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ABSTRACT

In the transition from fossil fuel to electrified heating, several areas of the US are seeing a concerning pattern. After adding heat pumps (HPs), commercial building owners leave their gas-based units in place, creating hybrid (dual-fuel) systems that are difficult to integrate and control. Causes include a lack of trust in HPs, capacity constraints in certain climate zones, additional uses for gas, and progressive but partial equipment replacement based on end-of-life considerations. Current control products available on the market are unable to address the diversity and complexity of these systems. For example, infrared (IR) remote-controlled mini-splits are common in small-medium commercial buildings (SMCBs) but are especially difficult to integrate with each other or with existing equipment due to limited interoperability among other devices and poor control access. The poor control integration of the original gas-based systems and HP units, and the complexity of optimizing these systems, cause high greenhouse gas emissions and energy costs. This paper describes an open-source control application utilizing model predictive control (MPC) to coordinate and optimize operations of heat-pump and gas-fired (GF) heating dual-fuel systems while maintaining optimal comfort for the occupants in small commercial buildings. Model predictive control is designed and implemented to minimize greenhouse gas emissions by shifting peak load via pre-heating while considering the trade-off between the degradation of HP performance during cold weather and the high emission of the gas-fired boiler. The control application we have designed has been deployed in a small commercial building in New York to manage five IR remote-controlled ductless heat pump mini-splits and a thermostatically controlled furnace. This deployment fully utilizes low-cost IoT devices for both metering and control. The developed MPC and Baseline controls were implemented for 2 months of the winter heating season by alternating each control day by day, and the test results showed MPC reduced 27% of cost and 14% of electricity peak demand while completely eliminating GF usage via shifting 23.4% of the thermal load from occupied-peak time to non-occupied-non-peak time.

INTRODUCTION

To address the climate crisis, our national leadership is developing an accelerated roadmap to decarbonization. In the building sector, it has become clear that the only pathway to achieve such a goal is the massive electrification of space and water heating, and the replacement of natural gas systems (Jadun et al. 2017). However, the states that are

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leading this transformation are also witnessing that many customers that install heat pumps (HP) are retaining gas-based systems (Clark, T. et al. 2021). The resulting hybrid systems have diverse and complex configurations and given the long lifespan of packaged gas-based systems, may remain in place for more than a decade. The challenge of integrating gas-fired furnaces (GF) and HPs in hybrid heating systems has been recognized as a critical issue by the New York State Energy Research and Development Authority (NYSERDA). To address this problem, NYSERDA has proposed specifications for integrated controllers that utilize existing control products in the market (NYSERDA 2022). While these controllers are an improvement over controlling the two systems independently, they do not fully optimize the hybrid system's performance, reduce greenhouse gas emissions, or minimize utility costs.

The lack of advanced controls for hybrid systems is especially acute in small and medium commercial buildings (SMCBs). They may have less control-friendly systems, like infrared (IR)-remote control-based ductless mini-split heat pumps that can't easily be connected by standardized protocols. Additionally, small buildings often lack basic automation control of building systems, and there are fewer available control options for buildings of this size. This lack of availability combined with the cost and time required to upgrade controls reduces access to good control options for small buildings. The complexity and diversity of hybrid systems in these buildings, along with their varied operational requirements, make it challenging to develop an effective control solution.

Recently, the adoption of the Internet of Things (IoT) (e.g., WiFi-enabled thermostat) in SMCBs has become increasingly popular (Ford *et al.*, 2017) and provided the opportunity for advanced controls. IoT-enabled building controls and monitoring offer significant advantages, particularly in SMCBs, where cost-effective and scalable solutions are necessary. They can be installed with minimal disruption, and are modular, allowing for easy expansion and customization as the building's needs change. This is particularly useful for buildings with limited space and budget constraints, as they can adopt only the necessary IoT devices and expand the system later when necessary.

Model predictive control (MPC) is one of the most widely adopted approaches for the dynamic operation of heating, ventilation, and air-conditioning (HVAC) systems in research (Drgoňa *et al.*, 2020) and field implementations (Zhang *et al.*, 2022). By utilizing mathematical models for buildings and disturbance forecasts (e.g., weather), MPC optimizes the operation of an HVAC system with given constraints such as comfort boundaries. Additionally, MPC can handle flexible grid services (Satchwell *et al.*, 2021) such as load shifting according to various price signals from the grid (e.g., Time-of-Use (TOU) rate, real-time price). Historically, MPC has been implemented in large commercial buildings with complex HVAC systems where a central building automation system (BAS) system is available (Li *et al.*, 2015; De Coninck and Helsen, 2016; Blum *et al.*, 2022). However, recent studies (Kim *et al.*, 2016; Kim and Braun, 2018, 2022) have shown that MPC is suitable and scalable for SMCB where the detailed sensor and control infrastructure is not available without major retrofit because of its ability to include physical thermal dynamics in its model so that the model behaves in a physical manner. Yet, its applicability and performance have been demonstrated for multiple ON/OFF rooftop units (RTUs) (Kim and Braun, 2018, 2022), it has not been applied to the hybrid system except for a study (Cotrufo *et al.*, 2020) using black-box model with decision domain reduction via heuristics.

In this study, we present MPC for the hybrid system by modifying the MPC developed in our previous study (Kim and Braun, 2022). The MPC is designed to control the hybrid system while minimizing the use of GF and the energy cost for a one-day prediction horizon considering the price signal (i.e., Time-of-US (ToU) tariff). The MPC has been deployed in one zone in a commercial building served by 5 HPs and 1GF for 2 months of the winter season.

SITE DESCRIPTION

Building Description

This field demonstration was conducted at a small commercial building in New York State (Figure 1). In this building, the MPC controlled a single zone, marked as the "Target zone" in Figure 1. This zone is approximately 3,780 square feet (351.2m^2) of retail, office, and physical workspaces. In the past, one attic-mounted GF was used for the main heating device, but five Mitsubishi split-system HPs were recently installed. Before this demonstration, the HPs were operated by individual IR remotes, and the furnace was controlled by a manual (not programmable) thermostat. The HPs provided most of the heating, but the GF was also used in the early morning or on cold days.

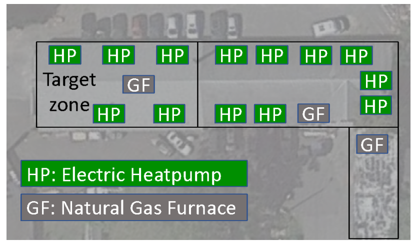


Figure 1. Demonstration site and HVAC system layout.

IoT Infrastructure for Data Collection and Control

The research team installed a suite of connected devices for these systems, as well as a 4G router to operate them independently from the existing network at the site as shown in Figure 2. WiFi-connected IR transmitters (Sensibo Sky) were installed to control the HPs. These devices have built-in temperature sensors and are able to set temperature setpoints and operating modes for each HP. The GF is controlled by a standard Wi-Fi-enabled thermostat (Ecobee). WiFi-enabled electricity meters (eGauge) were installed to measure HP powers for performance evaluation. All mentioned devices were connected to the internet by a 4G cellular router, and controlled via vendor cloud APIs. An Eclipse VOLTTRON-based software platform was used for data collection, monitoring, and control. VOLTTRON is an open-source middleware built for distributed control and sensing in buildings (Katipamula et al. 2016). The deployment costs are shown in Table 1, excluding the cost of researcher time developing and monitoring the MPC. The devices and installation cost of the MPC control infrastructure was $975, much cheaper than the usual cost of MPC infrastructure. The IoT devices used in this study are also simple enough for savvy site owners to self-install.

This approach had several advantages, including fast, easy, and low-cost integration, though it also had drawbacks. For instance, the use of vendor cloud APIs could reduce the overall effectiveness of the MPC control because of high communication latency or occasional site internet outages causing a lack of service. Additionally, the use of non-conventional IR remote-controlled devices has the potential to introduce inconsistencies that may impact the performance of the overall system. Unlike a standard thermostat, the IR transmitter is a one-way communicating device, so therefore, it only sends information to the HP. The variables and the control logic of the HP are not available. However, by considering the limitations of each device and implementing appropriate management strategies, it’s possible to mitigate these issues and achieve good performance.

Table 1. MPC and M&V Infrastructure Costs

Category	Task	Cost
Labor	Scoping	$2000
	Estimated Metering Installation	$2720
	Estimated MPC Infrastructure Installation	$320
	Commissioning and hand-off	$800
Equipment	Cellular Modem and Data Service	$110/Month
	Ecobee Thermostat	$205
	HP Controllers	$450
	Meters	$1700
	Miscellaneous	$110
Totals	Capital and labor cost for MPC control infrastructure	$975
	Capital and labor cost for metering for M&V	$7,220

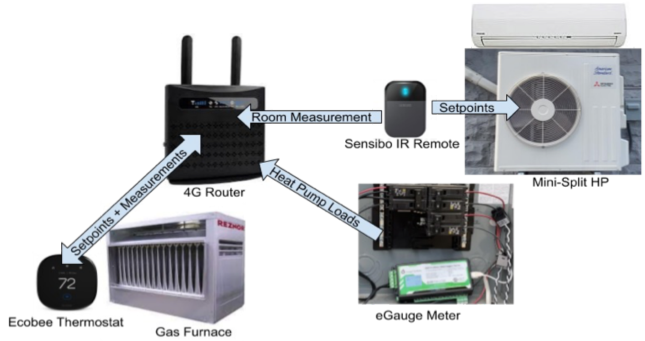


Figure 2. Communication diagram of retrofitted IoT device and power sensor.

Baseline Control Scenario

After setting up all the IoT infrastructure, we defined the Baseline control scenario based on the communication with the business owner because the HPs and GF were in operation all day long regardless of the business and occupancy schedule. In the Baseline control scenario, the dual-fuel hybrid system is operated using a schedule-based setpoint control. All systems were programmed to operate with an occupancy schedule of 7:00 AM - 8:00 PM. During occupied hours, the HPs had a heating setpoint of 70.0°F (21°C) and the GF had a heating setpoint of 68°F (20°C). During unoccupied hours, systems operated with a heating setpoint of 60.8°F (16°C). Because this test occurred during the winter, the HPs were put into heating mode. Table 2 contains a summary of the building, HVAC, occupancy schedule, and tariff information.

Table 2. Summary of HVAC Device, Tariff, and Occupancy Schedule

Device	- Mitsubishi ductless heat pump (Rated cooling: 4.4kW, Rated heating: 5.2 kW) - York/Luxaire gas furnace (Rated heating: 30.4kW) - Sensibo sky IR transmitter / Ecobee thermostat / eGauge power meters
Baseline Control	- Occupied time: Weekday 7:00 AM - 08:00 PM (heating setpoint: 70°F (21.1°C)) - Unoccupied time: all except mentioned above/weekends (heating setpoint: 60°F (15.6°C))
Electricity Tariff (conEdison ToU small business[1])	- 08:00-22:00: On-peak (18.62¢/kWh). - Other time: Off-peak (1.38¢/kWh)
Natural Gas Tariff (General firm sales service[2])	- 0-3 therms - $34.8 - 3-87 therms –101.21 ¢/therm

MPC DESIGN

In this study, the MPC algorithm that was developed in our previous study (i.e., UMPC in (Kim and Braun, 2022)) is slightly modified for the hybrid system. The objective function of the MPC algorithm is written as Eq. 1. This MPC provides optimal runtime fraction (*RTF*) for each HVAC device (i.e., HPs and GF) to minimize electricity cost for the prediction time horizon. The prediction time horizon is set to 24 hours to achieve the optimal load shifting (i.e., pre-heating) to the price signal (*ER*). While the amount of heating of HPs is internally controlled by the current temperature and setpoints, the GF behaves like an ON/OFF unit based on the setpoint. To capture the transition behavior between heating operation and idling in a short time, the heating operation signals (i.e., *RTF*s) are smoothed by MPC's sample time (i.e., MPC runs every 15 minutes). The *RTF* of the GF can be directly available from the thermostat's cloud API, but the *RTF*s of the HPs need to be inferred as IR transmitters are one-way communicating devices. After investigating the relationship between the IR transmitters and the power meter, the HPs

[1] https://www.coned.com/en/accounts-billing/your-bill/time-of-use
[2] https://lite.coned.com/_external/cerates/gas.asp

were modeled as behaving like proportional control with a proportional band of 2°C (3.6°F) while too small values were zeroed. This is an aggressive approximation, but we decided not to install additional sensors for HPs considering the cost and scalability for this control solution.

$$\begin{aligned}
\min \quad & \sum_{j=1}^{N_p}\sum_{i=1}^{n} ER(k+j-1)P_{\mathrm{HVAC},i}(k+j-1)\bar{u}_{\mathrm{HVAC},i}(k+j-1) + \omega_{\mathrm{d}}\delta + \omega_{\mathrm{l}}\Gamma_{\mathrm{l},i} + \omega_{\mathrm{u}}\Gamma_{\mathrm{u},i} \\
s.t. \quad & T_{\mathrm{l},i} - \Gamma_{\mathrm{l},i} \le \mathbb{E}[\bar{y}_i(k+j)|\mathcal{D}_k] \le T_{\mathrm{u},i} + \Gamma_{\mathrm{u},i}\ (\forall i \in \{1,\dots,n\}) \\
& \sum_{i}^{n} P_{\mathrm{HVAC},i}(k+j-1)\bar{u}_{\mathrm{HVAC},i}(k+j-1) \le \delta \\
& 0 \le \bar{u}_{\mathrm{HVAC},i}(k+j-1) \le 1\ \left(\forall j \in \{1,\dots,N_p\}\right)
\end{aligned} \tag{1}$$

where *ER* is electricity cost rate [$/kWh], $P_{\mathrm{HVAC},i}$ is *i*th HVAC device rated power [kW], N_p is prediction horizon, n is the number of HVAC units, *k* is current time step, *j* is prediction time step, $\bar{u}_{\mathrm{HVAC},i}$ is heating runtime fraction (RTF) of ith HVAC, δ is an upper bound of instantaneous power (demand), ($\Gamma_{\mathrm{l},i}, \Gamma_{\mathrm{u},i}$) are temperature violations, ($\Gamma_{\mathrm{l},i}, \Gamma_{\mathrm{u},i}$) are temperature violations from lower- and upper-temperature bounds for the *i*th zone, ($\omega_{\mathrm{l}}, \omega_{\mathrm{u}}$)are weights on optimization variables for ($\Gamma_{\mathrm{l},i}, \Gamma_{\mathrm{u},i}$), ω_{d} is weight on optimization variable for δ, ($T_{\mathrm{l},i}, T_{\mathrm{u},i}$) are lower and upper boundaries of comfort temperatures, $\bar{y}_i(k+j)|\mathcal{D}_k$ is the optimal j-step temperature prediction from the building model given the data (D_k), and D_k is data till time step *k*.

The target zone has 6 HVAC devices (5 HPs and 1 GF). Among various objectives (e.g., energy cost or GHG minimization), the objective is set to reduce the use of GF as much as possible unless necessary based on the project and customer's goals (i.e., electrification). So, we treat the GF as the HP with very low COP (i.e., high rated power) to limit its usage. However, we add MPC constraints to force the heat pumps to stop operating when the outdoor air temperature falls below -4°F (-20°C) based on catalog data, and the GF is used as the primary heating source. To do this, we set the rated power of GF as the same as ω_{l} or ω_{u}. In other words, GF is used when there is more than a temperature violation of 1°C only with HPs. However, for the demand term (*δ*), GF's operation is not directly related to the demand term, so we set the rated power of GF as 0 for the demand term calculation. $\omega_{\mathrm{l}}, \omega_{\mathrm{u}}$ and ω_{d} are set to 1000, 1000, and 10. δ is set to 70% of the summation of $P_{\mathrm{HVAC},i}$. Since there are 6 temperature measures, 12R-12C (2R-2C for one thermostat) gray-box model was established and trained as described in our previous research (Kim *et al.*, 2016).

RESULTS

Field Demonstration

Baseline and MPC data were collected in alternating blocks of days during the testing period, January-March 2023. This helped us compare Baseline and MPC data with similar outdoor conditions, in comparison to a traditional M&V approach of pre- and post-installation. Excluding weekends, holidays, and erroneous days (e.g., router outage), we obtained 19 and 13 days of Baseline and MPC days, respectively.

Day-by-day Comparison

Figure 3 shows a day-by-day comparison of Baseline and MPC controls. Two days that are typical of cold winter days are selected for comparison by day. In Baseline control (Figure 3 (a)), HPs started heating operations near 7 AM, and the room temperatures reached setpoints near 9-10 AM. The power consumptions before 7AM were due to defrost operations in cold weather. This happened during the non-heating time because some end-users left the office while having the fan to the always-ON mode. Due to the simultaneous operations of HPs, the peak electricity demand (HPs only) reached 6.52 kW near 8 AM while the GF was also being used for about 40 minutes though it is not shown in this figure. On the other hand, MPC control (b) started heating operations in the early morning near 3 AM, and it showed a more smooth building power profile compared to the Baseline. It both reduced the peak load to 5.6kW and completely eliminated GF operation. Since the temperatures were measured from IR transmitters, there is a limitation in comparison, but the room temperature profiles showed similar performance.

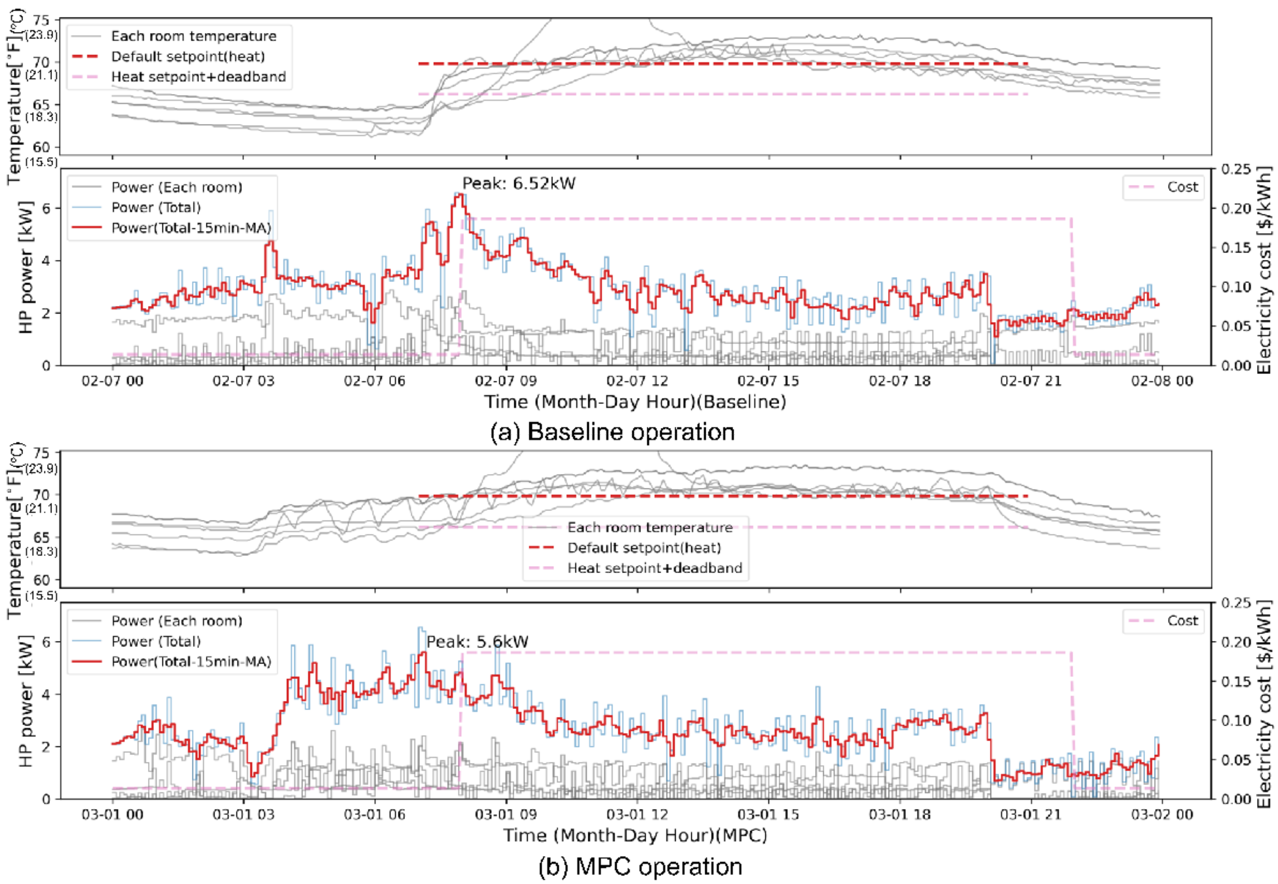
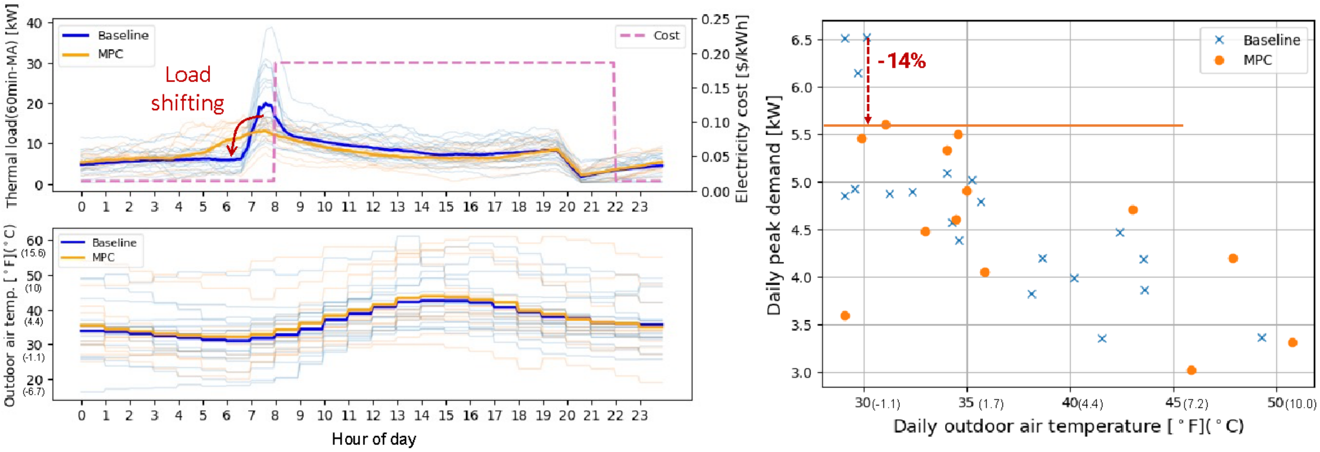


Figure 3. Day-by-Day comparison between Baseline and MPC

Load Shifting and Peak Demand Reduction

Figure 4 (a) shows the summary of the daily heating load profile of Baseline vs. MPC for all the experiment days. Due to the GF, the thermal load profiles are compared by multiplying rated heating power to the GF heating signal and HP powers instead of electricity profiles. In the top figure, each day's thermal load profiles are visualized in light-colored lines and the mean profiles of all days are shown in a thick line with the dotted line for the electricity cost on the right-side y-axis. Since the building's occupied schedule starts at 7 AM, the peak thermal profile avoided ToU peak time, but it is clearly shown that there is a morning heating peak between 7-8 AM in Baseline control. However, the MPC shifts the peak thermal load in the early morning time as it is designed, and it showed more smooth thermal load profiles. As a result, 23.4% of thermal load during 7 AM-10 PM was reduced (i.e., shifted to early morning) compared to the Baseline. Figure 4 (b) shows the daily electric peak load comparison of all days. In Eq. 1, the daily peak load is also included in the objective function, but it only sees the peaks in the day's prediction horizon, so the absolute value of monthly peak demand is not strictly regulated in the MPC. Despite this limitation, MPC shows a 14% of electricity peak reduction by doing load shifting even without using GF for the heating at all. However, since the peak demand is affected by the number of operating HPs, some MPC days showed higher peaks when there were defrost cycles or small heating loads.



(a) Summary of daily heating load profile

(b) Daily electric peak load (HPs only)

Figure 4. Summary of daily heating load profile and electric peak load.

Electricity, Cost, and Gas use Reduction

Figure 5 summarizes the electricity use, electricity cost, and GF usage hours during the demonstration periods. To account for the differences in the distribution of outdoor air conditions, we used the change-point model (Kissock et al. 2003) for evaluation. In the left-side figure, the electricity consumption of MPC and Baseline are similar, resulting in overlapping change-point models. Since MPC did not use GF at all (right-side figure) and used preheating, it was expected to use HPs more. However, due to the unmodeled power consumption of the HPs' defrost cycles and the small amount of GF usage time, the final consumption showed no significant differences. In the middle figure, MPC showed lower energy costs by preheating in non-peak times, resulting in a $62.2/month (27%) reduction. This was mainly achieved by the reduction in fixed natural gas cost (Table 2), but it could increase if the peak price time (from 8 AM) overlaps with peak demand time (7-8 AM). When the heating load was small, the pre-heating time decreased, resulting in a decrease in cost differences. Additionally, by not using GF at all MPC reduced GHG emissions by approximately 0.052 metric tonnes (0.051 imperial tons) per month based on a GHG equivalency calculation[3]. Finally, based on the cost information in Table 1, assuming the WiFi infrastructure is already established on the site, the capital costs would be paid back in approximately 13 months based on the heating operation.

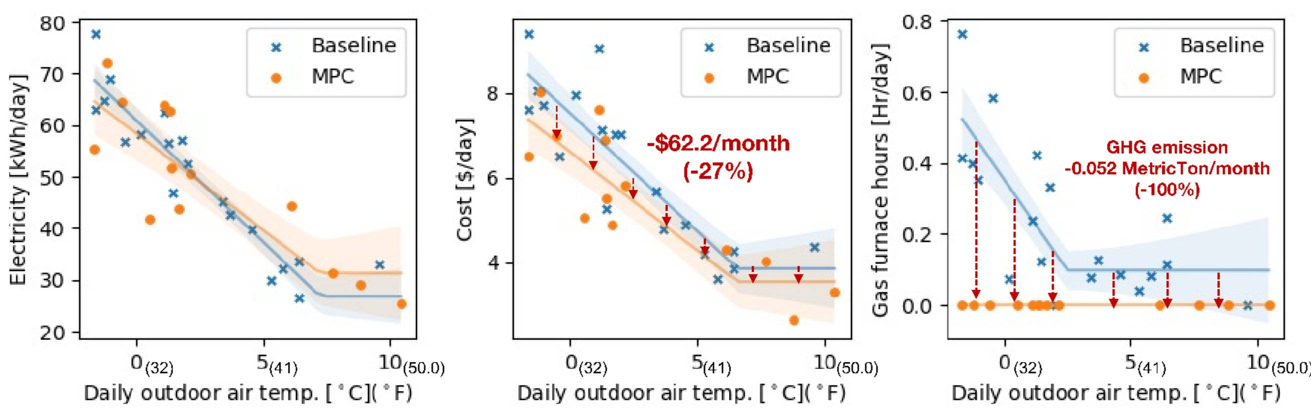


Figure 5. Summary of electricity, cost, and gas furnace usage over demonstration periods.

CONCLUSION AND DISCUSSIONS

[3] https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator

This paper describes an MPC to coordinate and optimize operations of HPs and GF heating dual-fuel systems for SMCBs. The MPC is developed with low-cost sensing and actuating devices and demonstrated for a real office building with 5 HPs and 1 GF for 3 months. The test results showed MPC reduced 27% of cost while completely eliminating GF usage by shifting 23.4% of the thermal load from occupied-peak time to non-occupied-non-peak time. The elimination of GF usage also resulted in a 0.052 metric tonnes (0.051 imperial tons) per month reduction of GHG emissions via simple calculation. Electricity marginal emissions signals were not used in this study, but they can bring more aggressive GHG reductions for the HP-side as well.

Although the MPC has shown success in a real building, there are several limitations and approximations in this research. The main limitation originated from the HPs communication interface. Since the IR transmitter is a one-way-communicating device, we have limited information regarding HP operations. Therefore, it is modeled as a simple proportional control unit. However, this can be improved by implementing a linear or piecewise linear COP map as a function of outdoor air temperature in the MPC. To overcome the limitation and cost reduction, it is also crucial to have interoperable communication services like typical smart thermostats for ductless HP products as they have become more popular in the market due to the urgent call for the nation's electrification.

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REFERENCES

Blum, D., Wang, Z., Weyandt, C., Kim, D., Wetter, M., Hong, T., & Piette, M. A. (2022). Field demonstration and implementation analysis of model predictive control in an office HVAC system. Applied Energy, 318, 119104.

Cotrufo, N., Saloux, E., Hardy, J. M., Candanedo, J. A., & Platon, R. (2020). A practical artificial intelligence-based approach for predictive control in commercial and institutional buildings. Energy and Buildings, 206, 109563.

De Coninck, R., & Helsen, L. (2016). Practical implementation and evaluation of model predictive control for an office building in Brussels. Energy and Buildings, 111, 290–298.

Drgoňa, J., Arroyo, J., Cupeiro Figueroa, I., Blum, D., Arendt, K., Kim, D., Ollé, E. P., Oravec, J., Wetter, M., Vrabie, D. L., & Helsen, L. (2020). All you need to know about model predictive control for buildings. Annual Reviews in Control, 50, 190–232.

Ford, R., Pritoni, M., Sanguinetti, A., & Karlin, B. (2017). Categories and functionality of smart home technology for energy management. Building and Environment, 123, 543–554.

Jadun, P., McMillan, C., Steinberg, D., Muratori, M., Vimmerstedt, L., & Mai, T. (2017). Electrification futures study: End-use electric technology cost and performance projections through 2050 (No. NREL/TP-6A20-70485). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1416113

Katipamula, S., Haack, J., Hernandez, G., Akyol, B., & Hagerman, J. (2016). VOLTTRON: An Open-Source Software Platform of the Future. IEEE Electrification Magazine, 4(4), 15–22.

Kim, D., Cai, J., Ariyur, K. B., & Braun, J. E. (2016). System identification for building thermal systems under the presence of unmeasured disturbances in closed loop operation: Lumped disturbance modeling approach. Building and Environment, 107, 169–180.

Kim, D., & Braun, J. E. (2018). Development, implementation and performance of a model predictive controller for packaged air conditioners in small and medium-sized commercial building applications. Energy and Buildings, 178, 49–60.

Kim, D., & Braun, J. E. (2022). MPC solution for optimal load shifting for buildings with ON/OFF staged packaged units: Experimental demonstration, and lessons learned. Energy and Buildings, 266, 112118.

Kissock, J. K., Haberl, J. S., & Claridge, D. E. (2003). Inverse modeling toolkit: numerical algorithms. ASHRAE transactions, 109, 425.

Li, P., Vrabie, D., Li, D., Bengea, S. C., Mijanovic, S., & O'Neill, Z. D. (2015). Simulation and experimental demonstration of model predictive control in a building HVAC system. Science and Technology for the Built Environment, 21(6), 721–732.

NYSERDA. (2022). NYS Clean Heat Integrated Controls Eligibility Guidelines. NYSERDA.

Satchwell, A., Piette, M., Khandekar, A., Granderson, J., Frick, N., Hledik, R., Faruqui, A., Lam, L., Ross, S., Cohen, J., Wang, K., Urigwe, D., Delurey, D., Neukomm, M., & Nemtzow, D. (2021). A National Roadmap for Grid-Interactive Efficient Buildings. Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States).

Clark, T., Aas, D., Li, C., de Villier, J., Levine, M., & Landsman, J. (2021). Maryland Building Decarbonization Study. Energy and Environmental Economics, Inc. (E3).

Zhang, K., Prakash, A., Paul, L., Blum, D., Alstone, P., Zoellick, J., Brown, R., & Pritoni, M. (2022). Model predictive control for demand flexibility: Real-world operation of a commercial building with photovoltaic and battery systems. Advances in Applied Energy, 7(100099), 100099.