Energy flexible building: predictive load management of passive and active energy storage under a Demand Response Program

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Abstract

Utility rates for business customers in Quebec include fees for power demand and energy consumption. Therefore, it is in the customer's interest to reduce consumption while properly managing demand. Customers can enroll in a Demand Response (DR) Program to get financial assistance for reducing the demand of their building(s) during winter peak times. A notification is sent to the customer one day before a DR event and the customer can alter their operation to reduce their peak demand during the event hours.

Technologies such as Electric Thermal Storage (ETS) can assist in building heating load management. The device stores energy during off-peak periods to meet future on-peak heating loads. Combining the buildings thermal storage with the devices storage, reductions in heating demand compared to a reference scenario are achieved. Calibrated resistance-capacitance models are used to study heating load flexibility and management to reduce bills and participate in DR programs.

The presented study shows that implementing model predictive control (MPC) with dedicated thermal storage can give energy flexibility to the grid during critical peak events. For example, with a notification is given to the customer from the utility 12 hours ahead of a 6AM event, the peak demand during the critical event hours can be reduced by 29 kW (62%) up to 36 kW (78%), depending on the utility rate structure. It was found that a dynamic rate structure is more successful in reducing the peak demand, while a greater reduction of energy consumption on a 24 hour period is seen with a rate structure with a peak demand charge.

Introduction

As the global focus to decrease Greenhouse Gas (GHG) emissions continues, the demand for cleaner electricity is increasing, however, this puts a strain on electric grids. Recently, utility grids have been incorporating more and more clean renewable energy generating resources as a way to increase their supply, such as photovoltaics (PV) or wind turbines. However, this increase in intermittent production results in a supply side that has variable output at times, creating new challenges for utilities and electricity customers.

Demand side management and Demand Response Programs are popular approaches to incentivize electricity customers - often buildings - to alter their electricity demand during critical times for the grid.

One can quantify or estimate the amount of energy flexibility a building can provide to the grid, and this flexibility can help alleviate strain on the grid at times when demand is nearing or higher than what it can safely supply. IEA EBC Annex 67 introduced the concept of "Energy Flexible Building", defined as *a building able to manage its demand and generation in accordance with local climate conditions, user needs and grid requirements* (IEA, 2020).

One of the major challenges associated with the integration of intermittent distributed renewable energy sources into the utility grid is that the peak consumption periods of buildings seldom coincide with the availability of power generation from these renewable sources. Peak consumption periods (morning and evening) do not coincide with the period of maximum solar generation in the middle of the day, as illustrated by the popular concept of the duck curve (Denholm et al., 2015). Furthermore, the price and the available power supplied by the electric grid are often significantly variable. Similar supply-demand mismatch issues are observed in other regions that are heating dominated, although for different reasons.

In Quebec, Canada, where greater than 99.8% (37.3 GW) of the electric power is generated through hydroelectric plants (Hydro-Québec, 2018), commercial buildings commonly use electricity as their sole energy source. This is a result of low electricity rates, high fuel prices and limited distribution of gas in certain regions. During winter, peak loads associated with space heating impose a heavy burden on the grid. Thus, there is increasing interest in quantifying the energy flexibility of buildings and increase participation Demand Response Programs, especially on cold winter days.

Today it is possible to consider the optimization of the entire electric energy system, not only the grid. This electric system spans from the generation units to the final customer end-uses. Buildings are part of this system as end-uses and can contribute to the energy flexibility of the electric system. Building science and advanced controls must be used to help make this flexibility available to the grid. This study incorporates the concept of Energy Flexible Building and the use of Model Predictive Control (MPC) for buildings in cold climate regions with thermal storage as a dispatchable storage medium.

Literature review

Building load flexibility can be described as the ability to reduce the building energy demand and/or peak load during a certain period of a day through shifting or postponing consumption compared to a reference scenario. Building energy flexibility combined with on site energy storage devices and advanced control strategies is a key factor to optimize energy consumption in order to match the availability of available energy at critical times for the grid (Jensen et al., 2017; Reynders et al., 2018). The implementation of advanced control strategies such as MPC is essential for the optimization of energy consumption while preserving occupant comfort.

In recent years, various international studies on the quantification and utilization of building energy flexibility have been conducted and there is now a breadth of published work in this relatively newly defined area (IEA, 2020).

The adjustability or flexibility of the heating and cooling system has been the subject of many studies. In general, these studies investigate the impact of different DSM strategies either on the building level, (e.g. the occupants thermal comfort or energy and/or cost savings by increasing PV self-consumption) or on the energy infrastructure level (e.g. peak shaving, load shifting, valley filling or mitigation of production losses).

Most studies have looked at the energy flexibility potential of a single building. Le Dréau and Heiselberg (2016) assessed the potential of residential buildings to modulate the heating power and develop control strategies to exploit the flexibility potential, while considering thermal comfort. Two control studies were evaluated: 1) heat storage (i.e. increase of setpoint) and heat conservation (i.e. decrease of setpoint). While Hurtado et al. (2017) proposed a novel approach to quantify the available demand flexibility of individual buildings, while taking into account the underlying building energy physics. This method includes a development of building energy simulations to assess the effects of weather variations, construction types, and comfort constrains on demand flexibility. Studying different climate regions, they found that buildings located in a hot climate could offer higher flexibility potential during shorter time ranges, while buildings in a cold climate could offer lower flexibility potential but during longer time ranges. While others have concluded that specific technologies and parametric optimizations are needed to maximize the potential of energy flexibility residential buildings. Weiß et al. (2019) found that for buildings in Austria built after 1980, 50% of domestic heating peak loads can be shifted to off-peak periods.

Other studies have considered a group of buildings together and the potential aggregated energy flexibility. Vigna et al. (2018) expanded the study of energy flexibility on a single building to a cluster of buildings. This allows for the exploitation of the variation in energy consumption patterns between different types of buildings and the coordination of load shifting. Foteinaki et al. (2018) investigated the physical potential for flexibility of low-energy buildings and analyzed the thermal storage capacity existing in the structural mass. The study showed that low-energy buildings can remain autonomous for several hours and that when many buildings are aggregated together, rather than a stand alone building, the flexibility becomes significant.

Effective control strategies should be able to manage the various systems of a building, including thermal and/or electrical storage devices, and should take advantage of the thermal inertia of the building structure (Junker et al., 2018; Liu and Heiselberg, 2019; Reynders et al., 2017). The operation of a building is directly affected by the fluctuations in weather and occupancy, which result in large load fluctuations between day and nighttime (which in turn yield large fluctuations in the electricity demand). To deal with these fluctuations, a good understanding of the dynamic behaviour of buildings and a focus on energy management (rather than simply indoor temperature control), is necessary.

Concept of Building Energy Flexibility Index (BEFI)

Building control can take advantage of thermal mass to shift power consumption from one critical period to another. Different end-uses can be rescheduled before or after a specific period without adverse impact, such as a reduction of thermal comfort. We can think also of specific systems within HVAC (Thermelec for example) or embedded in the building like heavy radiant floor that can be used to shift energy consumption without affecting occupant comfort. When coordinating these different systems, future or expected needs, availabilities and constraints that may depend on occupant activity schedule, weather, grid state, day in week, etc must be considered. Model predictive control is an optimal tool to achieve this.

The most current application of energy flexibility is demand response to face peak demand during the period of high demand on grid. A Building Energy Flexibility Index (BEFI) could be used to quantify potential participation of a customer for such a demand response event.

BEFI is an informative concept in a simulation to identify relevant actions to be undertaken to maximize flexibility from a building for the electric grid.

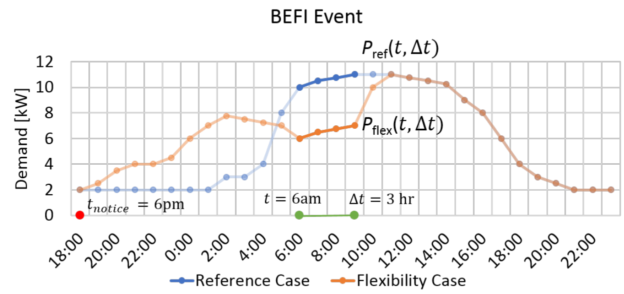

Figure 1: Example: Building Energy Flexibility Index

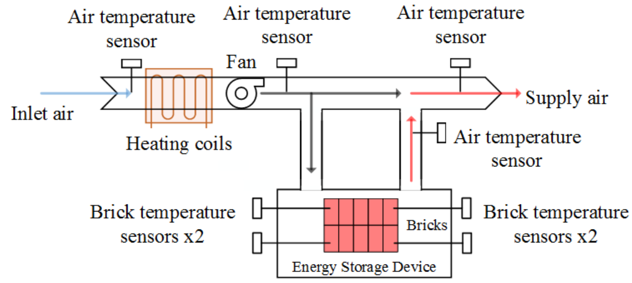

Figure 2: HVAC system with ETS and temperature sensor locations (Date et al., 2020)

Optimization could be done to maximize the index at specific period of time. It may become a valuable aid to support decision regarding relevant equipment or systems to be installed in a building.

A well-designed index would help to quantify the flexibility available from a building, to improve its design to increase the potential flexibility, to control the building in order to get maximum available flexibility when needed and to compare different systems or designs. A depiction of a demand response event is shown in Figure 1. Equation (1) shows a representation of the BEFI used in this paper.

$$BEFI\,(t, \Delta t, t_{notice}) = \min[P_{flex} - P_{ref}]_{,during\ DR\ event} \quad (1)$$

where $BEFI$ is the Building Energy Flexibility Index, t is the start time of event, Δt is the duration of event, t_{notice} is time of notification for the event, P_{ref} (kW) is the power demand from the reference scenario during an event, and P_{flex} (kW) is the power demand from a flexibility case during an event. As a conservative value, the $BEFI$ is minimum difference between the power demand of the reference case, P_{ref} and the power demand of the alternative "flexibility scenario", P_{flex}, for the given event duration Δt, shown in equation 1. The available power to the grid will always be equal to BEFI or greater during the critical period. BEFI could also be represented as a percentage by dividing it by the value of P_{ref}. A revised definition and less conservative equation is explained in (Athienitis et al., 2020) and (Date et al., 2021).

Methodology

This study was carried out in several steps. First, real building measurement data was collected from the (BAS. Data included such things as building power kW, zone air temperature, weather data, and specific data related to the ETS in question. Next, numerical thermal building or device control-oriented models were developed. These models are physics-based ROM grey-box RC thermal networks. These models were then calibrated using the collected data from the first step. Critical parameters were identified using the gradient descent based optimization function *fmincon* in MATLAB. A detailed explanation of the model development process for the ETS device is found in (Date et al., 2018, 2020). The last step was to identify control studies for optimized peak load management and building energy flexibility by quantifying the BEFI depending when a signal from the utility is given to the customer (building owner). A heuristic approach and is compared to optimized control MPC using *fmincon* in MATLAB.

Case study

The building used in this study is a warehouse section of a larger office building. The building is located in Sherbrooke, Canada, and the warehouse section is equipped with an air-based ETS device. This two-storey building, built in 1989, has a total floor area of 9,000 m^2. Measurements at 15-min intervals have been collected since 2014. The peak load of the building was measured in February 2015 at 600 kW, with a monthly consumption of 166 MWh. The on-site 106 kW ETS can supply hot air to a specific warehouse area within the building. The warehouse zone serviced by the ETS has a floor area of 1650 m^2.

The warehouse zone is conditioned by the air-based system shown in Figure 2. Air temperatures are measured throughout the HVAC system and brick temperatures are measured in four locations. When the ETS is in use, part of the air supply is drawn through the device to provide additional heat energy to the zone.

ETS systems convert electrical power to stored heat during low electricity price periods (or when demand on the grid is low) and provide heat to the building during peak demand periods (Moffet et al., 2012). They can provide a significant reduction of the electricity bill when there exists a demand charge in the utility pricing structure (Bedouani et al., 2001; Syed, 2011) or take advantage of dynamic tariffs. ETS systems use bricks as a medium to store heat from electricity and release heat from the bricks to the building when the electricity supplies are expensive. The air-based ETS device in this study has a maximum charging input of 106 kW and a storage capacity of 640 kWh.

Control-oriented thermal model

The control-oriented models of the ETS described below are based on two-dimensional lumped parame-

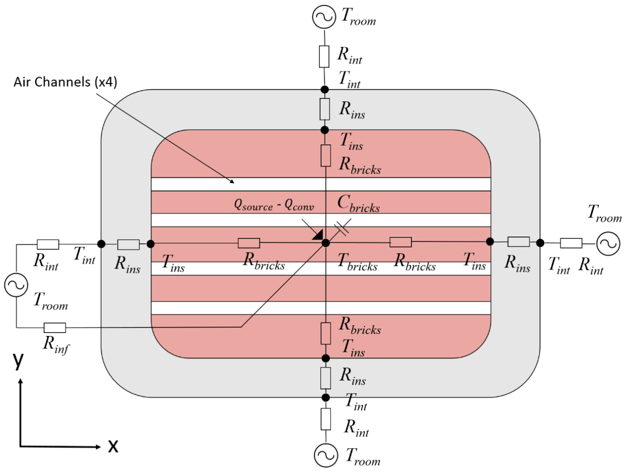

Figure 3: Top view of ETS 1-capacitance thermal model (Date et al., 2020)

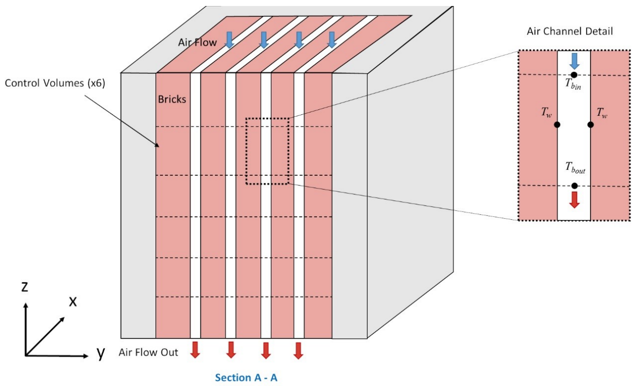

Figure 4: Side view schematic of brick discharging model (Date et al., 2020)

ter equations for heat conduction and energy conservation. These models use a grey-box modeling approach, where physically-meaningful parameters are calibrated with measurement data.

The developed MATLAB code was written to easily modify the order of the model: the two-dimensional grid of brick thermal capacitance nodes can be adjusted by specifying how many rows and columns of brick nodes are wanted. The resulting number of brick capacitance nodes is then the number of rows multiplied by the number of columns. An example of the 1-capacitance model is shown in Figure 3. Figure 4 shows the side view schematic of the bricks in the ETS. The heat transfer from bricks to airflow of the ETS system was modeled using the general equation for heat exchange through a channel (Lienhard Iv and Lienhard V, 1986).

Electricity is passed through the wires embedded in the bricks to charge the ETS device. The wires heat up the bricks, transferring thermal energy to the bricks. The lumped parameter finite difference method used in this study is based on a space discretization of the material into control volumes, where a node is located at the centroid of the control volume. The heat flux between adjacent nodes is described by using resistance analogies: the flux is calculated as proportional to the difference between the temperature of the two nodes. Between control volumes, the conductance is calculated as kA/L, where k is the thermal conductivity of the material, A the area of the surface of contact and L is the distance between adjacent nodes. If the node has considerable thermal mass, it is assigned a thermal capacitance, representing the heat storage capacity of the control volume.

A fully explicit finite difference approach was used to solve the energy balance equations at each node in the models, where it is assumed that the current temperature of a given node depends only on its temperature and the temperature of the surrounding nodes at a previous time step. The term with the time derivative can then be discretized as follows:

$$C_i \frac{dT_i}{dt} \approx C_i \frac{\Delta T_i}{\Delta t} = C_i \frac{T_i^{p+1} - T_i^p}{\Delta t} \tag{2}$$

By solving for temperature at the next time step $p+1$, the general equation for control volumes with capacitance terms is:

$$T_i^{p+1} = T_i^p + \frac{\Delta t}{C_i} \left[Q_i^p + \sum_{j=1}^{n} \frac{T_j^p - T_i^p}{R_{i,j}} \right] \tag{3}$$

where Q_i represents the heat generated at a node i or received directly by it from source(s), $R_{i,j}$ represents the thermal resistance between nodes i and j (either conductive or convective terms), T is the temperature at node i or adjacent node j, and C is the thermal capacitance at node i ($C = \rho c_p A dx$). n is the total number of adjacent nodes to node i.

Due to high brick temperatures of up to 871 °C, there are non-negligible heat losses from the ETS device to the ambient air of the mechanical room. There are both convective and radiative losses from the device to the room which are calculated using simplified heat transfer coefficient equations (4) (American Society of Heating Refrigerating and Air-Conditioning Engineers", 2009), and (5), where $T_{surface}$ is the mean value of the surfaces of the walls in the mechanical room ($T_{surface}$ is assumed to be the same temperature as room air temperature).

$$h_{conv} = 1.26 \cdot |T_{int} - T_{room}|^{1/3} \tag{4}$$

$$h_{rad} = \epsilon\sigma \cdot \left(T_{int}^2 + T_{surface}^2\right) \cdot \left(T_{int} + T_{surface}\right) \tag{5}$$

The heat transfer from bricks to airflow of the ETS system was modeled using the general equation for heat exchange through a channel (Lienhard Iv and Lienhard V, 1986). T_w (temperature of the wall surface of the channel) in this case is taken as the average brick temperature T_{brick}, h is the convective heat transfer coefficient between channel surface and air in the channel, P is the perimeter of the channel and L is the length of the channel. If $T_{b_{out}}$ is replaced by $T_{b(x)}$, L is replaced by $Z(i)$, and h is adjusted accordingly, the above equation can give the variation of air bulk temperature ($T_{b_{out}}$ and $T_{b_{in}}$) along the channel as a function of the distance from the inlet (x) . Temperatures at the exit of each control volume are calculated as follows:

$$T_{b_{out}}(p,i) = T_w(p) + [T_{b_{in}}(p,i) - T_w(p)] \cdot e^{\frac{-2 \cdot Z(i)}{a(p)}} \quad (6)$$

$$\text{where } a(p) = \frac{M(p)c_p\rho}{Wh(p)} \text{ and } h = \frac{Nu \cdot k}{DH}$$

Nu is the Nusselt number, k if the conductivity of the brick and DH is the hydraulic diameter of the air channel. The energy extracted from the bricks in the air channels (which is subtracted from the brick node energy balance equation) is calculated as follows:

$$Q^p_{conv} = 4 \cdot M(p)c_p\rho \left[T_{b_{out}}(p,L) - T_{b_{in}}(p,0)\right] \quad (7)$$

The exit temperature of each channel section, $T_{b_{out}}(p,i)$, is used as the inlet temperature of the next section, $T_{b_{in}}(p,i+1)$. It was found that a model with at least six sections was necessary to follow the measured data and produce accurate outlet air temperature results.

As an example, in the case of Figure 3 (1-capacitance model) the following equation (8) calculates the temperature at the next time step of the brick node:

$$\begin{aligned} T^{p+1}_{bricks} = T^p_{bricks} + \frac{\Delta t}{C_{bricks}} \Big[Q^p_{source} - Q^p_{conv} \\ + 4 \cdot \frac{1}{R_{bricks}} (T^p_{ins} - T^p_{bricks}) \\ + \frac{1}{R_{inf}} (T^p_{room} - T^p_{bricks}) \Big] \quad (8) \end{aligned}$$

For further details regarding model development, calibration methodology and model performance, refer to work presented in Date et al. (2020).

Electricity rates in Quebec

There are several utility rates available, depending on the energy consumption and peak power demand of a building, or group of buildings owned by the same customer. Rate M, which is for the large commercial building sector, has a demand charge and two energy prices (Hydro-Québec, 2020), as outlined in Table 1. A unique feature of this rate is that at any given month, the minimum demand charged applied is set as 65% of the peak winter load. This means that appropriate attention should be given to the operation strategies over the winter period where peak demand is highest due to large space heating loads.

Table 1: Structure of utility rate M (Hydro-Québec, 2020)

Rate M Large Commercial Building Sector	
Demand Charge	\$14.37 / kW
Price of Energy:	
- First 210,000 kWh	4.93 ¢/ kWh
- Remaining	3.66 ¢/ kWh

Table 2: Structure of utility rate Flex G

Flex rate G Small power commercial building sector		
	Summer period: Apr. 1 - Nov. 30	**Winter period: Dec. 1 - Mar. 31**
Price of energy used outside peak demand events	9.90 ¢/ kWh	8.26 ¢/ kWh
Price of energy used during peak events	N/A	50.00 ¢/ kWh

Rate Flex G, which is outlined in Table 2 is a newly released dynamic rate that can save the customer money if they are able to change their operation from typical behaviour. Electricity is cheaper than the base rate in winter, except during peak demand events, when it is more expensive. Rate Flex G applies to contracts with no billing demand or with a minimum billing demand of less than 65 kW.

Though Flex Rate M has not yet been released, if we were to extrapolate from the Flex Rate G shown in Table 2, a Flex Rate M can be proposed with a winter period cost at a 17% reduction from the summer period price, as shown in Table 3. In this study, Rate M and Rate G will be used as cost functions in order to identify parameters that will minimize the cost to the building owner due to utility prices.

MPC Strategies

Currently, the control of the power charging input to the ETS is determined based on a linear scale function relating outdoor temperature to the power input, as shown in Table 4.

By incorporating predictions of occupancy and weather over the next day or two into the control sequence, optimal values of the maximum ETS charging input at each hour will be identified that will minimize electricity costs. Simultaneously, the zone temperature profile is identified, which minimizes the following cost functions.

Two cost functions incorporating the aforementioned utility rate structures have been implemented and their results compared to the typical manual control currently in place.

Table 3: Structure of utility rate Flex M

Flex rate M Large Commercial Building Sector		
	Summer period: Apr. 1 - Nov. 30	**Winter period: Dec. 1 - Mar. 31**
Price of energy used outside peak demand events	4.93 ¢/ kWh	4.09 ¢/ kWh
Price of energy used during peak events	N/A	50.00 ¢/ kWh

Table 4: Control of ETS power input: scale function

$\mathbf{T_{ext}}$	$\mathbf{P_{ETS}}$	**Brick Temperature**
0 °C	0%	93 °C
-18 °C	**100%**	871 °C

The first MPC cost function relates to the utility rate M in Table 1 and is shown in equation (9).

$$
\begin{aligned}
\min_{T_{SP},\, P_{ETS,maxSP}} \quad & \left(\sum_{i=1}^{N} P_i \Delta t\right) \cdot (\text{Cost}_{\text{Energy}}) \\
& + \max(\mathbf{P}) \cdot (\text{Cost}_{\text{Demand}}) \\
\text{subject to} \quad & T_{SP,min} \leq T_{SP} \leq T_{SP,max} \\
& 0 \leq P \leq P_{max} \\
& 0 \leq P_{ETS,maxSP} \leq P_{ETS,max}
\end{aligned} \tag{9}
$$

A second cost function to consider is the minimization of the electricity cost for the proposed Flex Rate M shown in Figure 3. This cost function has no minimization element related to peak power, and rather has a variable energy cost over the day, with a higher cost during peak hours specified by the utility.

$$
\begin{aligned}
\min_{T_{SP},\, P_{ETS,maxSP}} \quad & \left(\sum_{i=1}^{N} P_i \Delta t\right) \cdot (\text{Cost}_{\text{Energy},i}) \\
\text{subject to} \quad & T_{SP,min} \leq T_{SP} \leq T_{SP,max} \\
& 0 \leq P \leq P_{max} \\
& 0 \leq P_{ETS,maxSP} \leq P_{ETS,max}
\end{aligned} \tag{10}
$$

Where N is the number of time steps over the prediction horizon PH, P_i is the power demand at time i and Δt is the simulation time step. The objective is to identify two variables that minimizes the cost associated with the utility rate charge: 1) an optimized setpoint schedule for the room temperature T_{SP}, and 2) the maximum charging power input to the ETS, $P_{ETS,maxSP}$. The setpoint is constrained by a lower ($T_{SP,min}$) and upper ($T_{SP,max}$) bound. The demand due to space heating P is constrained by the size of the heating equipment P_{max}. Similarly, the maximum charging power input to the ETS is constrained by the specifications of the device, $P_{ETS,max}$.

Results & Discussion

MPC simulations were carried out over a 48 hour period, with outdoor temperature conditions ranging from -15 °C to -5 °C. For the scenario of a notification given 12 hours ahead, the notification is given to the building owner at 6PM indicating an event on the following day at 6AM and lasting for 3 hours. At the time the notification is given, the MPC algorithm is implemented at an hourly time step in order to identify an optimized zone temperature setpoint profile and an optimized maximum allowable power input for charging the ETS device at each timestep. A similar approach is done when the notification is given 4 hours ahead at 2AM.

Table 5: Simulation Results for BAU and 1) BAU with thermal storage

	BAU without thermal storage	**1) BAU with thermal storage**
Event Peak [kW]	56	22.4
Wh/m^2 in 24 hours	678	850
BEFI [kW/%]	–	27 / 57%

Table 6: MPC Simulation Results for improved operation of ETS and zone temperature setpoint

	2) MPC: Rate M	**3) MPC: Rate Flex M**
12 hours ahead notification (6PM)		
Event Peak [kW]	21.6	13.2
Wh/m^2 in 24 hours	510	700
BEFI [kW/%]	29 / 62%	36 / 78%
4 hours ahead notification (2AM)		
Event Peak [kW]	21.5	17.1
Wh/m^2 in 24 hours	615	703
BEFI [kW/%]	29 / 62%	32 / 69%

Table 5 and Table 6 show the simulation results for the four scenarios. The scenarios 1) BAU with ETS, 2) MPC Rate M, 3) MPC Rate Flex M are compared to the “Business as Usual (BAU)” case without ETS.

Figure 5 shows that implementing MPC with active thermal storage can increase BEFI and give energy flexibility to the grid during critical peak events and operation is also a improved compared to BAU with ETS. As shown in Table 6, with a notification from the utility to the customer given at 6PM (12 hours ahead of an event at 6AM) a BEFI of 62% to 78% is achieved. In other words, the peak demand during the critical event hours can be reduced by 29 kW (62%) up to 36 kW (78%) for 3 hours, depending on the utility rate structure. It was found that Rate Flex M is more successful in reducing the peak demand, while a greater reduction of energy consumption on a 24 hour period is seen with Rate M.

Similarly, with a relatively short notification time of 4 hours, MPC can help reduce the peak demand during the critical hours and can achieve a BEFI of 32 kW (69%) for 3 hours with Rate Flex M (Table 6). The results show that implementing MPC with active thermal storage can increase BEFI and give energy flexibility to the grid during critical peak events.

Conclusion

This paper presented the implementation of MPC strategies to a building equipped with a dedicated active thermal storage device in order to maximize the Building Energy Flexibility the building could provide to the electric grid. Two cost functions were

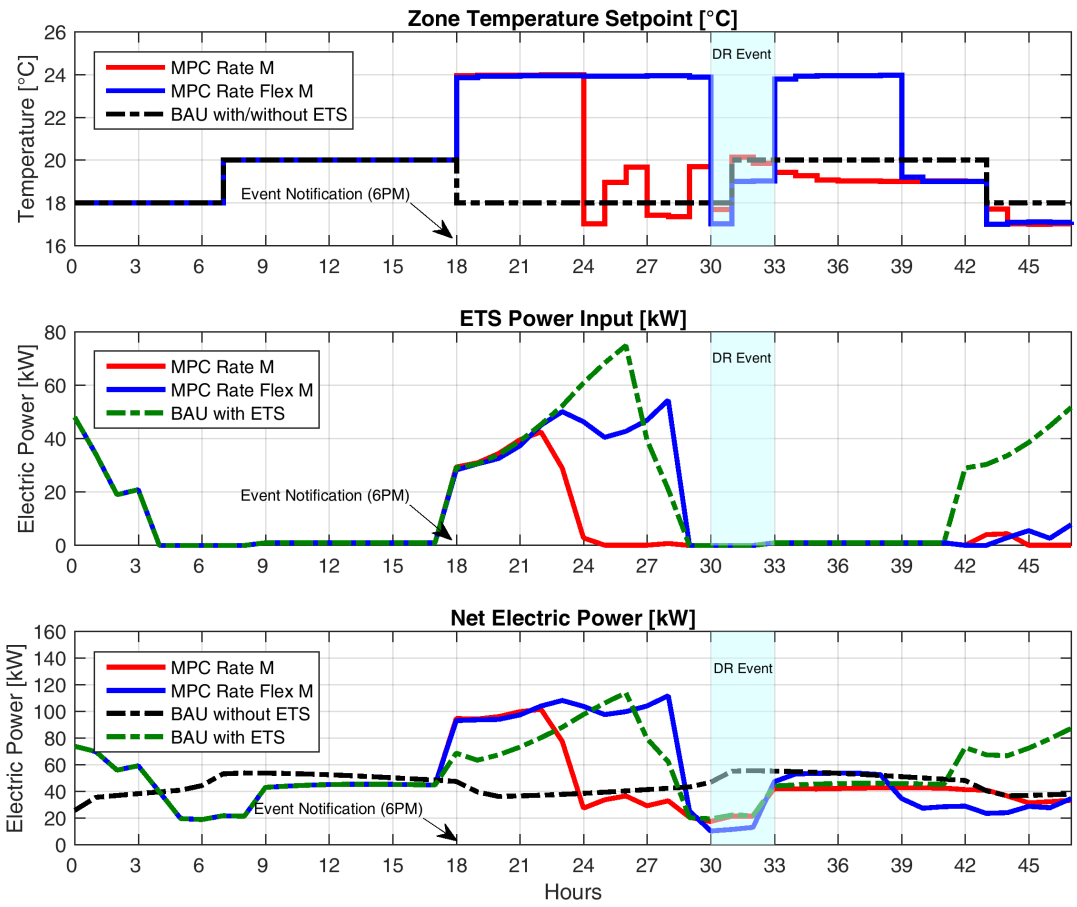

Figure 5: MPC study with notification 12 hours ahead

studied: 1) the minimization of electricity cost subject to a utility rate with peak demand charge (Rate M) and 2) the minimization of electricity cost subject to a utility rate with dynamic pricing (Rate Flex M).

Given a notification four or 12 hours ahead of a demand response event with given duration, MPC was implemented at an hourly time step to identify an optimized zone temperature setpoint profile and an optimized dynamic maximum allowable power input for charging the thermal storage device.

The results show that implementing MPC with thermal storage can increase BEFI and give energy flexibility to the grid during critical peak events and is better than manual control. For example, with a notification from the utility to the customer 12 hours ahead of a 6AM event, a BEFI of 62% to 78% is achieved. In other words, the peak demand the critical event hours can be reduced by 29 kW (62%) to 36 kW (78%), depending on the utility rate structure. It was found that Rate Flex M is more successful in reducing the peak demand, while a greater reduction of energy consumption on a 24 hour period is seen with Rate M. It is seen that optimizing not only the zone profile is important but also optimizing (limiting) the maximum allowable power to the thermal storage device aids in reducing both peak demand and energy consumption of the building.

It should be acknowledged that thermal comfort conditions for the different scenarios are different than that of BAU case and that should be considered when choosing a strategy. Since the zone in this study is a warehouse, more flexibility in the comfort limits could be assumed when compared to an office or residential building.

Though the scope of this study was limited by data availability, the developed methodology could be suitable for other similar convectively conditioned buildings and clusters of buildings for participation in community scale energy aggregator events. A greater focus on occupancy modeling could be incorporated into this methodology in the future. Work still exists regarding widespread implementation of methodologies such as this into real building energy management systems.

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References

American Society of Heating Refrigerating and Air-Conditioning Engineers" (2009). *Ashrae Handbook: Fundamentals*. Atlanta, Ga: Ashrae.

Athienitis, A. K., E. Dumont, J. A. Candanedo, N. Morovat, K. Lavigne, and J. Date (2020). Development of a dynamic energy flexibility index for buildings and their interaction with smart grids. *Proceedings of ACEEE Summer Study 2020 Conference*.

Bedouani, B. Y., B. Labrecque, M. Parent, and A. L. R (2001). Central electric thermal storage (ETS) feasibility for residential applications : Part 2 . Techno-economic study. (June 1999), 73–83.

Date, J., J. A. Candanedo, and A. K. Athienitis (2021). A methodology for the enhancement of the energy flexibility and contingency response of a building through predictive control of passive and active storage. *Energies 14*(5).

Date, J. A., J. A. Candanedo, A. K. Athienitis, and K. Lavigne (2018). Control-Oriented Modeling of an Air-Based Electric Thermal Energy Storage Device. *Proceedings of ASHRAE Winter Conference 2018*. Chicago, Illinois.

Date, J. A., J. A. Candanedo, A. K. Athienitis, and K. Lavigne (2020). Development of reduced order thermal dynamic models for building load flexibility of an electrically-heated high temperature thermal storage device. *Science and Technology for the Built Environment*.

Denholm, P., M. O'Connell, G. Brinkman, and J. Jorgenson (2015). Overgeneration from Solar Energy in California. A Field Guide to the Duck Chart. (November).

Foteinaki, K., R. Li, A. Heller, and C. Rode (2018). Heating system energy flexibility of low-energy residential buildings. *Energy and Buildings 180*, 95–108.

Hurtado, L., J. Rhodes, P. Nguyen, I. Kamphuis, and M. Webber (2017). Quantifying demand flexibility based on structural thermal storage and comfort management of non-residential buildings: A comparison between hot and cold climate zones. *Applied Energy 195*, 1047 – 1054.

Hydro-Québec (2018). Annual Report.

Hydro-Québec (2020). Hydro-Québec - Rates for Business Customers. Available at `http://www.hydroquebec.com/business/customer-space/rates/`.

IEA (2020). IEA EBC Annex 67. http://www.annex67.org/.

Jensen, S. Ø., A. Marszal-Pomianowska, R. Lollini, W. Pasut, A. Knotzer, P. Engelmann, A. Stafford, and G. Reynders (2017). IEA EBC Annex 67 Energy Flexible Buildings. *Energy and Buildings 155*, 25 – 34.

Junker, R. G., K. B. Lindberg, G. Reynders, R. A. Lopes, R. Relan, A. G. Azar, and H. Madsen (2018). Characterizing the energy flexibility of buildings and districts. *Applied Energy 225*(February), 175–182.

Le Dréau, J. and P. Heiselberg (2016). Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy 111*, 991–1002.

Lienhard Iv, J. H. and J. H. Lienhard V (1986). A heat transfer textbook. *Journal of Heat Transfer 108*(1), 198.

Liu, M. and P. Heiselberg (2019). Energy flexibility of a nearly zero-energy building with weather predictive control on a convective building energy system and evaluated with different metrics. *Applied Energy 233-234*(October 2018), 764–775.

Moffet, M. A., F. Sirois, G. Joos, and A. Moreau (2012). Central electric thermal storage (ETS) heating systems: Impact on customer and distribution system. In *Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference*.

Reynders, G., R. Amaral Lopes, A. Marszal-Pomianowska, D. Aelenei, J. Martins, and D. Saelens (2018). Energy flexible buildings: An evaluation of definitions and quantification methodologies applied to thermal storage. *Energy and Buildings 166*, 372–390.

Reynders, G., J. Diriken, and D. Saelens (2017). Generic characterization method for energy flexibility: Applied to structural thermal storage in residential buildings. *Applied Energy 198*, 192 – 202.

Syed, A. M. (2011). Electric Thermal Storage Option for Nova Scotia Power Customers : A Case Study of a Typical Electrically Heated Nova Scotia House. *Energy Engineering 108:6*(March), 69–79.

Vigna, I., R. Pernetti, W. Pasut, and R. Lollini (2018). New domain for promoting energy efficiency: Energy flexible building cluster. *Sustainable Cities and Society 38*, 526 – 533.

Weiß, T., A. M. Fulterer, and A. Knotzer (2019). Energy flexibility of domestic thermal loadsa building typology approach of the residential building stock in Austria. *Advances in Building Energy Research 13*(1), 122–137.