in this study was previously investigated by Lavigne et al. (2014), who used an offline demand response approach to optimize the operation of the building to reduce the building's total power demand during peak periods while maintaining comfort for occupants.

Simulink, MATLAB's graphical environment, is used in this study to model and visualize the MPC process. Simulink is a graphical programming environment for modelling, simulating and analysing multi-domain dynamic systems. Its primary interface is a graphical block diagramming tool and a customizable set of block libraries.

The main objectives of this study include:

- To investigate the performance of an MPC algorithm for the planning of setpoint trajectories in a commercial building under utility rates commonly used in Quebec, and in a heating-dominated climate.
- To investigate how a short-term optimization of a few days might impact annual electrical energy bills. For instance, a high peak in winter has an effect on the electricity bill even in the summer months.
- To perform a sensitivity study on how the length of the prediction horizon affects the overall cost.
- To explore the potential of a graphical interface (Simulink) to test predictive control and showcase its performance, For example, the simulation will continuously display the projected monthly bill based on energy use and the maximum power measured since the end of the last billing period.

Building Description

This study is based on an existing 427 m^2 (4,600 ft^2) single storey commercial building built in 2009, shown in Figure 1. The building is located 150 km north of Montreal in Trois-Rivières, Canada, and is used as a retail bank establishment. The wall insulation is 3 $K{\cdot}m^2/W$ (R-17), roof insulation is 6 $K{\cdot}m^2/W$ (R-34) and it is slab on grade construction. The windows are double-glazing with low-e coating and an air gap or 12.7 mm. The building has an average energy consumption of 269 kWh/m^2 and a maximum power demand of about 50kW. The building is an all-electric building conditioned with convective heating and cooling systems. It is serviced by three rooftop units: two for heating and cooling and the third for cooling only The third unit is an assembled system recirculating air with a condenser on the roof for cooling and services an unoccupied zone, thus requiring no fresh air. In addition, there are terminal reheat units and baseboard heaters throughout the building.

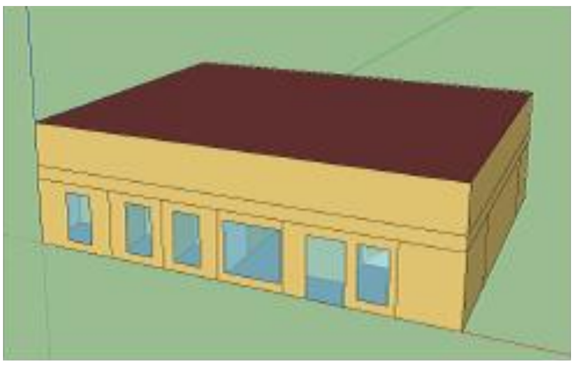

Figure 1: Rendering of the building (Lavigne et al., 2014)

The building's winter daily load profile follows the typical pattern of buildings in this region. A nighttime set back of the temperature setpoint is initiated during unoccupied times as a method to reduce overall energy consumption and is brought back to levels that are more comfortable just before occupants arrive. While this strategy is aimed at reducing energy use, it results in high peak demand in the morning when the temperature is raised (e.g., from 18°C at night to 23°C during the day).

Electric Utility Rate: Effect of Winter Peak

There are several utility rates available, depending on their overall energy consumption and peak power demand. This study will concentrate on the rate structure labelled Rate M (Table 1) by the utility provider (Hydro-Québec, 2016b).

Rate M has a demand charge and two different energy prices: one for the first 210,000 kWh and a second for any remaining consumption. This rate has the particularity that, at any given month, the minimum demand charge applied is set as 65% of the peak winter load. This rule means that special attention must be given to the control strategies over the winter period.

Table 1: Structure of utility Rate M

Rate M (Medium Sized Business Customers)	
Demand Charge ($Cost_{Demand}$):	\$14.37 / kW
Price of energy ($Cost_{Energy}$)	
• **First 210,000 kWh**	4.93¢ / kWh
• **Remaining**	3.66¢ / kWh

Methodology

This study makes use of MATLAB and Simulink (MATLAB'S graphical simulation environment), as a tool to investigate and evaluate MPC strategies.

For this exercise, a simple Resistance-Capacitance (RC) thermal network is used to model the building using the explicit finite difference method and is employed as the "simulation model" (i.e., intended to represent as accurately as possible the building's response). The model is based (calibrated) on real measurement data at 15-min intervals of whole-building power demand.

A second low-order model (a "control-oriented" model) is used to search for a near optimal temperature setpoint schedule over a prediction horizon of 1-2 days, thus leveraging the thermal mass of the building.

A fully explicit finite difference approach was used to solve the energy balance equations at each node in the model. Equation (1) and (2) were used for nodes with and without a thermal capacitance term, respectively.

$$T_{i,p+1} = T_{i,p} + \frac{\Delta t}{C_i}\left(Q_{s,i} + \sum_{k=1}^{n} \frac{T_{k,p} - T_{i,p}}{R_{k,i}}\right) \qquad (1)$$

$$T_{i,p+1} = \frac{Q_{s,i} + \sum_{k=1}^{n} \frac{T_{k,p}}{R_{k,i}}}{\sum_{k=1}^{n} \frac{1}{R_{k,i}}} \qquad (2)$$

Simulation Model

The building was modelled as a single zone with five effective thermal capacitances (one for the air, one for the exterior walls and roof, one for interior partitions and two for the concrete floor slab). The effect of solar radiation on the behaviour of the building was also incorporated into the model. It is assumed that 50% of solar radiation transmitted through the windows is absorbed by the floor while the other 50% is absorbed by the other five interior surfaces. It is also assumed there is a carpet over the concrete floor slab.

The simulation model plays the role of the "real building" and facilitates rapid simulation studies of MPC strategies. The simulation model (Figure 2) was fed the temperature setpoint found by the control model (used for the optimization calculations). The Simulink PID controller block was used to model heating/cooling control.

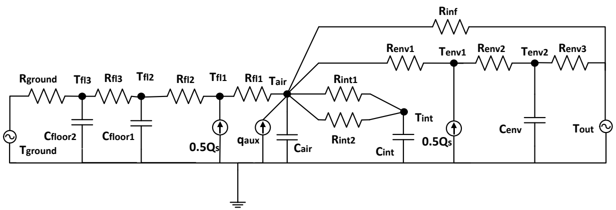

Figure 2: Simulation model schematic

Control Model

A second RC thermal network model was developed for the control model (Figure 2). This second model was slightly less detailed and consisted of four effective thermal capacitances. Details of the two RC thermal models can be found in Table 2. The purpose of this control model is to predict the optimal operation of the building for a future prediction horizon based on the current state of the building and forecasts of future disturbances. A cost function is minimized over a prediction horizon in order to determine optimal control moves (i.e., setpoint schedule) calculated for a control horizon. This identified setpoint schedule is then sent to the "real building" (simulation model) for the time steps corresponding to the next control horizon.

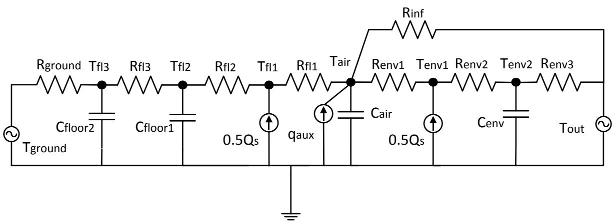

Figure 3: Control model schematic

The heating control for the controller model (Figure 3) was approximated with proportional-integral control. In proportional-integral (PI) control, commonly used in buildings, the auxiliary heating or cooling is equal to the error between the setpoint temperature and the actual zone temperature multiplied by a proportional constant plus the magnitude of the error and the duration of the error multiplied by an integral constant.

$$Q_{\text{aux},i} = K_{\text{p}} \cdot e_i + K_{\text{int}} \cdot \sum_{i=1} (e_i \cdot \Delta t) \tag{3}$$

where:

K_{p} = proportional control constant

K_{int} = integral control constant

Δt = control simulation time step

and

$$e_i = T_{\text{sp},i} - T_{\text{air},i} \tag{4}$$

where:

$T_{\text{sp},i}$ = air temperature setpoint at time step i

$T_{\text{air},i}$ = actual measured (or calculated/predicted) air temperature at time step i

Table 2: Details of the two RC thermal models

	Control Model	Simulation Model
Order	4	5
Time Step	5 minutes	15 seconds
Controller settings	PI controller coded in MATLAB script	Simulink PI controller block
CV-RMSE	14.1%	10.4%
NMBE	-2.8%	2.2%

It is acknowledged that the simulation model and control model are quite similar to one another. Nevertheless, in this investigation, the main objective is to study the building operation results based on the objective function that incorporates the Rate M electricity cost structure and it suffices to have two slightly different models to illustrate this point. The intention is to analyse whether whole year utility charges can be reduced when this cost function is implemented into the optimization routine of the control model.

The MPC simulation was "warmed up" for several days before gathering the results for the whole year simulations. This allows enough time for the models to thermally stabilize and give suitable representative results. At the beginning of each control horizon, the current states of the simulation model are fed to the control model as initial conditions. This allows the control model to have knowledge of the current building operation at the start of the new control horizon.

The statistical indices of CV-RSME and NMBE were used for the model validation process. ASHRAE Guideline 14 (Gillespie et al., 2002) suggests that a CV-RMSE below 30% and NMBE below 10% on an hourly basis ensures a calibrated model (shown in Table 2).

System Disturbances

Real and predicted disturbances (namely weather data for this investigation) typically differ slightly from one another. To consider the inaccuracies of weather forecast into the prediction control model, noise was added to the real weather data of outdoor air temperature and solar radiation using the *rand()* and *randi()* functions within MATLAB, as shown in Figure 4 and Figure 5 for four winter days.

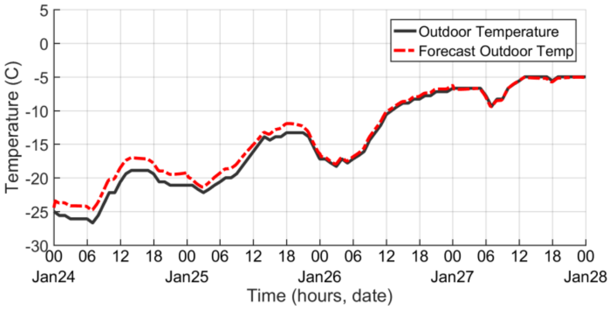

Figure 4: Outdoor temperature and forecast temperature for four winter days

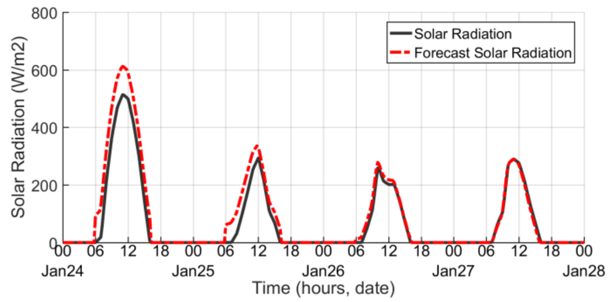

Figure 5: Solar radiation and forecast data for four winter days

Cost Functions & Constraints

MPC studies have often focused on the operation of active energy storage (ice banks, chilled water tanks, etc.), mostly for cooling applications, and under time-of-use rates, but in this study a more unique cost function was implemented. Two cost functions have been executed and their results compared. The first cost function implemented is shown in equation (5) and is based on the Utility Rate M described in Table 1.

$$J_{PH} = \left(\sum_{i=1}^{N} P_i \Delta t \right) \cdot \left(\text{Cost}_{\text{Energy}} \right) + \max(\mathbf{P}) \cdot \left(\text{Cost}_{\text{Demand}} \right) \tag{5}$$

In winter, the electricity peak demand in Quebec occurs on weekday mornings between 6 a.m. and 9 a.m. and weekday evenings between 4 p.m. and 8 p.m. For this study, the morning peak was investigated, as evening peaks largely occur from residential customer demands.

The objective function that incorporates a demand penalty between 6 a.m. and 9 a.m. is shown in (6).

$$J_{PH} = \left(\sum_{i=1}^{N} P_i \Delta t \right) \cdot \left(\mathrm{Cost}_{\mathrm{Energy}} \right) + 0.5 \cdot \max(\mathbf{P})_{\mathrm{PeakHours}} \cdot \left(\mathrm{Cost}_{\mathrm{Demand}} \right) + 0.5 \cdot \max(\mathbf{P}) \cdot \left(\mathrm{Cost}_{\mathrm{Demand}} \right) \quad (6)$$

An objective function such as the one proposed in Equation (6) should be applied with some caution, as it might result in shifting the peak to a different time.

Where *PH* is the prediction horizon (24, 36, 48 hours etc.), *N* is the number of time steps over the prediction horizon, P_i is the power demand at time *i* and Δt is the simulation time step. The setpoint is constrained by a lower and upper bound to ensure comfort for the occupants. An optimized setpoint schedule is identified at 1-hour intervals, from prediction control simulations at 5-minute intervals. This optimization is repeated at periodic intervals (e.g., 6 hr).

Real-Time Optimizing Algorithm

The MATLAB function *fmincon* finds the minimum of a constrained nonlinear multivariable function. The optimization algorithm identifies a setpoint schedule at hourly intervals. These identified values are then fed to the simulation model ("real building") and linearly interpolated to a time interval of 15 seconds (the time step used in Simulink).

Prediction and Control Horizons

The optimal control problem is solved periodically by looking ahead at the expected weather over the "prediction horizon" (i.e., the period for which we have future information, ranging from a few hours to a few days). Then, by solving an optimization algorithm based on the data corresponding to the prediction horizon, the MPC strategy determines an optimal sequence of control moves. These moves are applied to a "control horizon", which is often shorter than the prediction horizon. The simulation proceeds by applying the calculated "moves" over the duration of the control horizon. At this point, the optimization exercise is performed again for the next prediction horizon. This sequence of events is repeated until the end of the simulation time (e.g., one year).

It was assumed that operation of the building during the months from May through September is always the same as the original operation. In other words, the MPC set up for this study was only applied to the winter operation (because of the rate M structure, this also affects the summer energy bill). The topic of enhanced operation during the summer will be studied in future work.

Results & Discussion

A parametric analysis has been performed on combinations of the control horizons (update frequency) and prediction horizons. First, different combinations were evaluated with the first cost function in equation (5) under temperature constraints. These scenarios are shown in Table 3. Next, the same combinations were evaluated with the cost function in equation (6), shown in Table 4.

The yearly utility bill and peak power reduction (in percentage) is outlined in both of the above tables. In general, all MPC scenarios result in similar significant reductions in both utility bills and peak power demand. For example, it is seen that scenario 2 with a control horizon of 12 hours and a prediction horizon of 24 hours results in a cost savings of 25% and a peak power reduction of 38%, simply by implementing a new optimized temperature schedule every 12 hours.

Table 3: MPC results for varying update frequencies and prediction horizons

Scenario #	Control Horizon (hr)	Prediction Horizon (hr)	Yearly Utility Bill ($)	Peak Reduction (%)
REF	**N/A**	**N/A**	**$12,889**	**N/A**
1	6	24	$9,709	36%
2	12	24	$9,647	38%
3	24	24	$9,684	38%
4	6	36	$9,828	35%
5	12	36	$9,695	36%
6	24	36	$9,722	36%
7	36	36	$9,648	37%
8	6	48	$9,783	36%
9	12	48	$9,646	36%
10	24	48	$9,637	36%
11	36	48	$9,649	37%
12	48	48	$9,659	37%

Table 4: MPC results for varying update frequencies and prediction horizons (add penalty during peak hours)

Scenario #	Control Horizon (hr)	Prediction Horizon (hr)	Yearly Utility Bill ($)	Peak Reduction (%)
REF	**N/A**	**N/A**	**$12,889**	**N/A**
13	6	24	$10,019	36%
14	12	24	$9,825	37%
15	24	24	$9,773	37%
16	6	36	$10,058	36%
17	12	36	$9,916	35%
18	24	36	$10,048	30%
19	36	36	$9,779	35%
20	6	48	$10,037	36%
21	12	48	$10,048	35%
22	24	48	$10,148	30%
23	36	48	$9,789	36%
24	48	48	$9,738	36%

Figure 7 shows a comparison between typical operation and MPC scenario 2 of the heating load for four winter days. The weather details of these four days are shown previously in the System Disturbances section.

Figure 8 shows the optimized set point of scenario 2. The main difference between the typical temperature setpoint schedule and the optimized setpoint schedule is a preheating of the building in the hours prior to the start of occupation and a slightly reduced temperature during occupied times.

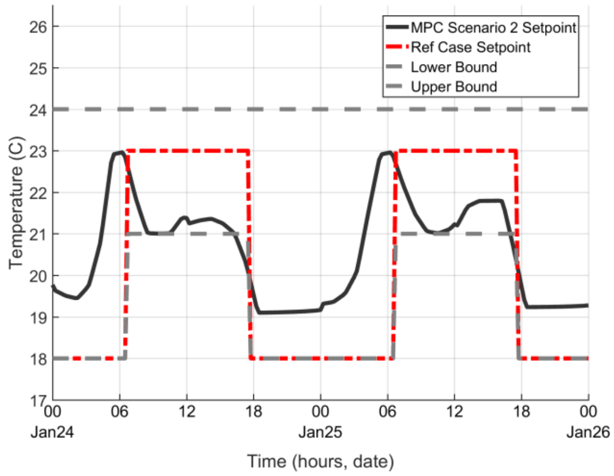

Figure 6: Typical vs. MPC optimized temperature setpoint for two cold winter days

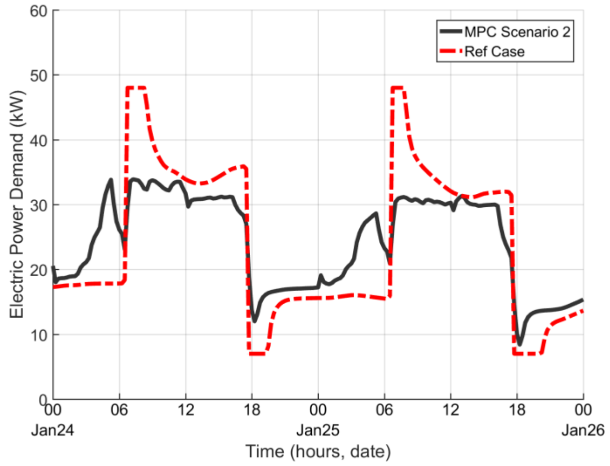

Figure 7: Power demand with and without MPC for two cold winter days

Effects of MPC on the monthly utility bill

As shown in Figure 8 for MPC scenario 2, there is significant peak reduction during every winter month, and the effect of this on the yearly utility bill is shown in Figure 10. By reducing the 12-month winter peak (from 54.5 kW to 33.9 kW), not only are the winter month utility bills reduced, a reduction in the summer month utility bills is also observed. Even though the peak demands in the summer months have not been reduced, the summer month bills depend on maximum peak over the previous 12-month period. It is also evident that overall building energy consumption for the 12-month period is slightly decreased (Figure 9). By implementing MPC during the winter months, the overall utility bill for the year can be reduced by 25%; results of each month are shown in Figure 10 in Canadian dollars.

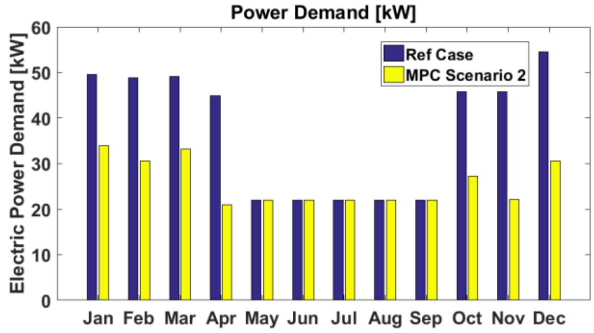

Figure 8: Monthly peak demand for MPC scenario 2 (control horizon = 12h, prediction horizon = 24h)

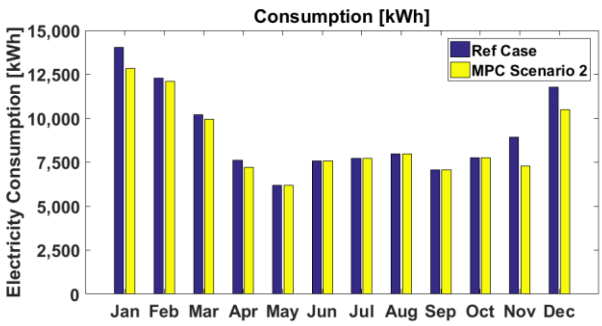

Figure 9: Monthly consumption for MPC scenario 2 (control horizon = 12h, prediction horizon = 24h)

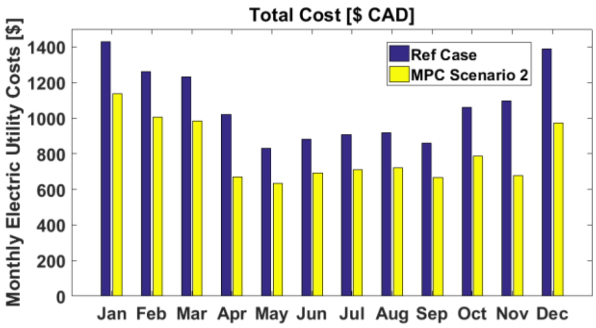

Figure 10: Monthly utility bill for MPC scenario 2 (control horizon = 12h, prediction horizon = 24h)

Effects of MPC on the yearly utility bill

From the implementation of MPC with the two introduced cost functions, the most significant improvement is the reduction in the peak demand, while only slight improvements to energy consumption are found. The main difference between the typical temperature setpoint schedule and the optimized setpoint schedule is a preheating of the building in the hours prior to the start of occupation. By leveraging the thermal storage capacity of the building structural materials, preheating allows to smooth out the peak heating in the morning when the building is transitioning from the unoccupied to occupied time of the day. It is also evident that this incorporation of preheating the building for a few hours, with an optimized temperature schedule, does not increase the overall building's energy consumption.

Though in theory, a more frequent control update should produce the improved results, it seems that a control horizon of six hours is not the most optimal length and a longer control horizon should be used. Update frequencies of 12 hours or more show good results for both cost savings over the year and reduction of the peak demand. There are a number of possible reasons for these results, such as discrepancies between the simulated forecast and the real weather. Another cause could be due to the control model "initializing" more often when a shorter control horizon is used, resulting in an increase of model warm up periods ("stabilization") which occur at the beginning of each prediction horizon. In addition, it is seen that by incorporating increased future information with longer prediction horizons, there are diminishing improvements. The longer prediction horizons (48 hr vs. 24 hr) may have more significant results in a building with a large thermal mass within the building materials than the building used for this study. Realistically, a prediction horizon longer than a few days could not be employed due to the limitations of the accuracy of the weather forecast over longer periods of time. A multi-zone control model will be used in a future study to obtain more accuracy and control options.

The reader should keep in mind that the building used in this study is rather small and is a very standard and basic construction. There are no special features, systems or storage technology, but by simply implementing an optimized setpoint schedule based on weather forecast over a day or two, occupancy schedules and comfort constraints, significant savings and peak power reductions can be achieved. These results could be even more notable in a building ten times larger (e.g. 50,000ft^2), and could result in tens of thousands of dollars of savings in electric utility charges per year.

If MPC is widely adopted in the building operation sector, several advantages can be envisioned. Firstly, as seen from this study, the utility bill of the customer can be reduced by up to 25%. The occupants of the building can obtain improved comfort, and the stability of the electric grid is improved as large heavy loads are now smoothed out over time. For the utility provider, another advantage is the overall energy consumption of the customer is not necessarily lower, while peaking times can be reduced. This allows the utility provider to consider increasing its customer base by inviting customers from out of province, as the surplus of supply will be available anytime of the year. Currently, peaking power days where the demand is greater than supply only occurs a few times per year in the winter in Quebec. If this trend continues and peaking days were to increase due to things such as population increase or infrastructure growth, the province may need to buy electricity from out-of-province utility companies (which would likely come from non-renewable sources) or Hydro-Quebec may need to invest in infrastructure to increase the grid capacity, such as new hydroelectric dams.

Conclusion

This paper presented an example of implementing MPC in a conventional building (a building of basic construction, systems and technologies) with the goal of reducing the yearly utility bill and avoiding the summer peak load penalty given to the customer. Through the software program Simulink, two cost functions were studied with different control and prediction horizons. The cost function aimed to minimize the utility rate during each prediction horizon while meeting upper and lower indoor temperature constraints. Through a parametric study it was seen that longer control horizons (greater than six hours), produced better results for this building. A cost savings of 25% on the yearly electric utility bill and a peak power reduction of 38% were achieved, simply by implementing a new optimized temperature schedule for the building every 12 hours. The main difference between the typical operation temperature schedule and the optimized setpoint schedule is a preheating of the building in the few hours prior to the start of occupation.

The development of self-learning control models for both building response and optimization represents an area of research that has yet to be fully explored in relation to buildings. Learning techniques should help overcome system challenges such as building-use hours, or a change in HVAC (heating, ventilation and air conditioning) equipment that alters the building response. Further research should focus on evidence that directly compares the performance of specific optimization algorithms, parameters (timestep, horizon), and climate forecast accuracy for the same scenario. It is suggested that the sensitivity analysis of timestep and horizon, and climate forecast accuracy be further explored to understand the effects they have on performance. This will enable better methods to minimize and deal with these uncertainties in using MPC for building control. The topic of enhanced operation during the summer months will also be studied in future work.

As there is no standard software available to test and develop control strategies in buildings (Candanedo, Dehkordi, & Lopez, 2013), Simulink, or a similar tool with a graphical interface, may be an option for this problem. In theory, once a flexible and robust structure has been established for the connections between the weather forecast, the control model and the building simulation, Simulink could be used to rapidly test MPC in different buildings (via simulation) by easily swapping out control models and building models within the Simulink file. However, much work is still needed to improve the user-friendliness and flexibility of this approach. For example, considerable care is needed in keeping track of time scales of the various data. The weather data, control model time step, identified schedule time step, and building simulation time step may all be different and thus proper time synchronization is crucial for obtaining reliable MPC simulation results.

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