A Practical Data-Driven Multi-Model Approach to Model Predictive Control: Results from Implementation in an Institutional Building

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A Practical Data-Driven Multi-Model Approach to Model Predictive Control: Results from Implementation in an Institutional Building

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ABSTRACT

Model-based Predictive Control (MPC) is an effective solution to improve building controls. It consists of the use of weather and occupancy forecasts along with a control-oriented model to predict the behaviour of the building a few hours or days ahead, and thus optimize the operation of its systems. Although the potential of MPC is widely recognized, and plentiful operational data is often available, the development of a model requires a great deal of effort, significant technical expertise and knowledge of building systems. The challenge of creating a model is a hurdle that makes the on-site implementation of MPC in buildings relatively rare.

This study tackles the development of a multi-model approach to optimize the operation of electric and natural gas boilers in an institutional building to reduce greenhouse gas (GHG) emissions while maintaining the required level of comfort. This methodology leverages Machine Learning techniques to rapidly develop and calibrate control-oriented models using a limited number of input variables (indoor air temperature and temperature set-points, weather conditions, power meter data). The proposed multi-model approach consists of five models used to estimate the building total heating demand, the electric baseload, the natural gas boiler power, and the indoor air temperature under free floating conditions and during warming-up periods in the morning. The models are calibrated and validated with operational data and they are then used to optimize the transition between nighttime and daytime indoor air temperature. Since these are black-box models that require only a basic understanding of the building system and a few inputs, the model development was considerably reduced while the modularity of the proposed method makes it flexible. Such an approach could therefore be easily replicated in other buildings equipped with similar pieces of equipment.

This methodology has been implemented in a Canadian institutional building, located in Varennes (QC). Results in 2020-21 showed that the COVID-19 pandemic has significantly impacted building performance and reduced energy use, thus creating a new baseline. The MPC strategy allowed to achieve an additional 20.2% GHG emission reduction compared to this new baseline while thermal comfort was improved. Nevertheless, energy costs increased, which was mainly due to the impact of the pandemic, which eventually made the pre-COVID-19 model and optimization parameters outdated; lower costs are expected with model recalibration, currently ongoing.

1. INTRODUCTION

In recent years, model-based predictive control (MPC) has received significant attention as a promising pathway to improve energy efficiency and load management in buildings. MPC has often been associated to a laborious modelling approach, a cumbersome formulation of an optimization problem, and a challenging implementation in the building automation system. As a result, MPC is often perceived as expensive and time-consuming. While there have been some success stories in the application of MPC to real cases, this control approach is still not a mainstream practice in the industry.

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The team by Cigler et al. (2013) investigated the problem of the implementation of MPC in two case studies. The authors underscored the suitability of MPC to the supervisory control of building with significant thermal mass using simple models. The need to consider controls at the design stage is also mentioned. The authors illustrated their methodology with two field pilot test cases – a 70,000-m^2 building in Prague, and a 20,000-m^2 office building in Munich. The mathematical models developed for the two cases employed system identification to find state-space models for both buildings. Zacekova et al. (2014) focused on the problem of identifying an appropriate control-oriented model (which requires, among other criteria, sufficient accuracy, repeatability, ease of calibration and implementation within a control algorithm), a central problem for the development of an MPC solution. The authors mentioned the difficulties associated with missing data, faulty sensors, and selected a grey-box approach, in which each of the five floors was modelled with a 3rd order thermal network.

Sturzenegger et al. (2014) presented Building Resistance-Capacitance Modeling (BRCM), a MATLAB® Toolbox for the creation of physical grey-box models for controls. Sturzenegger et al. (2016) presented the results of a comprehensive MPC study in a Swiss office building. The authors employed a bilinear control-oriented model based on physical principles and measured data. The study considered simultaneously thermally activated building systems, ventilation and motorized blinds for the entire building. The authors incorporated a supervisory control layer (reminiscent of the approach presented in this paper). The implementation of MPC was successful, with estimated savings of 17% in comparison with an EnergyPlus benchmark. The authors mentioned that while the effort involved seems too high for most engineering projects, "*a model predictive building automation framework, a modeling tool and the training of engineers*" may push the technology into the net benefit range. It is worth mentioning that the time and effort required to create a model are seldom reported in the literature. This issue is far from trivial since this is a critical consideration for field implementation and eventual mass adoption of MPC.

In Canada, Kavgic et al. (2015) investigated considerations to justify the deployment of MPC in a building; these considerations include significant levels of thermal mass, high ventilation rates, predictable internal and external gains and fluctuations between levels of occupancy. Hilliard et al. (2017) employed a combination of measured data and synthetic data to create a black-box model (random forest) of a 10,000-m^2 building. The resulting model was then used as the control-oriented model of an MPC strategy, focused on "nudging" zonal temperature setpoints. The MPC strategy achieved 29% savings of electric energy and 63% in thermal energy.

Drgona et al. (2020) presented a comprehensive overview of MPC for buildings. This paper contains significant and thorough information on MPC modelling, optimization and performance assessment. The discussion on modelling methods (white, grey, and black-box models) provides an overview of implementation pathways. The authors emphasized the need for multidisciplinary education to enable the widespread adoption of advanced controls.

This paper presents recent results of the implementation of an MPC solution in an institutional building. This approach is based on the identification of relevant control variables for the objective at hand (in this case, the reduction of natural gas consumption), a control-oriented model based on a judicious application of a machine learning approach and the availability of building automation data. This article complements and updates the information presented in the paper by Cotrufo et al. (2020).

2. CASE STUDY

2.1 Building description

The building under study is a Canadian institutional building located in Varennes (Quebec, Canada). This 5,257-m^2 one-story building hosts 120 workstations and 10 meeting rooms, with typical occupancy schedules from 6:30 to 17:30 during working days. To satisfy space heating demand, a 200-kW electric boiler and two 470-kW natural gas boilers are used. In Quebec, electricity is generated from hydroelectric plants, making electricity generation almost free of greenhouse gas (GHG) emissions. Therefore, the electric boiler is operated as the first priority; natural gas boilers are used when heating demand cannot be fulfilled by the electric boiler alone. To avoid significant monthly electric peak demand (which impacts the electricity bill), the total building electric power is kept below a certain limit, the *dynamic electric peak*, which is reset every month based on educated guess values and adjusted when the total building electric power exceeds dynamic electric peak (e.g. high electric baseload). This total building electric power is the sum of the electric boiler power and the electric baseload power, which accounts for occupancy-related activities (workstations, lighting, appliances, plug loads, ventilation, experimental test benches, etc.). When the total building electric demand approaches the "dynamic electric peak", the electric boiler contribution is thus reduced.

The Building Automation System (BAS) collects measurements such as temperatures, flow rates and powers at 10-min intervals. The existing database covers several years, although there is a significant amount of missing values due to technical issues (e.g. network or sensor failures). The building is composed of four main sections, served by four secondary loops connected to the central heating plant. On a typical winter workday, the average indoor air temperature is kept at 22.5°C during the day and lowered to 19.6°C at night. When it is cold outside (i.e. below -5°C), two sections "cancel" the night temperature setback and stay at 22.5°C, which makes an average building indoor temperature setpoint of 21.0°C. In normal operation, the transition between nighttime and daytime occurs at 6:30 a.m., using a sharp setpoint step transition. Since the electric boiler capacity is not able to satisfy the heating demand to achieve such an abrupt change, the gas boilers must be turned on. Such operation is denoted *Business As Usual* (*BAU*) in this paper.

2.2 Predictive control in the building: previous work

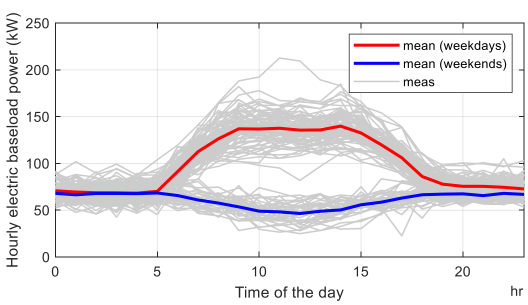
Prior predictive control work was performed and implemented in the building during winter season 2018-19 (Cotrufo & Saloux 2019; Cotrufo et al. 2020). The strategy consisted in optimizing the transition from nighttime to daytime conditions to minimize natural gas consumption. Based on weather forecasts 24 hours ahead, the algorithm used outdoor air temperature predictions to virtually test several indoor air temperature setpoint profiles to go from night setback (19.6°C) to daytime setpoint (23°C) to minimize the use of natural gas.

Simulations were used to study the response of the building in the 24-h period between 18:00 and 18:00 the next day. Different ramps for the transition were tested, ranging from a sudden step to a nearly flat setpoint; the resulting optimal profile leading to minimum gas consumption was then applied at 18:00. For this initial implementation, the total building electric power limit was kept constant at 230 kW. Results showed that 22% natural gas savings were achieved by smoothly warming-up the building using the electric boiler at night, although a 4% additional heating demand was observed. While the tests were successful, several details needed to be addressed. For example, a sharp nighttime-daytime transition at particularly low temperatures may affect occupant's thermal comfort in the morning. Conversely, ramps that are too "smooth" will cause excessive heating consumption in milder weathers.

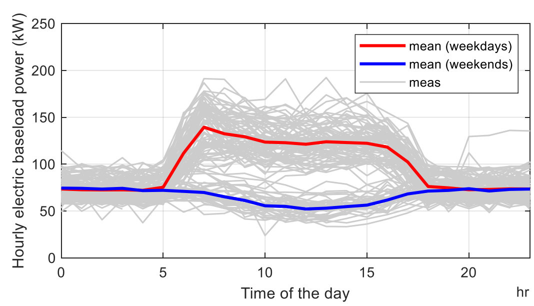
This paper presents an MPC strategy that builds upon the one proposed by (Cotrufo & Saloux 2019; Cotrufo et al. 2020) and the results from the MPC strategy deployment in a real building during 2020-21 winter season. This new MPC strategy includes the following new features: 1) a free-floating model that estimates the average room temperature when building rooms cool down to night setback, 2) a thermal comfort model that calculates the average indoor air temperature at 7:00 and 8:00, 3) a new objective function to avoid excessive heating demand, 4) new temperature setpoint profiles with additional night setbacks, and 5) dynamic electric peak variations.

2.3 Impact of the COVID-19 pandemic

The COVID-19 pandemic had a significant impact on building operation and performance. Most employees have been teleworking since March 2020, but a non-negligible fraction is back in the office. Obviously, such a major change in occupancy affects the building thermal behaviour, specifically, internal gains due to occupants and electric baseload power. However, since this effect is difficult to account for, the same model was used for the implementation. It is worth mentioning that a lower electric baseload power was observed, which might increase the contribution of the electric boiler and thus reduce natural gas consumption. In turn, internal gains due to occupants and lighting are expected to be lower, which might increase building heating demand and natural gas consumption.



(a)



(b)

Figure 1: Hourly electric baseload power as a function of the hour of the day: (a) before COVID-19 pandemic (Nov 2019-Mar 2020), (b) after the beginning of COVID-19 pandemic (Nov 2020-Mar 2021).

Figure 1 shows the electric baseload power as a function of the hour of the day before and after the beginning of the COVID-19 pandemic. These figures show typical profiles during weekdays and weekends, before and after the beginning of the pandemic. The behaviour during weekends (in blue) was barely affected, with a mean value between 47 and 69 kW before COVID-19 and between 52 and 72 kW after the pandemic beginning. During weekdays from 9:00 to 15:00 (in red), the mean value was reduced from 137 kW down to 122 kW. This 15-kW difference, which might correspond to an internal gain reduction, is expected to be available for the electric boiler, when needed. Conversely, there are around 75 fewer occupants in the building, which might account for 6-kW internal gain losses (assuming 75 W/person). A morning peak (139 kW in average) in Fig. 1b can also be noticed.

3. METHODOLOGY

3.1 Control-oriented model

Figure 2 shows the schematic of the new multi-model approach. The control-oriented model developed in previous work (Cotrufo & Saloux 2019; Cotrufo et al. 2020) was composed of three black-box models targeting: 1) the heating demand, 2) the electric baseload and 3) the natural gas boiler power. Different Machine Learning techniques were assessed by Cotrufo et al. (2020) and Gaussian Process Regression (GPR) showed a good promise trade-off between accuracy and flexibility in terms of architecture (essentially, a Kernel function to select) as opposed to artificial neural networks. The model inputs were determined using a combination of thermodynamics considerations, practical issues and correlation analysis. The model inputs were selected so that they are either: (a) non-controllable, but known hours ahead (hour of the day, dynamic electric peak, forecasted outdoor air temperature) or (b) controllable variables (temperature setpoints). It is worth mentioning that all models use hourly average values. The original formulation included these three models:

- The *heating demand* is a function of the outdoor air temperature (OAT), the air temperature setpoint (TSP), and the temperature setpoint variation (dTSP). The latter was included to account for the additional power needed for temperature change. The GPR model used the *ardexponential* Kernel function.
- The *electric baseload* mainly depends on occupancy, which in turn depends on the hour of the day (HH). However, since the "baseload" is calculated as the total electric power minus the electric boiler power, it implicitly includes other heating elements. For this reason, the OAT was also used as an input. Although both the temperature setpoint and electric baseload follow the occupancy, it is worth mentioning that the temperature setpoint was *not* included as an input model, since the proposed approach intends to adjust setpoints independently of occupancy. The GPR model used *exponential* as Kernel function.
- The *natural gas boiler* is turned on when the electric boiler, whose contribution depends on the electric demand margin (see below), does not suffice to fulfill the building heating demand. Thus, electric demand margin (EDM) and heating demand (HD) were used as inputs. The GPR model used *exponential* as Kernel function.

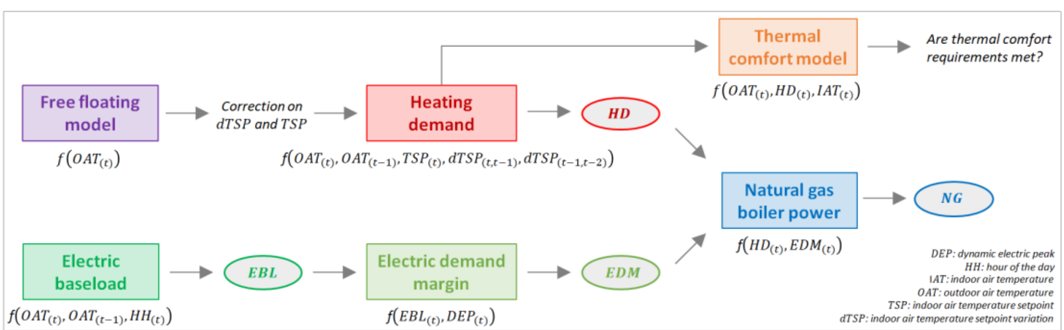


Figure 2: Schematic of the control-oriented model

Three new models were added to the original version: 1) free-floating model, 2) electric demand margin and 3) thermal comfort model.

- The *free-floating model* is a 1R-1C thermal network model (no heat source) that aims to provide a correction on the indoor air temperature setpoint and setpoint variation that are inputs of the heating demand model. This model accounts for the thermal delay of the building and the difference between the setpoint and the real temperature. A "corrected" setpoint is then used as the input for the *heating demand model*.

- The *electric demand margin* is the difference between the dynamic electric peak (DEP) and the electric baseload (EBL), and helps estimate the electric boiler contribution.
- The *thermal comfort model* aims to estimate the building behaviour during the ramp-up period. Indoor air temperature is calculated from 3:00 to 10:00 and model uses outdoor air temperature and heating demand as inputs. The GPR model used *ardexponential* as Kernel function.

3.2 The indoor air temperature setpoint profiles

Figure 3 shows the 21 profiles that were tested as transitions from nighttime (19.5°C) to daytime (22.5°C). As in Cotrufo et al. (2020), starting time of the transition varies (Figure 3, left): it can occur at 6:00 or start earlier at night (up to 19:00). Other profiles consider ramping up at 18:00 at higher night setback (20.5°C, 21.5°C) while another option is a 22.5°C constant temperature setpoint. New temperature setpoint profiles were also included with additional night setbacks at 18.5°C (Figure 3, middle) and 17.5°C (Figure 3, right).

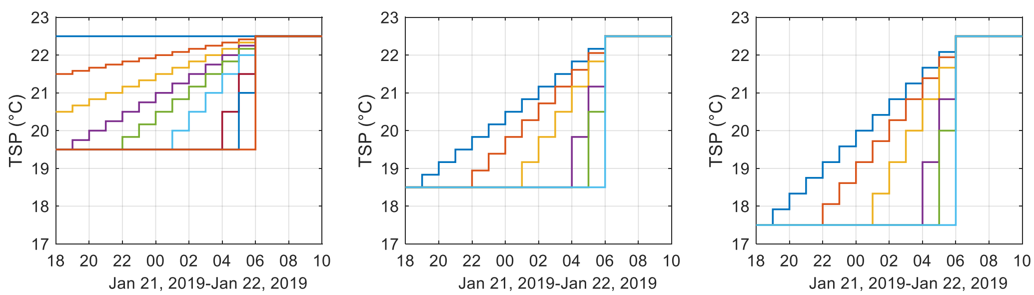


Figure 3: Indoor air temperature set-point profiles tested in the predictive control strategy (left: #1-9, middle: #10-15, right: #16-21; #1: 22.5°C constant setpoint).

3.3 Formulation of the optimization problem

The objective of the predictive control strategy is to minimize natural gas consumption while maintaining or even improving thermal comfort and avoiding excessive energy costs. The optimization problem, which minimizes the function J evaluated over the prediction horizon Λ, is written as follows:

$$\min_{TSP_i} J, \quad \text{where } J = 0.6\left(\frac{\int_t^{t+\Lambda} NG_{TSP_i}(t)dt - \int_t^{t+\Lambda} NG_{BAU}(t)dt}{\int_t^{t+\Lambda} NG_{BAU}(t)dt}\right) + 0.4\left(\frac{\int_t^{t+\Lambda} HD_{TSP_i}(t)dt - \int_t^{t+\Lambda} HD_{BAU}(t)dt}{\int_t^{t+\Lambda} HD_{BAU}(t)dt}\right) \tag{1}$$

$s.t.$

$i \in [1, 21]$

$IAT_{7:00} \geq 21.5°C$

where TSP_i is the i^{th} indoor air temperature profile, NG_{TSP_i} and HD_{TSP_i} are the natural gas consumption and heating demand of the i^{th} indoor air temperature profile, and NG_{BAU} and HD_{BAU} are the natural gas consumption and heating demand under the "Business As Usual" strategy. There is a constraint on indoor air temperature (IAT) at 7:00 (first occupants' arrival), which must be higher than 21.5°C. Weighting factors (0.6 and 0.4) were manually tuned to prevent choosing a profile with a small reduction in natural gas but a high increase in heating demand.

3.4 Predictive control strategy

The MPC routine was written in MATLAB® and was run automatically the evening before each workday (Sunday to Thursday), slightly before 18:00. The indoor air temperature for the free-floating model was assumed to be at 18.5°C at 18:00 on Sunday evenings, and at 22.5°C the other days. The MPC strategy was implemented during the winter season 2020-21, from Nov 12 to Mar 19. The predictive control strategy consists of the following steps:

1- Weather forecasts with a prediction horizon of 24 hrs are retrieved using a software tool developed by Natural Resources Canada (Natural Resources Canada 2017; Candanedo et al. 2018).
2- Dynamic electric peak is retrieved from the BAS.
3- Weather forecasts and dynamic electric peak are used along with the control-oriented model to estimate from 18:00 to 18:00 the next day the objective function associated to each indoor air temperature profile.
4- The indoor air temperature profile that minimizes the objective function is sent to the BAS via a virtual controller and is applied to each room of the building from 18:00 until daytime building operation overrides nighttime operation (6:30).

3.5 Assessment of savings

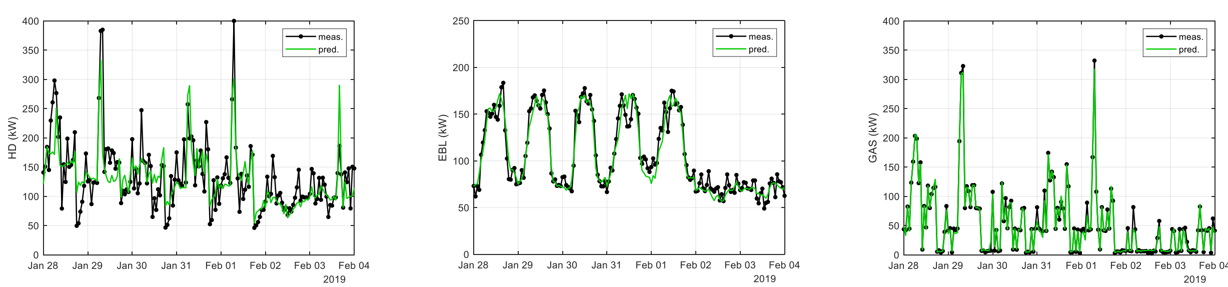
Two benchmark models were used to evaluate building performance on a daily basis: 1) under "*BAU*" strategy before COVID-19 and 2) under "*new BAU*", during the COVID-19 pandemic. The first model helps assess the effects of COVID-19 by providing a pre-COVID-19 baseline. The second model helps evaluate the impact of MPC strategy by providing a *new BAU* baseline. *BAU* models are GPR type and calculate heating demand (*Matern32* Kernel function) and natural gas consumption (*Matern52* Kernel function) as a function of daily average outdoor air temperature; they were trained using 2015-18 data (Cotrufo et al. 2020). *New BAU* models are linear and quadratic type due to the low amount of available data. For the economic analysis, as building peak demand occurs during the day, electricity cost is estimated using only the energy rate (5.03 CAD c/kWh). Compared to previous work (Cotrufo & Saloux 2019; Cotrufo et al. 2020), natural gas price is now based on gas utility average cost over winter months (5.42 CAD c/kWh), which includes transportation, balance fees, etc. Finally, GHG emissions were assumed to be 0.00036 t-CO2eq/GJ for electricity and 0.0507 t-CO2eq/GJ for natural gas.

4. RESULTS

4.1 Model training and validation

4.1.1 Control-oriented models: each model of the multi-model approach was individually calibrated using building operational data, between November 2017 and March 2019. The dataset was cleaned (outliers, missing values, etc.) and non-stratified random partition was used to divide the data into training and validation datasets. For the thermal comfort GPR model, data between 3:00 and 9:00 were considered. For the free-floating RC network model, less data is required and only 2018-19 winter season was considered. Values between 18:00 and 22:00 were considered, when the building was more likely to be in free floating mode. Most of the time, *there is* a heating demand, even when the indoor air temperature is higher than the setpoint; this is most likely a result of local control rules designed to dampen load fluctuations and avoid equipment cycling. It was not considered for the calculation of RC parameters (R=0.560 K/W, C=351,726 J/K, equivalent to a 55-hr time constant) but was kept in the calculation of HD.

Figure 4 shows model predictions at time *t* for one week during winter 2019 for heating load, electric baseload and natural gas consumption and Table 1 gives dataset and model accuracy for each model. Values similar to those provided by Cotrufo et al. (2020) were obtained for HD, EBL and GAS. While EBL and GAS perform well, HD model struggles more to catch peak loads. This can be explained by the fact that the heating demand was calculated with the sum of electric boiler and natural gas boiler contributions, and that natural gas boiler power mainly shows peaks, deduced from pulse readings. For temperature models (free floating, thermal comfort), the error remains below 0.2°C, which fall inside sensor uncertainty range.



(a) (b) (c)

Figure 4: Control-oriented model hourly predictions for one week during winter 2019: (a) heating load, (b) electric baseload, and (c) natural gas boiler power.

Table 1: Control-oriented model dataset and accuracy

Variable	**Heating demand**	**Electric baseload**	**Gas boiler power**	**Free floating**	**Thermal comfort**
Dataset	4305 hourly values (50% for training)			207 hourly values	808 hourly values (50% for training)
RMSE - GPR (train/val)	25.1 / 34.0 (kW)	11.9 / 15.0 (kW)	4.4 / 7.3 (kW)	-	0.12 / 0.22 (°C)
RMSE - RC network	-	-	-	0.14°C	-

Figure 5 shows model results when the outdoor air temperature varied between -8°C and 1°C. Indoor air temperature in free floating mode decreases until it reaches the setpoint and HD only depends on OAT during this period. From this point onwards, TSP and dTSP become inputs of HD model. At 3:00, the thermal comfort model calculates the indoor air temperature for the next 7 hours by considering, as initial condition, that the indoor air temperature is equal to the setpoint. Note that at 10:00 the value is close to 23°C, slightly higher than the setpoint (22.5°C). In fact, the model training was done on a period when the daytime setpoint was 23°C, not 22.5°C. HD is shown in orange and the fraction of HD covered by natural gas (GAS) in blue. PID parameters could have been included in the free floating model but the current model gives a reasonable estimation of the starting time of equipment ramp-up.

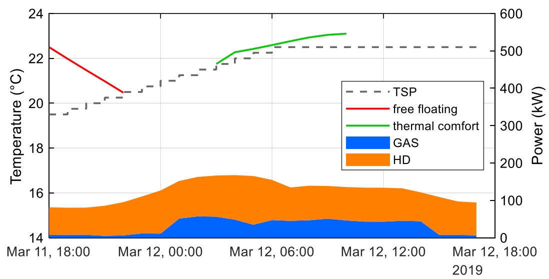
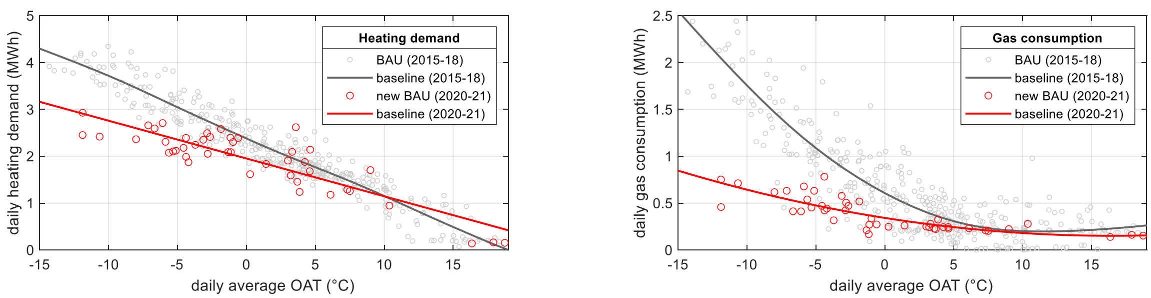


Figure 5: Control-oriented model results for a typical day and a given temperature setpoint profile.

4.1.2 Benchmark models: Figure 6 shows measured data under *BAU* operation (2015-18), *new BAU* (2020-21) and benchmark models (baseline) for daily heating demand and natural gas consumption. Table 2 gives model dataset and accuracy for *BAU* and *new BAU*, which includes pandemic effects. GPR models were based on daily values in 2015-18 (Cotrufo et al. 2020); in turn, the *new BAU* models only considered few values of 2020-21 data. The impact of the COVID-19 pandemic is discussed in the next subsection.



(a) (b)

Figure 6: Benchmark model for building performance under *BAU* and *new BAU*: (a) daily average heating demand and (b) daily average natural gas boiler consumption as a function of daily average outdoor air temperature.

Table 2: Benchmark model accuracy

Variable	**Heating demand (*BAU*)**	**Gas consumption (*BAU*)**	**Heating demand (*new BAU*)**	**Gas consumption (*new BAU*)**
Dataset	369 daily values (70% for training)		45 daily values	
GPR (train/val)	0.269 / 0.255 (MWh)	0.241 / 0.283 (MWh)	-	-
Linear, quadratic	-	-	0.316 (MWh)	0.100 (MWh)

4.2 Energy savings and GHG emission reduction

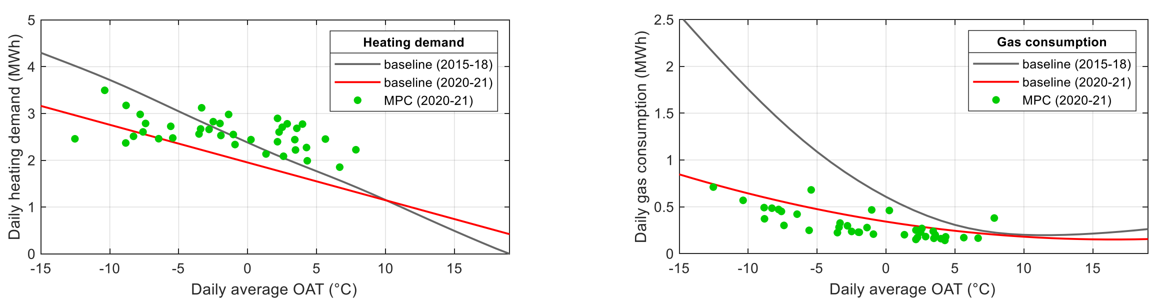
Table 3 and Figures 6-7 show results from *new BAU* and MPC implementation in 2020-21.

- *Effects of the COVID-19 pandemic* can be evaluated by comparing *BAU* with *new BAU* in Table 3, and the grey line (*BAU* baseline) with red dots (*new BAU* implementation results) in Figure 6.
- *Benefits of the MPC strategy* can be evaluated by comparing MPC with *new BAU* in Table 3, and the red line (*new BAU* baseline) with green dots (MPC implementation results) in Figure 7.

Table 3: Performance obtained from *new BAU* and MPC implementation during winter 2020-21

Variable	**BAU (baseline)**	**New BAU (meas.)**	**Difference**	**New BAU (baseline)**	**MPC (meas.)**	**Difference**
Building heating demand	107.5 MWh	87.4 MWh	- 18.7 %	78.4 MWh	98.0 MWh	+ 25.0 %
Electric boiler consumption	72.8 MWh	70.6 MWh	- 3.0 %	63.4 MWh	86.3 MWh	+ 36.0 %
Natural gas boiler consumption	34.7 MWh	16.8 MWh	- 51.5 %	15.0 MWh	11.7 MWh	- 21.8 %
Total energy cost	5,542 CAN$	4,463 CAN$	- 19.5 %	4,003 CAN$	4,976 CAN$	+ 24.3 %
GHG emissions	6.43 t CO_2eq	3.16 t CO_2eq	- 50.8 %	2.81 t CO_2eq	2.25 t CO_2eq	- 20.2 %

The COVID-19 pandemic has affected the building performance: heating demand was reduced by 18.7% and natural gas consumption by 51.5%. This reduction was quite significant at low outdoor air temperatures. With the MPC strategy, there are clear benefits in terms of gas consumption, achieving an additional 21.8% reduction compared to *new BAU*. This was obtained by increasing electric boiler use during off-peak periods, but also at higher heating demand (25.0%) and energy costs (24.3%). MPC showed substantial reduction at low outdoor air temperature for a similar or modest increase in heating demand; however, it was less effective in warmer weather, as heating demand was significantly increased for low natural gas savings. The trade-off between heating demand increase and gas consumption reduction was handled within the objective function (Eq. 1) and is still based on operational data under the original *BAU*, not the *new BAU*. When compared to BAU, heating demand and energy cost would have been similar (0.4% and 1.7% decrease, respectively, not shown in Table 3). Recalibration with data under the new BAU could adjust model and optimization parameters to the new reality and lower energy costs would be expected, as obtained by Cotrufo et al. (2020).



(a) (b)

Figure 7: (a) Daily average heating demand and (b) daily average natural gas boiler consumption as a function of daily average outdoor air temperature under MPC in 2020-21.

4.3 Trends in the selection of indoor air temperature setpoint profiles

Cotrufo et al. (2020) investigated the selection of indoor air temperature profiles. It was found that at lower outdoor air temperatures, a sharp transition between nighttime to daytime conditions was optimal; at higher temperatures, smooth transitions were selected. In fact, at low temperatures, the natural gas boilers are already operating at night and building preheating causes an increase in heating demand and thus, in gas consumption. In contrast, this is not the case when it is warmer outside: natural gas consumption in the morning during ramp-up can be shifted into electric boiler consumption at night.

Figure 8 shows temperature setpoint profile as a function of daily outdoor air temperature. Adding new night setbacks and thermal comfort constraints makes the interpretation of profile selection less evident, although the trend is similar. Smooth transitions (profiles #1-4) were selected at higher temperatures; profile #2 (21.5°C night setback and starting time at 18:00) was even selected 40% of the time. Profiles #12-16-18 with 17.5-18.5°C night setback were selected at low temperatures and on Sunday evening when indoor temperature was already at 18.5°C.

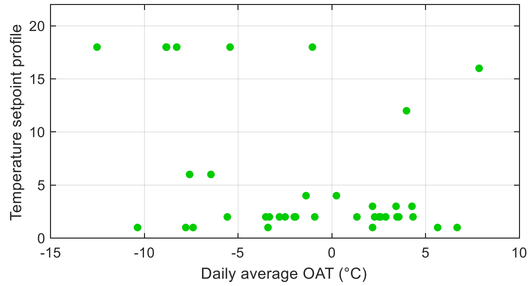
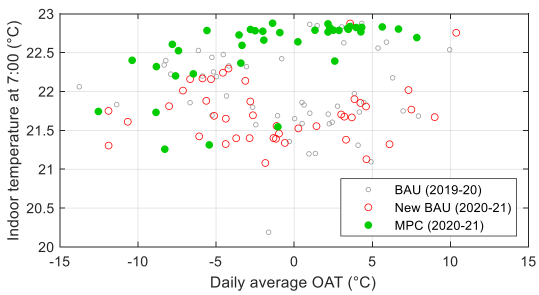


Figure 8: Indoor air temperature setpoint profile selected by the MPC strategy as a function of the daily average outdoor air temperature.

4.4 Thermal comfort

Building daytime schedule starts at 6:30 and occupant's thermal comfort should be satisfied soon after. Thermal comfort was assessed by plotting indoor air temperature at 7:00 (first occupant's arrival) and 8:00 (indoor air conditions expected to be achieved). Results are shown in Figure 9. The constraint on thermal comfort in the optimization problem helped increase the indoor air temperature in the morning, by excluding setpoint profiles that might have caused discomfort. Compared to *BAU* and *new BAU*, MPC was able to almost consistently achieve 21.5°C at 7:00 while under *BAU* and *new BAU*, temperatures between 21°C and 22°C were frequently achieved.



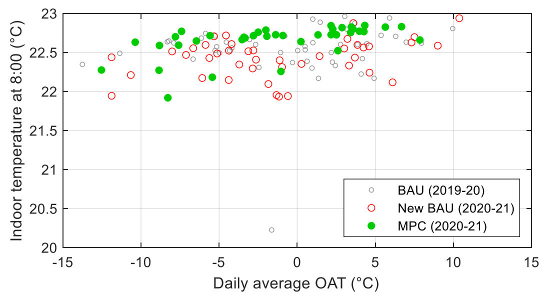


Figure 9: Indoor air temperature as a function of daily average outdoor air temperature: (a) at 7:00 and (b) at 8:00.

5. LESSONS LEARNED FROM IMPLEMENTATION

The development of data-driven black-box models is no easy task and it strongly depends on data availability and quality ("*garbage in, garbage out*"). The followed approach intended to develop a strategy that relies on very few inputs (essentially, indoor temperatures, electric boiler power, total building electric power and natural gas boiler power) for replicability purposes and to maximize data availability. Indeed, it barely happens that all required monitoring data is available at the same time and using hourly average values helped increase data availability. Training data covered a total of 10 months, on which only 59% of hourly average values were compiled in the training dataset due to missing periods (mainly for building total electric power and outdoor air temperature) ranging from a few hours to a few days. Averaging indoor temperatures and temperature setpoints was also beneficial, as it allowed to exclude missing data (12-26% of the 10-min dataset) for specific rooms within a zone. With data availability in mind, Deep Learning models such as long-short term memory artificial neural networks are very appealing in terms of accuracy but their actual implementation in typical real buildings might be difficult as they require consecutive time-series data.

Another challenge was the bi-directional communication with the BAS. The optimization consisted in predefined setpoint profiles that were manually entered in the control system in such a way that the optimal profile number was sent to the BAS and the corresponding profile was applied. A more automatic approach could be explored while the compatibility with commercial tools that are given permission to send commands to the BAS could be worth of investigation.

6. CONCLUSIONS AND FUTURE WORK

While a significant transformation in the training of building engineer professionals (e.g. in control engineering) is desirable, and even necessary, to fully exploit the potential of MPC, the severity and urgency of environmental problems call for a practical approach for the deployment of predictive control, even if only a fraction of MPC capabilities are achieved. The replicability and the affordability of the method is one of its interesting features. The impact of deploying an "imperfect" (but simple and cheap) methodology in hundreds of buildings would surpass the benefits of a "full" MPC implementation considering a detailed model with numerous controlled variables.

Future work includes applying the MPC strategy to other commercial or institutional buildings (under way) to see whether similar conclusions (savings, operational trends) could be achieved. Moreover, control-oriented models should be recalibrated to account for the new performance under COVID-19 pandemic. The proposed strategy was also not very efficient on warmer periods; a dedicated model could be developed for these conditions, targeting heating demand reduction while maintaining thermal comfort and low natural gas consumption. In this study, indoor air temperature profiles were applied uniformly to all the rooms. This supervisory control strategy could be refined with local controls for groups of systems or rooms. Peak load management to support electric grid needs could be investigated using a similar approach, with models targeting flexibility, focusing on electric power, while natural gas consumption would be treated as a penalty term. Such work could target both heating and cooling systems, focusing on occupied hours as the electric peak generally occurs during the day. In this situation, a multi-model approach could be very useful. To better quantify flexibility, load disaggregation could be investigated in depth.

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