# Carbon Responsive Control of Building Thermal Loads

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## ABSTRACT

Buildings account for 35% of total energy-related carbon dioxide emissions in the U.S. and thereby play an important role in achieving the decarbonization goals set by the administration. Renewable energy such as solar and wind can help reduce grid emissions by displacing fossil fuel; however, the uncertainty and intermittency of renewable energy resources can cause both diurnal and seasonal variability of the electricity carbon intensity. This paper first presents an analysis of the carbon variation patterns across eleven locations in the U.S. A carbon savings potential indicator is introduced to afford first-order estimation of carbon reduction potential based on diurnal variability of the carbon intensity. This analysis is followed by a model predictive control strategy to minimize building carbon emissions through optimized thermal load shifting in response to time varying carbon intensity signals. The control strategy was tested using a commercial building case study subject to hourly marginal carbon emissions of two U.S. electricity markets – the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO). The test results show that for the NYISO market, the carbon responsive strategy could save 3.4% carbon emissions compared to the energy minimizing strategy, while for the CAISO market, up to 33.5% carbon emission reduction could be achieved because of the more aggressive intro-day variation of the electricity carbon intensity.

## 1. INTRODUCTION

To curb climate change, research and development of decarbonization technologies have witnessed rapid growth in recent years. In the U.S., buildings contribute to 35% of the overall energy-related $CO_2$ emissions and can play a pivotal role in the attainment of the decarbonization goals established by the administration. Renewable energy such as solar and wind can help reduce grid emissions by displacing fossil fuel; however, the uncertainty and intermittency of renewable energy resources can cause both diurnal and seasonal variability of the electricity carbon intensity. As a result, the carbon footprint of the overall power system is not only affected by how much but also by when electricity is consumed. Shifting of flexible energy uses to low-carbon hours, e.g., when the natural gas power or renewable energy is marginal, can effectively reduce the cumulative carbon emission of the power system. Building thermal loads are flexible and deferrable thanks to the thermal inertia of the construction materials and strategic control thereof, e.g., load shifting from periods of high carbon intensity to cleaner hours through precooling or preheating actions, holds good promise for decarbonization of the building sector in a cost-effective manner.

There are numerous studies in carbon responsive control of building heating, ventilating, and air-conditioning (HVAC) systems. Two types of control strategies have been investigated – rule-based and optimization-based. Wang et al. (2023) introduced and validated a rule-based carbon-responsive control framework to coordinate HVAC systems, batteries, and electric vehicles (EVs) charging in all-electric buildings. The control framework adjusts HVAC thermostat setpoints, battery and EV charging rates by comparing the instantaneous carbon intensity with a pre-determined threshold. The strategy was tested using a simulation model of an all-electric mixed-use community in a cold climate. Results show that this control strategy could reduce building annual carbon emissions by 6.0% to 20.5% with limited impact on energy costs, peak demand, and thermal comfort. Clauß et al. (2019) examined predictive rule-based control strategies aimed at reducing annual $CO_2$ equivalent greenhouse gas emissions for a Norwegian single-family detached house, focusing on the control of the building's heat pump system. Historical weather and carbon emission data from 2015 were employed for simulation tests. However, the study found that carbon-responsive control failed to decrease annual carbon emissions, mainly attributed to the limited daily variation of the average carbon intensity for the Norwegian electricity generation mix. It highlighted the need to investigate the carbon diurnal pattern and their implications for control development.

Optimization-based model predictive control (MPC) has also been reported for building carbon reduction. Leerbeck et al. (2020) devised a carbon-minimization MPC heat pump controller for space heating in a house and an office building, equipped with radiator heating and floor heating systems. Using weather and power grid conditions during a full-year period in 2017–2018 for the power bidding zone DK2 (East, Denmark), the MPC controls the operation of the heat pump to satisfy the required temperature bounds. The sensitivity analysis showed that both insulation and thermal mass influence the achievable demand flexibility. The study demonstrated that $CO_2$ emission savings can reach 17% using floor heating and 12% using radiators relative to a conventional thermostat controller. Péan et al. (2019) investigated the efficacy of carbon-minimization MPC developed and evaluated within a co-simulation framework which couples an optimization software (YALMIP tool in Matlab) with a dynamic building simulation tool (TRNSYS) for a Spanish residential building equipped with heat pump systems. The MPC cycles the heat pump on and off with a 12-minute timestep within a 24-hour control time horizon. Encouraging results were obtained demonstrating noteworthy $CO_2$ marginal emission savings ranging from 19% to 29% by load shifting. Bird et al. (2022) presented a case study of a food-retail building in the UK, outlining the detailed design, installation, and cost of a generalizable MPC framework for its HVAC system. With external temperature and grid carbon intensity forecasts, the MPC calculates the optimal air temperature to minimize overall carbon emission while ensuring occupants' thermal comfort, and then passes the calculated temperature setpoint to the existing local controller of the air-handling unit (AHU) and heating system. A simulation test spanning two months showed negligible carbon savings due to the poor thermal performance of the building. The study highlighted that factors such as the thermal characteristics of the building envelope, air exchange requirements, and occupancy patterns could influence the benefits of advanced control. The study of Gasser et al. (2021) considered building flexibility associated with the operations of air-sourced heat pumps, domestic hot water, thermal energy storage, and electric vehicles through MPC. Results indicate that an MPC with a carbon minimization objective could result in carbon savings of up to 21% compared to existing rule-based controllers. Tamashiro et al. (2023) proposed a smart apartment building (SAB) model where multiple distributed power sources are shared among multiple consumers to lower operation costs and carbon emissions. The study optimized the capacities of photovoltaic (PV) and battery energy storage system and generated a Pareto front for multi-objective optimizations aimed at reducing the total cost and $CO_2$ emissions in the design phase. The SAB framework was shown to achieve 44.4% cost reduction and 54.7% carbon reduction compared to a baseline without distributed generation, energy storage, and smart control.

Although some of the existing studies discussed the impact of local electricity markets on the carbon savings ability of building load control, no national or regional impact analysis has been conducted. To fill the gap, this paper first introduces a carbon saving potential indicator that allows first-order estimation of the carbon reduction potential based on diurnal variability of the carbon intensity for a given local electricity market. We applied this metric to marginal emission data of 11 locations in the U.S. collected from 2020 to 2023. Next, the paper presents an optimization-based MPC strategy to minimize a building's energy-related carbon emission through optimally shifting its thermal load in response to the carbon intensity forecast. Simulation test results are presented for two representative days for two electricity markets, one with a time-varying carbon intensity and the other with a relatively constant carbon emission signal.

## 2. CARBON SAVING POTENTIAL ASSESSMENT

The marginal carbon emission data provided by WattTime is used in this work for analysis of the carbon savings potential of the proposed carbon responsive strategy. WattTime uses an empirical model to evaluate the marginal carbon emission of U.S. electricity markets, based on Continuous Emissions Monitoring System's data reported through the Environmental Protection Agency' Clean Air Markets Program Data. WattTime's empirical model is driven almost purely by data and can be applied to different locations across the U.S. with different weather and power system conditions.

Before deployments of advanced control solutions like MPC which often involve high computational expenses, it is necessary to perform a first-order assessment of the carbon emission savings potential of building load control across the different electricity markets in the U.S. To this end, we introduce the carbon saving potential indicator (CSPI) to quantify the carbon diurnal variability of a specific location to justify whether and how much building load control could help reduce electricity consumption-related carbon emissions.

We selected 11 major electricity power markets in the U.S. for this analysis using historical marginal carbon intensity data from 2020 to 2023. The locations of interest are AZPS (Arizona), CAISO_LONGBEACH (California), CAISO_NORTH (California), ERCOT_NORTHCENTRAL (Texas), ISONE_NEMA (Massachusetts), MISO_INDIANAPOLIS (Indianapolis), NYISO_NYC (New York City), PJM_DC (Washington, D. C.), PSCO (Colorado), SCL (Washington), and SPP_OKCTY (Oklahoma). These locations are chosen to cover the major populated areas and also include at least one location for each of the seven regional transmission organization/ independent system operator territories in the U.S.

## 2.1 Carbon Saving Potential Indicator

Building carbon responsive control can lower a building's energy-related carbon emissions by shifting its load from hours of high carbon intensity to hours with clean electricity generation. Like conventional price-responsive control strategies where the electric utility cost savings potential is highly dependent on the peak-to-off-peak price ratio, a building's carbon reduction potential is largely influenced by the diurnal variability of the electricity carbon intensity. In general, we can think of the highest carbon intensity of a day as the nominal carbon emission level for electricity generation in a particular area (usually the marginal emission rate of the least expensive and most polluting coal power plants), and a dip in the carbon intensity is mostly associated with peaker natural gas plants being marginal or renewable energy curtailment. Then we can define the carbon saving potential indicator of a day as follows:

$$CSPI = 1 - \frac{\sum_{i=1}^{24} C_i}{24 \times C_{highest}} \tag{1}$$

where $C_i$ is the carbon intensity at the $i$-th hour, and $C_{highest}$ is the highest carbon intensity of a day. Figure 1 illustrates the definition of the indicator – unity less the ratio of the shaded area to the rectangular area. If the indicator has a value close to zero, then the carbon dip (shallow grey area) is little to none leading to relatively constant carbon intensity and low carbon reduction potential of load shifting control. On the other hand, an indicator close to unity suggests a good carbon savings potential with good diurnal variability in the carbon intensity.

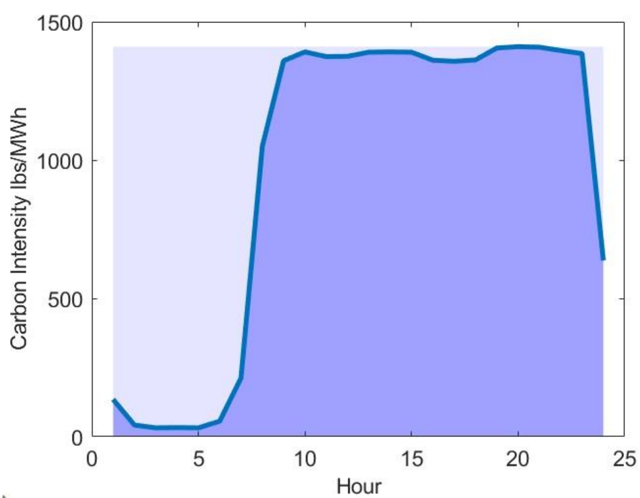



**Figure 1:** Illustration of the carbon saving potential indicator

We have calculated the CSPI values for each day of the four-year period from 2020 to 2023 across the 11 regions to generate insights into the carbon reduction potentials of the different locations. Figure 2 shows the number of days with the CSPI value greater than thresholds of 0.2, 0.25, and 0.3 for the four years of interest and for the different locations. Taking PSCO as an example, there are over 700 days with the CSPI value greater than 0.2 out of the 1460 days analyzed; using a threshold of 0.25, the number of carbon saving days would be reduced to 518. It can be seen from Figure 2 that the highest carbon saving locations are CAISO_LONGBEACH (California), CAISO_NORTH

(California), ERCOT_NORTHCENTRAL (Texas), PSCO (Colorado), SCL (Washington), and SPP_OKCTY (Oklahoma).

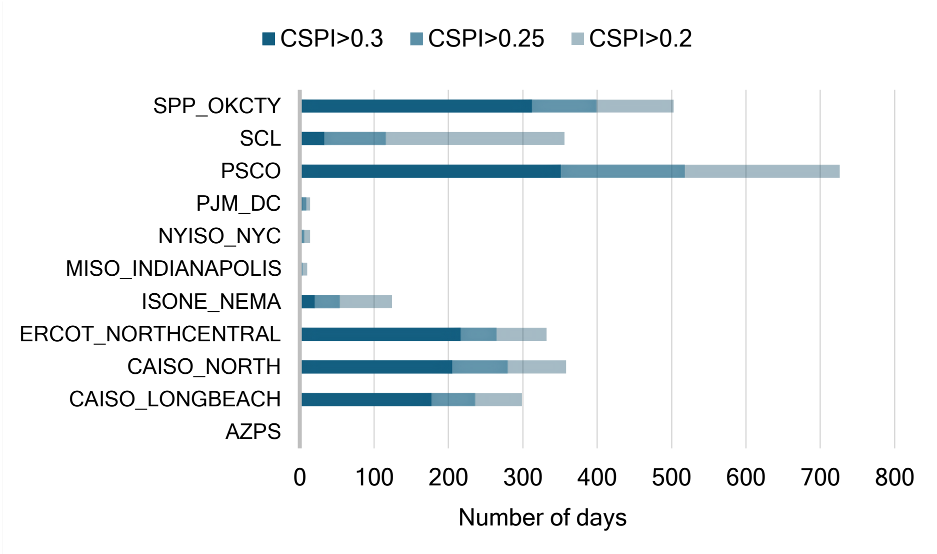
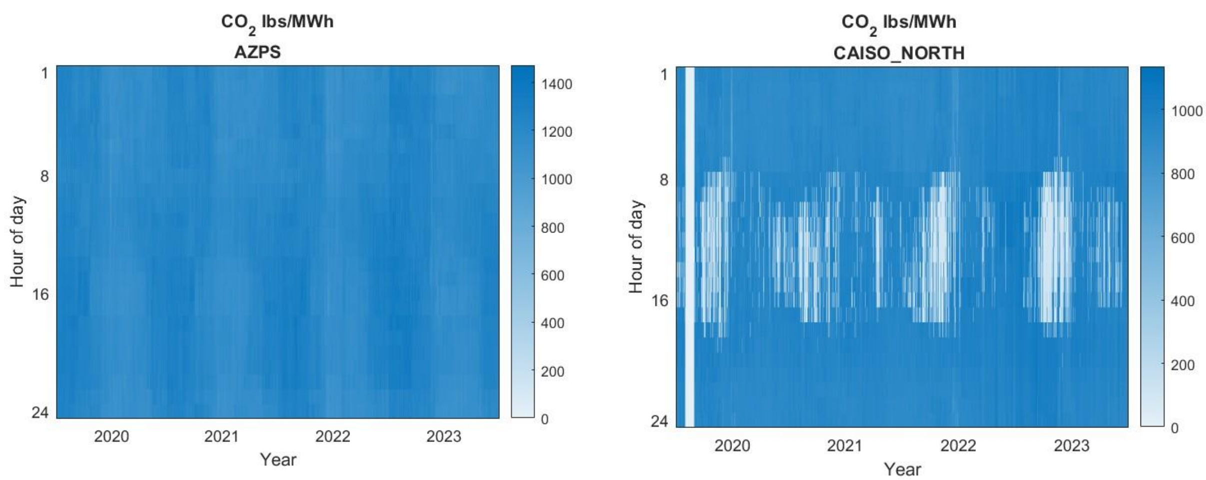



**Figure 2:** The number of potential carbon saving days with different thresholds from 2020 to 2023

## 2.2 Diurnal Carbon Emission Patterns

Through analyses of the diurnal carbon patterns, we have categorized the 11 regions into 4 groups: no variation, variation with diurnal and seasonal features, high variation with no diurnal and seasonal feature, and low variation with no diurnal and seasonal feature. One representative location was selected from each group and the carbon heat maps for these four locations (AZPS, CAISO_NORTH, PSCO, ERCOT_NORTHCENTRAL) are presented in Figure 3. Note there are 8 months of missing data in the total 528 months of data cross the 11 regions analyzed. We set the missing carbon intensity to 0. In Figure 3, the vertical axis is the hour of the day, and the horizontal axis corresponds to the days of the four-year period. The shade of color represents the level of the carbon intensity.



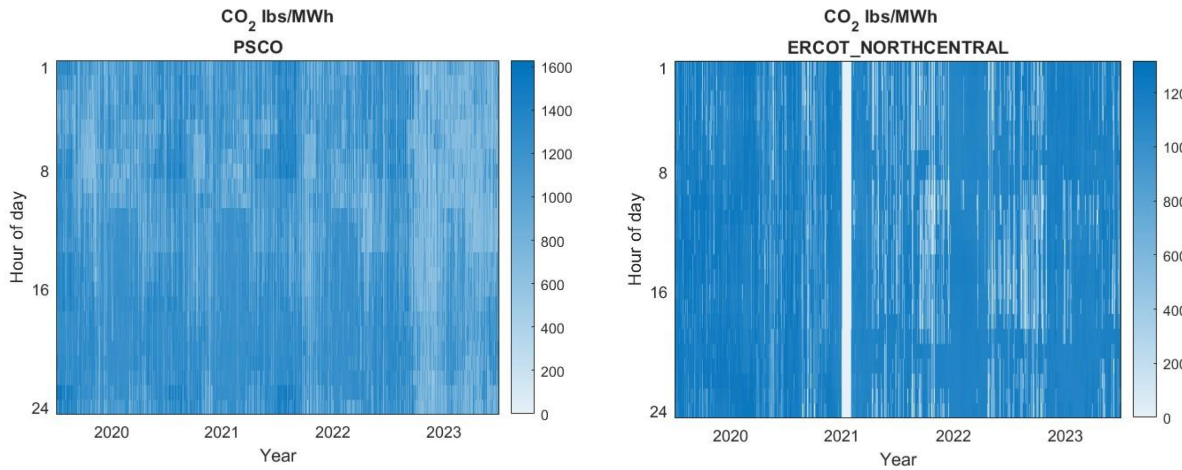



**Figure 3:** Heat maps of the carbon intensity from 2020 to 2023 of four representative locations

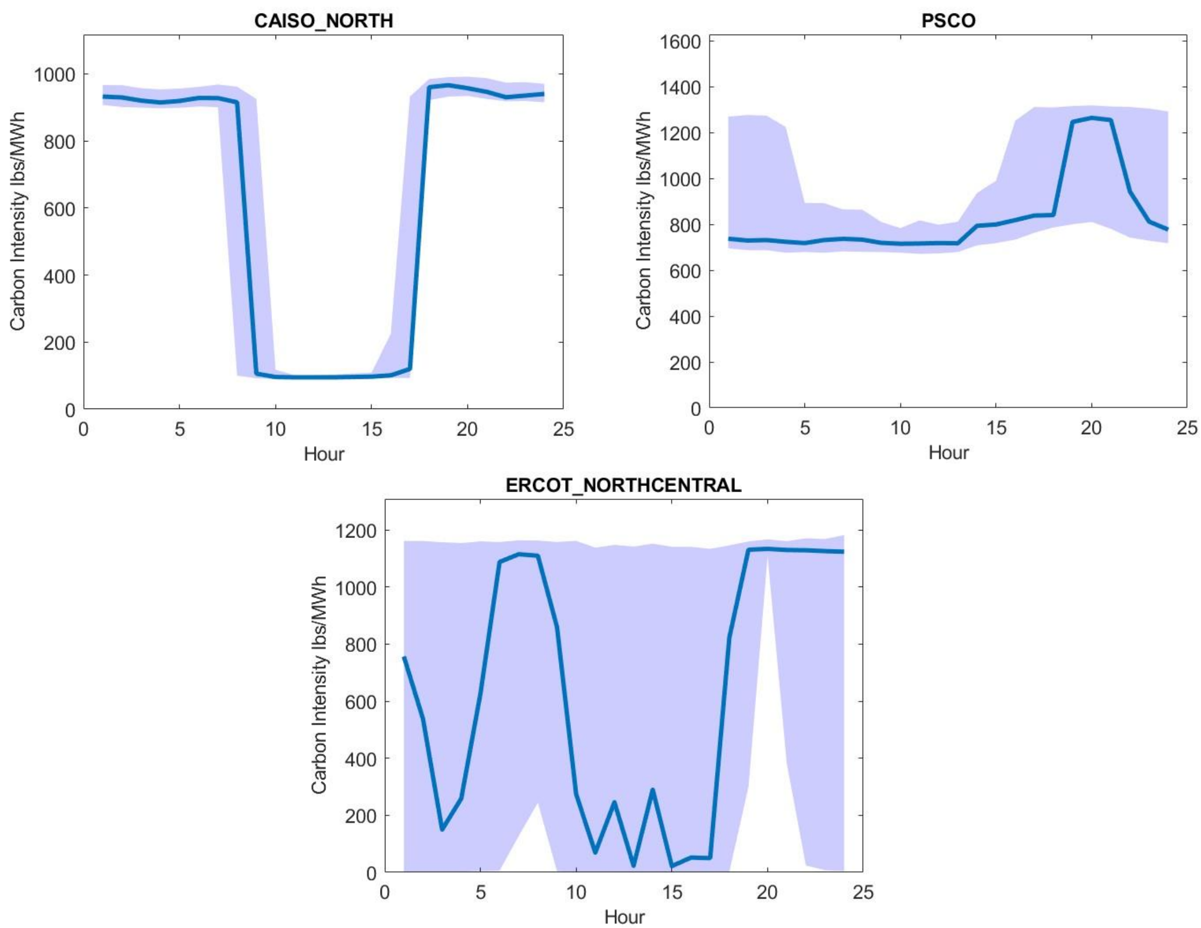



**Figure 4:** Day pattern in three representative regions

The CSPI defined above offers a quick, first-order method to estimate carbon reduction potentials based on electricity carbon variability. However, the actual carbon reduction achievable is also dependent on the diurnal load profile as well as load flexibility. For a hot summer day in California, the carbon intensity is the lowest during the daytime which coincides with the high cooling energy use for office buildings, while the cooling load is little to none during nighttime when the electricity is the dirtiest. For this case, there is not much carbon reduction potential through load shifting.

Therefore, we need to investigate the diurnal pattern of electricity carbon variation to better understand the actual carbon reduction potential.

To analyze the diurnal variation patterns, we filtered out the days with low CSPI values and analyzed the rest of the days with CSPI values greater than 0.2. Figure 4 shows the diurnal variations of the median carbon intensity as well as the 75% and 25% percentiles for three representative locations. The horizonal axis is the hour of the day and the vertical axis represents the carbon intensity. It can be seen that the electricity carbon intensity varies with location, season, and time of a day. For the no-variability group consisting of AZPS, ISONE_NEMA, MISO_INDIANAPOLIS, NYISO_NYC, and PJM_DC, there is almost no carbon intensity variation with time. On the other hand, the other locations under study feature noticeable carbon variabilities; however, the diurnal pattern differs from one location to another caused by the different generation mixes. For the CAISO market, due to the rich solar energy generation, the carbon intensity exhibits significant variations throughout a day with a clear diurnal pattern – the carbon intensity is close to zero in the daytime due to the solar energy curtailment (solar is marginal) but bounces back to a higher level during nighttime. More than 90% of the electricity in Colorado (PSCO) is generated by coal, natural gas, and wind power plants and the carbon intensity is mostly dependent on the percentage split of the marginal energy sources. With coal and natural gas power being marginal for most of the time, the electricity carbon intensity for PSCO is higher than the other markets. Although natural gas is the major energy source for ERCOT, the market is also rich in solar and wind energy. Wind energy can become marginal during nighttime when curtailment takes place. That is why the carbon intensity dips in the early morning; it is also lower during daytime when there is excess solar generation. However, due to the large share of natural gas power and the unpredictability of wind energy, there is significant variance in the diurnal carbon intensity profile.

## 3. CARBON RESPONSIVE CONTROL

This section introduces the MPC formulation and implementation for the carbon responsive control strategy as well as a baseline energy-minimizing strategy. The objective functions and constraints are presented separately below.

### 3.1 MPC Objective Functions

Two MPC strategies are introduced as constrained linear programs, with the same constraints but different objective functions. Both strategies assume a 24-hour look-ahead time horizon and are implemented in a receding horizon scheme with the decision step being one hour. At each decision step, the strategies use the weather and internal gain forecasts, both assumed to be perfect in this study, to identify optimal control actions to minimize their respective cost functions, defined below.

3.1.1 Energy Minimization Control (E_min): The first strategy minimizes the sum of cooling energy consumption at each time step over a prediction horizon (e.g., 24 hours in the case study) for maximum energy efficiency. The cost function is as follows:

$$W_1 = \sum_{t=t_i}^{t_f} P^t \tag{2}$$

where $t_i$ and $t_f$ are the first and the last time steps of the prediction horizon, and $P^t$ is the cooling power at the $t$-th time step.

3.1.2 Carbon Minimization Control (C_min): The second strategy minimizes the cumulative carbon emission within the prediction horizon:

$$W_2 = \sum_{t=t_i}^{t_f} (r^t \cdot P^t) \tag{3}$$

where $r^t$ is the marginal carbon emission rate (lb/kWh) that may change with the time of the day.

### 3.2 Control Constraints

Control decision making needs to respect all operational constraints. The first set of constraints are associated with the thermal dynamics of the building, represented by a discrete-time state-space model in the following form:

$$x^{t+1} = Ax^t + B_w w^t + B_u Q_z^t \tag{4}$$
$$T_z^{t+1} = Cx^{t+1} \tag{5}$$

where $x^t$ is the state vector including all nodal temperatures of the thermal network that characterizes the load dynamics, $Q_z^t$ is the average cooling rate in each time step, $T_z^t$ is the indoor zone temperature, and $w^t$ is the disturbance vector consisting of outdoor temperature, internal heat gains, and solar radiation. The state-space matrices $A$, $B_w$, $B_u$ and $C$ are time-invariant and only dependent on the thermal network itself. The parameter values used in the case study can be found in Cai and Braun (2016). The power used by the HVAC system can be estimated from the cooling rate:

$$P^t = Q_z^t / COP \tag{6}$$

where the coefficient of performance (COP) assumes a constant in this study.

In addition to the load dynamics constraints above, two more sets of constraints need to be satisfied in the control optimization. The first set represents the indoor comfort requirement, formulated as a box-type constraint shown in Equation (7) where $T_{max}^t$ and $T_{min}^t$ are the temperature upper and lower bounds, respectively. The comfort band can change with occupancy in a building. The other constraint is associated with the physical thermal capacity of the HVAC equipment shown in Equation (8). Note that the constraints discussed in this section need to be satisfied throughout the whole look-ahead control horizon.

$$T_{min}^t \leq T_z^t \leq T_{max}^t \tag{7}$$
$$0 \leq Q_z^t \leq Q_T \tag{8}$$

## 4. CASE STUDY RESULTS

A simulation study was conducted to compare the baseline and the carbon responsive control behaviors. The case study uses a simulation model for an office building, calibrated with field data. The detailed model validation results can be found in Cai (2015). The simulation model has a time step of one hour. The MPC strategies assume a 24-hour prediction horizon with a one-hour decision step. The control optimization problem is solved using the CVX package in MATLAB (Grant and Boyd, 2013). The zone temperature comfort bounds vary with occupancy of the building – the occupied period is assumed to be from 9AM to 6PM while the building is unoccupied for the rest of the day. The upper and lower temperature bounds are assumed to be 21.5°C and 23.5°C during the occupied hours, and 19.5°C and 25.5°C during the unoccupied period, respectively.

### 4.1 Simulation Locations and Days

To illustrate the control behaviors subject to different carbon diurnal patterns, we tested the control strategies for two locations of different CSPI values. As discussed in Section 2, CAISO (California Independent System Operator) shows good carbon savings potential with the most significant carbon variation. Simulation tests were carried out for May 2023 with an average CSPI value of 0.35. For comparison, we also conducted simulation tests over the whole month of April 2023 for the NYISO_NYC (New York Independent System Operator) market with an average CSPI of 0.08.

### 4.2 Simulation Test Results

Fig. 5 compares the control test results for the baseline and carbon responsive strategies and for the two locations under study, over two representative days. The top subplots show the variations of the zone temperature as well as the comfort bounds. The middle subplots depict the cooling power consumption while the bottom subplots show the marginal emission rate of the local electricity market. Table 2 shows the total energy consumption and the carbon emission for the different cases over the whole month.

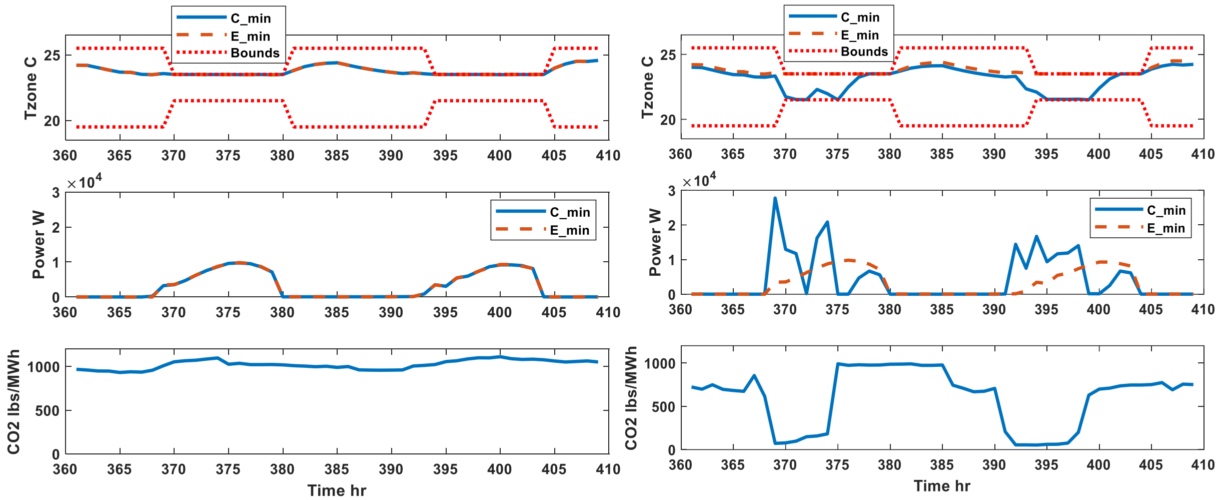



**Figure 5:** Simulation test results for NYISO_NYC (left) and CAISO (right).

**Table 1:** Detailed simulation results for NYISO_NYC and CAISO

| | **Energy Use (kWh)** | | **Carbon Emission (lb)** | |
|---|---|---|---|---|
| | NYISO April 2023 | CAISO May 2023 | NYISO April 2023 | CAISO May 2023 |
| E_min | 3127.2 | 3296.8 | 2768.1 | 1619.9 |
| C_min | 3209.0 | 3463.3 | 2673.2 | 1077.6 |

As shown in the left plot of Fig. 5, NYISO_NYC features small variations in the marginal carbon emission over the two demonstration days in April 2023. The baseline and carbon responsive control strategies led to almost identical control behaviors – no major precooling took place because the round-trip efficiency loss could easily outweigh the associated carbon benefit. Over the whole month of April 2023, the carbon emission minimization strategy saved 3.4% carbon emissions compared to the baseline strategy with a total cooling energy increment of 2.6%. The carbon reduction achieved was limited because of the relatively flat carbon intensity. In contrast, the CAISO market experienced significant variation in its carbon intensity throughout the day, as shown in the right plot of Fig. 5. The carbon minimization strategy could foresee the diurnal variation and engage precooling to shift the cooling load from high-carbon hours to periods with cleaner electricity generation. Since the valleys in the carbon intensity were mostly caused by solar energy curtailment on the local power system, the load shifting actions could help reduce energy waste caused by curtailment. Over the whole month of May 2023, the carbon minimization strategy saved 33.5% carbon emissions compared to the baseline strategy with a total energy rebound of 5.1%. This demonstrates the significant carbon reduction potential in the CAISO market.

## 5. CONCLUSIONS

This paper presented a carbon reduction potential assessment for building load control through optimal zone air temperature scheduling across eleven locations in the U.S. The diurnal variability of the carbon intensity of the locations under study was analyzed with historical emission data from 2020 to 2023. The analyses showed that California, Colorado, Washington, Texas, and Oklahoma electricity markets feature adequate diurnal variability with good carbon reduction potentials through optimal load control, while Arizona, Massachusetts, Indiana, New York City, and Washington D.C. have almost flat carbon intensity with limited carbon reduction potential. For the markets with varying carbon intensity, the causes of such variability and thereby the diurnal pattern differ from one location to another. California is rich in solar energy and low carbon intensity occurs during daytime when solar energy curtailment takes place. In Oklahoma, wind energy is abundant during nighttime leading to reduced carbon intensities. The diverse diurnal patterns can lead to different carbon reduction abilities across different locations, seasons and building types.

The carbon variability analyses were followed by the development of a model predictive control (MPC) strategy aimed at minimizing building carbon emissions by optimizing the thermal load schedule in response to time-varying carbon intensity signals. The control strategy was tested using a commercial building case study, subject to hourly marginal carbon emissions from the California Independent System Operator (CAISO) and NYISO (New York Independent System Operator) markets for a whole month. The performance was assessed through the comparison to the conventional energy minimization strategy. The results of the tests reveal that, for the NYISO market in April 2023, the carbon-responsive strategy could lead to 3.4% reduction in carbon emissions compared to the energy-minimizing strategy, with almost identical total energy use. In contrast, for the CAISO market in May 2023, attributed to the high intra-day variation of electricity carbon intensity, the strategy could achieve a more substantial carbon emission reduction of up to 33.5%, with a 5.1% total energy use increment. This comparative study clearly shows the tradeoff between energy cost and carbon emission during control decision making. Actual behaviors of a resident may fall between the two extremes and could be analyzed through a mixed strategy with the objective function being a weighted sum of the cost and emission. This will be investigated under a game theoretic setting in future work.

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