

Demand Flexibility Evaluation for Building Energy Systems with Active Thermal Storage Using Model Predictive Control

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ABSTRACT

Model Predictive Control (MPC) has been demonstrated to be an efficient way to reduce building operating costs, especially for buildings with thermal storage systems, by changing the power demand profiles. Different parameter settings of MPC have also been shown to have significant influence on building power usage, which may therefore influence building demand flexibility. In this study, we estimate how MPC parameters such as the prediction horizon (PH) can influence building demand flexibility. A virtual high-fidelity building testbed was created in Modelica based on actual measurement data from a chiller plant with an ice storage tank system. Then the virtual system was randomly perturbed to generate training data for the MPC models. The MPC was formulated as a nonlinear programming problem and solved using a global optimization solver. We found that MPC can reduce operating costs by 15.8 % and reduce the peak power demand by 24.8 % compared with rule-based storage-priority control. The building demand flexibility initially increases as the PH increases and then reaches its plateau when the PH is longer than 20-hours. Evaluation of the building demand flexibility will provide insights into choosing the suitable MPC formulation for a grid-interactive efficient building.

INTRODUCTION

Background and Literature Review

One approach to tackle increasing average global temperatures and reduce CO₂ emissions is to deploy more distributed energy resources (e.g., solar PV and wind turbines) to generate electricity in the modern grid structure. However, the intermittent energy production of these systems hampers the integration of renewable sources into the power grid (Tarragona et al. 2021). Therefore, there is a growing need for flexibility in the grid to balance dynamic loads from both the supply and demand sides. Demand flexibility in buildings is an effective way to provide grid-responsive support by reducing, shifting, shedding or modulating electrical loads, and/or generating onsite electricity (Neukomm et al. 2019). However, the evaluation of building demand flexibility is a major challenge because it is affected by many factors, including weather conditions, occupant behaviors, and control design (Chen et al. 2019).

Model Predictive Control (MPC) has been shown to be a promising advanced control strategy for providing demand flexibility from buildings with active thermal energy storage systems (Lee et al. 2020; Li et al. 2015). It has many advantages, including considering future disturbances and incentives, coordinating multiple systems towards a common objective, handling constraints and uncertainties, handling time-varying system dynamics, and controlling the system at

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both the supervisory and local loop levels (Afram and Janabi-Sharifi 2014). However, one of the main challenges of MPC implementation in practice is the requirement of tailored modeling and control design since every building is a unique system. Trained practitioners are also required for the design, tuning, deployment, and maintenance of MPC (Drgoňa et al. 2020).

There have been several studies on the factors of MPC performance and the impact of MPC on building demand flexibility. Blum et al. (2019) analyzed seven practical factors that affect MPC controller performance, including building design, model structure, identification algorithm, initial parameter values, size of the training data, noise and gaps in the training data, and strategies for accounting for missing data. Huang et al. (2021) evaluated the combined impacts of selected time intervals for model discretization and control sampling on MPC performance. They pointed out that the time interval for the model discretization has a much greater influence on MPC performance than that for the control sampling by affecting the prediction performance, cost reduction, and computation time simultaneously. Finck et al. (2019) developed economic model predictive control (EMPC) for a heating system with thermal storage tanks in a residential building. They quantified the performance of EMPC using flexibility indicators in terms of energy and power, energy efficiency, and energy costs. Van Cutsem et al. (2019) investigated the performance of different EMPC formulations under multiple time-of-use (TOU) electricity charges and various summer conditions. They evaluated the demand flexibility in terms of monthly bill reduction, load shifting, and peak demand reduction. Although a wide spectrum of MPC and demand flexibility related topics have been covered in existing studies, there is still a lack of information on how MPC parameters such as prediction horizon can impact demand flexibility.

Contributions of this work

The purpose of this study is to evaluate the influence of MPC parameter settings on the demand flexibility of a building heating, ventilation, and air conditioning (HVAC) system with an ice storage tank. Figure 1 presents the research flowchart. A five-zone office building with a chiller plant and ice storage tank is first implemented in Modelica to serve as a virtual building, which is then used to generate training data for control-oriented models used in MPC. Control-oriented predictors such as the total power consumption predictor and ice tank State-of-Charge (SOC) predictor are represented by multilayer perceptron artificial neural networks (ANN). The MPC minimizes the energy cost over a prediction horizon while maintaining thermal comfort in response to time-varying occupancy and electricity prices. The nonlinear MPC problem is solved by use of a global solver using the differential evolution algorithm (Feoktistov 2006). The resulting system power profiles from MPC are finally used for evaluating the building’s demand flexibility.

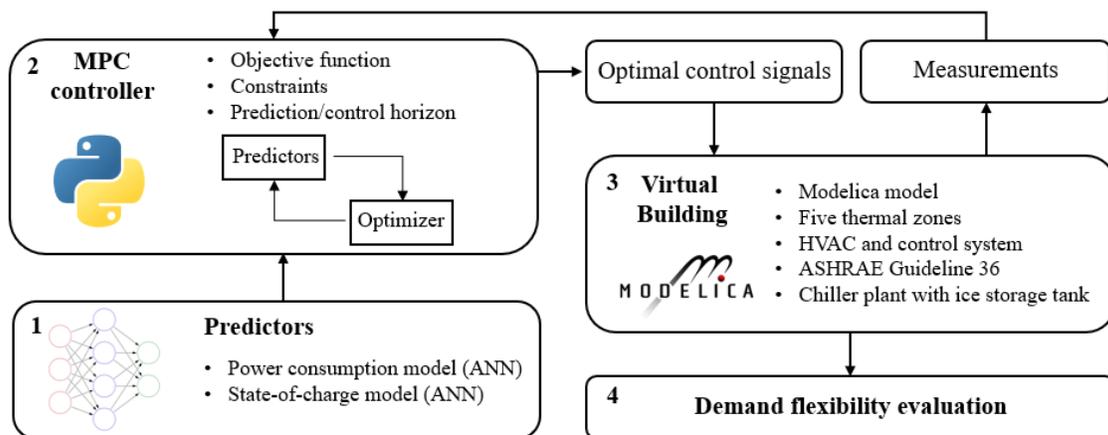


Figure 1 Flowchart of the MPC implementation and demand flexibility evaluation.

VIRTUAL BUILDING

Building HVAC System Model

Figure 2 describes the Modelica HVAC model of the medium office building used in this study. The Modelica model is based on and validated against the medium-size office prototype model developed by the U.S. Pacific Northwest National Lab (DOE 2018). The virtual office building is served by a single-duct Variable Air Volume (VAV) system and a chiller plant with an ice storage tank. One Air Handling Unit (AHU) connected to five VAV terminal boxes serves five thermal zones. Chilled water is supplied by a chiller that is connected in series with the ice storage tank, the model of which is validated against experimental data (Li et al. 2021). The chiller plant with the ice tank storage system is based on the actual system demonstrated in the Intelligent Building Agents Laboratory (IBAL) at the National Institute of Standards and Technology (NIST). The ice storage tank contains 3,105 L (820 gallons) of water and when fully frozen the ice has a cooling capacity of 274 kWh. The chilled water that flows through the ice tank is a 30 % PG and 70 % water solution (Pertzborn 2016).

The HVAC and control system models are built on the Modelica Building Library developed by the U.S. Lawrence Berkeley National Lab (Wetter et al. 2014). The system model consists of an HVAC system, a building envelope model, and a model for the air flow through building leakage and open doors based on wind pressure and flow imbalance of the HVAC system. The HVAC system is sized for Chicago, IL, which is climate zone 5A as defined by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). The envelope thermal properties meet ASHRAE Standard 90.1-2004. The air loop uses rule-based supervisory control logic recommended from ASHRAE Guideline 36 (ASHRAE 2018), and the water loop conforms to ASHRAE RP-1711. Details of this HVAC system can be found in (Fu et al. 2021).

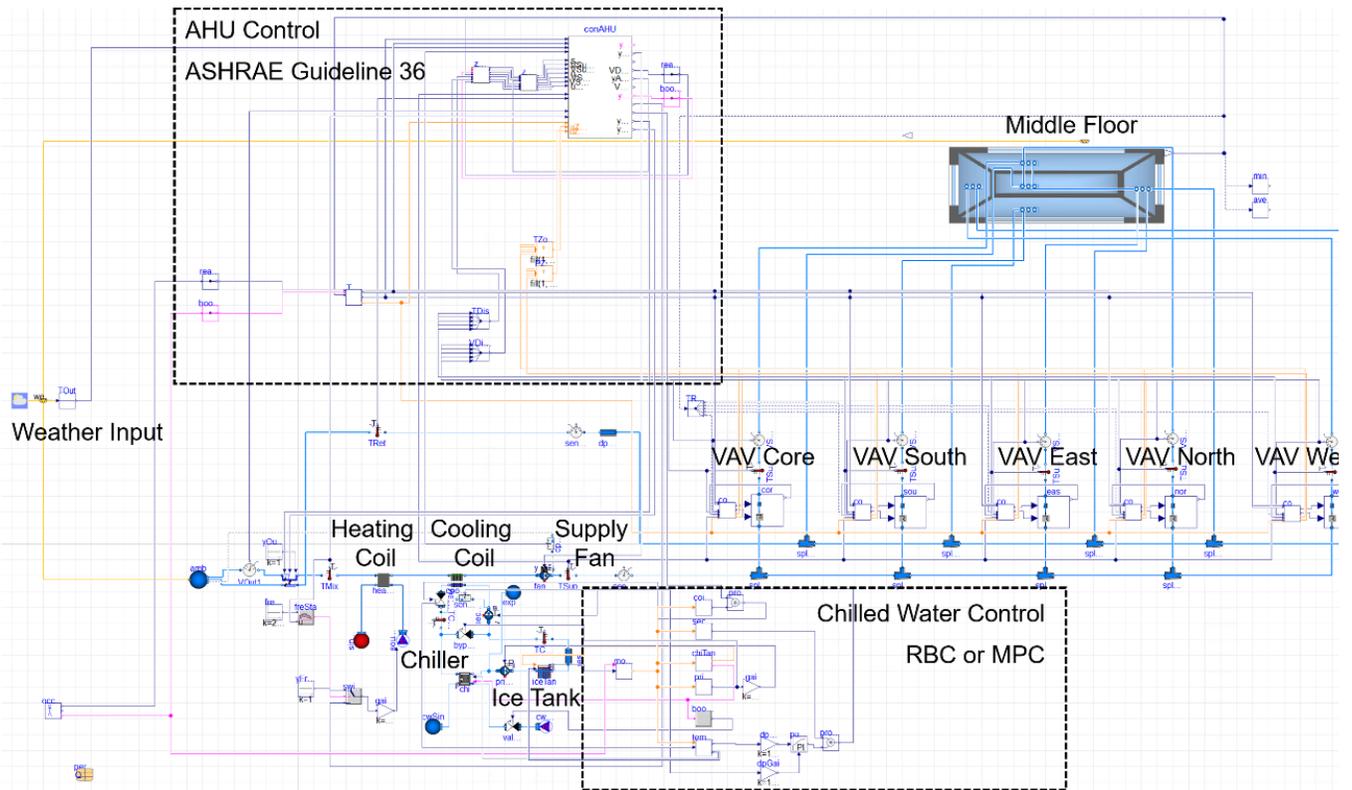


Figure 2 Modelica model of the studied HVAC system for a commercial building.

Rule-based Control (RBC) and MPC Operation Modes

The RBC used in this study adopts a storage-priority control as the baseline control for the waterside system. For storage-priority control, the ice storage tank will first be discharged to provide cooling until the SOC is 0 (full discharge). When all ice in the tank is melted, the chiller will then provide the cooling. MPC determines the optimal operating mode signal for each control timestep using one of five possible operating modes: 1) Off, 2) Operating both the chiller and storage, 3) Discharging the storage, 4) Operating the chiller, 5) Charging the storage.

MPC IMPLEMENTATION

Objective Function and Constraints

For the HVAC system in the study, the MPC objective is to minimize the energy cost during a prediction horizon (PH) as defined in Eq. (1) to Eq. (4). The MPC in this case only focuses on the waterside control, while the airside system is controlled following ASHRAE Guideline 36, which maintains zone temperature at the setpoint of 24 °C (75.2 °F) during the occupied time. Two of the control signals on the waterside are considered, the mode signal and the chilled water supply temperature setpoint, as shown in Eq. (3) and Eq. (4). To evaluate the different MPC settings' impact on demand flexibility, the control horizon is set as 1-hour, and the prediction horizon is set as 1-hour, 4-hour, 8-hour, 12-hour, 16-hour, 20-hour, 24-hour, and 28-hour, respectively.

$$\text{Minimize: } J = \sum_{k=0}^{PH-1} P^{t+k} \cdot R^{t+k} \quad (1)$$

$$P^{t+k} = f_{P,ANN}(u_{mode}, u_{Tchw}) \quad (2)$$

$$\text{Subject to: Mode Signal} = \begin{cases} 1: Off \\ 2: Operating Both \\ 3: Discharging Storage \\ 4: Operating Chiller \\ 5: Charging Storage \end{cases} \quad (3)$$

$$\begin{aligned} & \text{If occupied, } u_{mode} \in \{2, 3, 4\}; \text{ else, } u_{mode} \in \{1, 5\} \\ & u_{Tchw} \in [5 \text{ }^\circ\text{C (41}^\circ\text{F)}, 10 \text{ }^\circ\text{C (50}^\circ\text{F)}] \end{aligned} \quad (4)$$

In the above equations P^{t+k} is the predicted total power consumption at time $t + k$, R^{t+k} is the electricity rate at time $t + k$, as shown in Figure 3(a), u_{mode} is the optimal mode control signal out of five operating modes, and u_{Tchw} is the optimal chilled water supply temperature setpoint.

Model identification

The virtual system was perturbed by randomly selecting u_{mode} and randomly setting u_{Tchw} in a range from 5 °C (41 °F) to 10 °C (50 °F) in order to generate training data for the MPC model identification. We simulated the virtual testbed for one month (i.e., August) to generate hourly simulation data to train the ANN models. The dataset was randomly split into 80 % training data and 20 % testing data. To evaluate the accuracy of the proposed model, two statistical metrics are applied: the coefficient of determination (R^2), and the Coefficient of Variation of Root Mean Square Error (CV(RMSE)), which are defined in Eq. (5) and Eq. (6), where Y_i is the measured data, \hat{Y}_i is the predicted data, n is the number of data points, and \bar{Y}_i is the mean value of the measured data.

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y}_i)^2} \quad (5)$$

$$CV(RMSE) = \frac{\sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n}}}{\bar{Y}_i} \quad (6)$$

As per ASHRAE Guideline 14 (ASHRAE 2014), the predicted model shall have a CV(RMSE) up to 30 % using hourly calibration data. Table 1 lists the evaluation metrics for the ANN models. For the total power consumption model, the CV(RMSE) of 19.28 % indicates a good model fit with acceptable predictive capability. For the SOC model, the CV(RMSE) was less than 10 %, implying that the models are reliably predictive.

Table 1. Evaluation results of ANN models

ANN Models	R2		CV(RMSE)	
	Training dataset	Testing dataset	Training dataset	Testing dataset
Total power consumption	0.8817	0.8015	18.04 %	19.28 %
State of charge	0.9904	0.9839	6.64 %	9.28 %

RESULTS AND DISCUSSIONS

Simulation results

We conducted a one-day simulation during the cooling season using a weather file for Chicago, IL, USA. The prediction horizon was set to 1-hour, 4-hours, 8-hours, 12-hours, 16-hours, 20-hours, 24-hours, and 28-hours. Although MPC with a PH of 1-hour and 4-hour is not practical for an ice storage system, it is studied for comparison with cases with longer PHs. Figure 3(a) shows the TOU electricity rate; the peak-price period is 12:00 ~ 18:00 with a highest price of 0.3548 \$/kWh (1211\$/Btu). Figure 3(b) shows the SOC usage profiles for the different cases. For the storage-priority RBC, the ice storage tank is charged during the unoccupied time and the low-price period, and it's discharged during the occupied time until the ice storage is fully discharged. For the MPC strategy, there is a tradeoff between the time used for the charge or discharge of the ice tank. As the prediction horizon increases, the charging duration of the ice tank during the unoccupied time increases, and the ice storage is discharged more during the peak-price period.

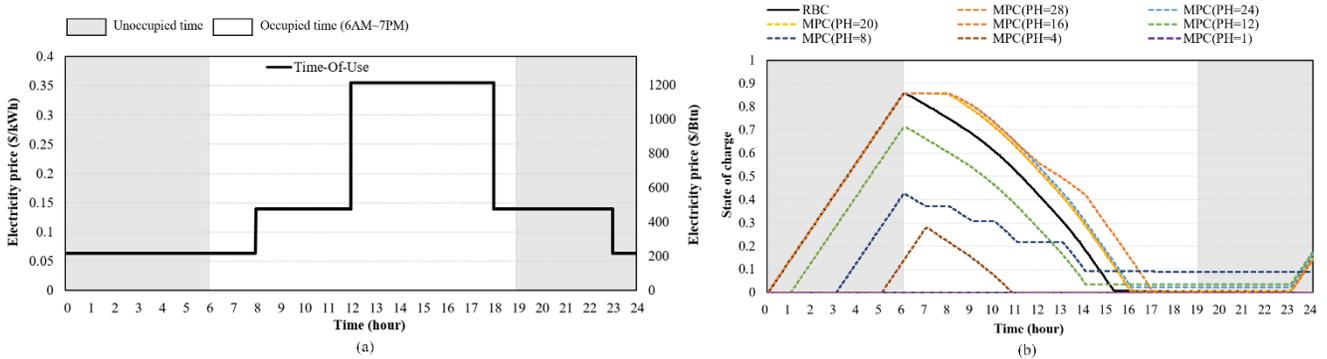


Figure 3 (a) Time-variant electricity prices and (b) SOC comparison of MPC with RBC.

Figure 4 presents the resulting power usage profiles. It illustrates how MPC reduces energy costs through load shifting by use of the ice storage tank. Take the MPC results with PH of 1-hour and 20-hours as examples. The MPC with a short PH of 1-hour can't forecast the benefits of the ice storage, so the ice tank is not charged during the unoccupied time and only the chiller is used to supply cooling during the occupied time. The MPC with a long PH of 20-hours controls the ice tank to be fully charged during the unoccupied time, and MPC then adopts an optimal discharging duration of the ice tank in response to the time-variant electricity prices during the occupied time. In this case study, as the PH increases, the power consumption during the peak-price period initially decreases and then reaches a stable state after the PH is longer than 20-hours. Note that the prediction horizon that will result in the best demand

flexibility is case-by-case, depending on the system dynamics and the TOU electricity rate.

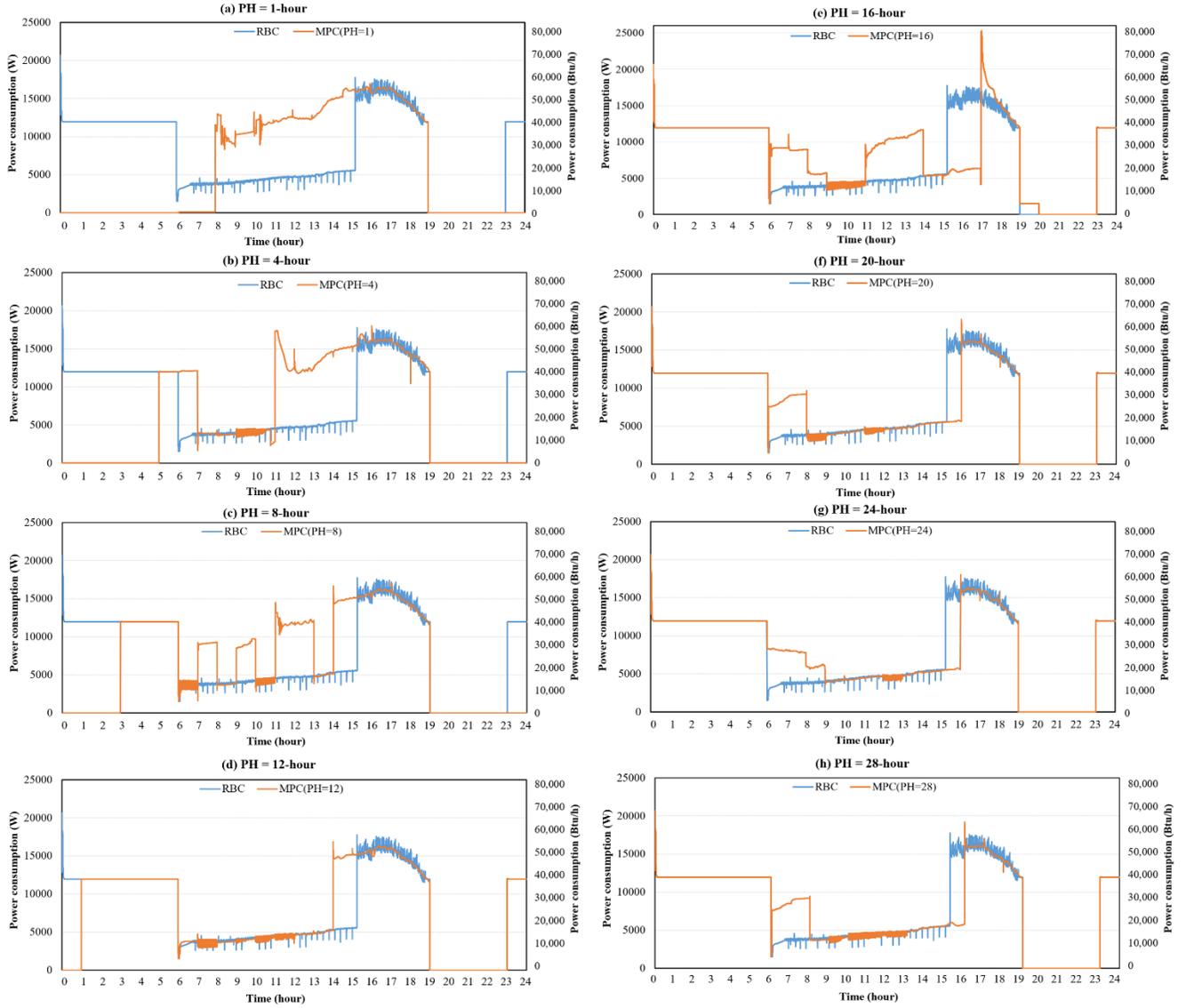


Figure 4 Power usage profiles of MPC with different PH (Baseline: RBC).

Evaluation metrics

Three performance metrics were applied to evaluate the demand flexibility in terms of three aspects: energy cost savings, peak power reduction, and the flexibility factor of energy. In addition to the demand flexibility evaluation, the computation cost for optimization is calculated under the following computer configuration: Intel i7-10700 CPU @ 2.90GHz and 8 Core(s) with 16 GB RAM. Table 2 lists the results of RBC and MPC with different PHs. The flexibility factor of energy is calculated based on Eq. (7). This factor illustrates the ability to shift the energy use from high to low price periods. The factor is 1 if energy is only used in the low-price period. The factor is -1 if energy is only used in the high-price period. The factor is 0 if energy use is similar in low and high price periods. So, a factor of 1 indicates the highest flexibility of the controlled system, and -1 correlates to inflexible energy usage (Finck et al. 2019).

$$\text{Flexibility Factor} = \frac{\int_{\text{lower price time}} \text{Power} \cdot dt - \int_{\text{high price time}} \text{Power} \cdot dt}{\int_{\text{lower price time}} \text{Power} \cdot dt + \int_{\text{high price time}} \text{Power} \cdot dt} \quad (7)$$

Table 2. Results of the RBC and different MPC formulations

Control Strategy	Peak Power (kW)	Peak Power (MMBtu)	Valley Power (kWh)	Valley Power (MMBtu)	Energy Cost (\$)	Energy Savings	Peak Power Reduction	Flexibility Factor	Average Computation Cost for optimization (hour)
RBC	68.80	0.23	112.42	0.38	34.33	Baseline	Baseline	0.24	0.01
MPC _{PH=1}	89.28	0.30	58.04	0.20	39.73	-15.74 %	-29.77 %	-0.21	0.01
MPC _{PH=4}	88.30	0.30	67.62	0.23	38.62	-12.50 %	-28.34 %	-0.13	0.07
MPC _{PH=8}	78.00	0.27	90.11	0.31	36.55	-6.48 %	-13.38 %	0.07	0.21
MPC _{PH=12}	70.92	0.24	108.60	0.37	34.32	0.02 %	-3.09 %	0.21	0.60
MPC _{PH=16}	56.88	0.19	128.26	0.44	31.30	8.83 %	17.32 %	0.39	0.84
MPC _{PH=20}	51.73	0.18	129.87	0.44	28.89	15.84 %	24.80 %	0.43	1.15
MPC _{PH=24}	51.68	0.18	131.48	0.45	29.15	15.07 %	24.87 %	0.44	2.40
MPC _{PH=28}	51.89	0.18	132.36	0.45	28.91	15.78 %	24.58 %	0.44	2.76

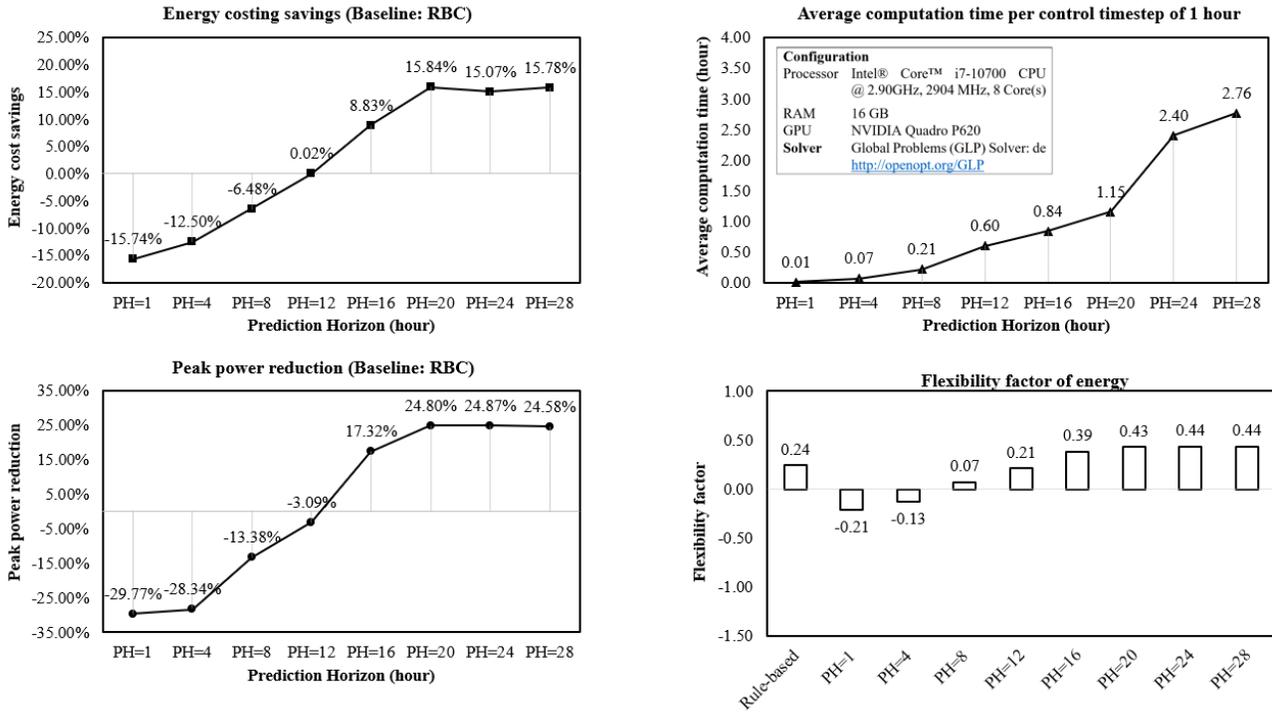


Figure 5 Metrics of MPC with different PH settings.

Figure 5 presents the three metrics for demand flexibility and the computation cost for optimization. As the prediction horizon increases from 1-hour to 28-hours, the energy cost savings increase from -15.7 % to 15.8 %, the peak power reduction increases from -29.8 % to 24.8 %, the flexibility factor of energy increases from -0.21 to 0.44, and the computation cost increases from 0.01 hour to 2.76 hours per control timestep. As the PH increases, the demand flexibility in the building initially increases and then reaches its plateau after the PH reaches 20-hours. The MPC has almost the same performance with PH of 20-hours, 24-hours and 28-hours since all these PHs are long enough to cover the three kinds of schedule: the charging/discharging cycle of the ice storage tank, the occupied duration, and the peak-price period. These results also show that once PH reaches 12 hours, MPC outperforms RBC on most factors in this case study.

CONCLUSIONS AND FUTURE WORK

This study investigated the impacts of different MPC prediction horizons on the demand flexibility of a commercial HVAC system with an ice storage tank. MPC reduced the energy cost of the studied HVAC system by up to 15.8 % and reduces the peak power consumption by up to 24.8 % compared with RBC in this case study. In addition, as the PH increases, the demand flexibility in the building initially increases and then reaches its plateau for PH greater than or equal to 20-hours in this case study. A longer prediction horizon also results in a higher computation cost for optimization, therefore it is valuable to identify the point at which increasing PH will no longer improve MPC. With the increasing computing power, it's anticipated that MPC will be increasingly deployed in practice and empower grid-interactive efficient buildings. In the future, more demand flexibility evaluation metrics and optimization solvers will be explored, the airside coupling with the waterside control will be studied, and additional settings will be investigated including different storage capacities of the ice tank, different objective functions, different constraints, and different control horizons, etc.

ACKNOWLEDGMENTS AND DISCLAIMER

The research reported in this paper was partially supported by the Building Technologies Office at the U.S. Department of Energy through the Emerging Technologies program under award number DE-EE0009153 and DE-EE0009150. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof. Certain commercial equipment, instruments, or materials are identified in this paper in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement by NIST, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

NOMENCLATURE

AHU	=	Air Handling Unit
ASHRAE	=	American Society of Heating, Refrigerating and Air-Conditioning Engineers
ANN	=	Artificial Neural Networks
CV(RMSE)	=	Coefficient of Variation of Root Mean Square Error
HVAC	=	Heating, Ventilation, and Air Conditioning
MPC	=	Model Predictive Control
NIST	=	National Institute of Standards and Technology
PH	=	Prediction Horizon
RBC	=	Rule-based Control
SOC	=	State of Charge
TOU	=	Time of Use
VAV	=	Variable Air Volume
p^{t+k}	=	Predicted total power consumption at time $t + k$
R^{t+k}	=	Electricity cost rate at time $t + k$
u_{mode}	=	Control signal of operation mode
u_{Tchw}	=	Control signal of the setpoint of chilled water supply temperature

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