Quantifying Office Building HVAC Marginal Operating Carbon Emissions and Load Shift Potential: A Case Study in California

Aoyu Zou
Student Member ASHRAE

Carlos Duarte Roa, PhD
Member ASHRAE

Stefano Schiavon, PhD
Member ASHRAE

ABSTRACT

The operational carbon emissions intensity of the electricity used in a building is commonly treated as a fixed value throughout the year but this is not accurate because grid carbon emissions factors have temporal and geographical variations, which makes building operating emissions dependent on when and where electricity is used. However, this has been frequently overlooked in the existing literature. Grid electricity carbon characteristics can be quantified by either average or marginal emission rates, there is an increasing debate within the building industry about which metric provides more accurate results for determining the effect of various decarbonization strategies. An example is the emission-based load-shifting strategy that attempts to shift the electricity usage of a building to a time period when the grid has lower associated carbon emissions. We advocate for the use of the marginal operating emissions rate (MOER) to evaluate the impacts of demand-side management. This is because the marginal emissions rate considers the generating plants' dispatch order and is able to reflect the change in emissions induced by demand management. In this study, we examined the benefits of emission-based load-shifting strategies, using an office building in Berkeley, CA as a case study. We first analyzed the annual temporal variations of the Northern California grid region and developed a virtual chiller load shift strategy similar to demand response but interacting with the grid MOER signal. The proposed control strategy attempts to shift the chiller load to better align with low-carbon grid electricity generation while not interfering with annual total HVAC energy use and comfort conditions. We then assessed its effect on the case study building by calculating the avoided emissions on a seasonal and annual basis through a numerical simulation. As a result, we found that for the Northern California region, shifting load is most effective during the spring season with 18% avoided carbon emissions when the grid has more renewable supply. However, the simulated annual result shows 2% avoided carbon emissions indicating the seasonal characteristics of the proposed strategy and the limitation of considering load shift strategy as the single solution to decarbonize.

INTRODUCTION

The building industry is one of the most energy-intensive sectors globally. It is estimated that 40% of energy is consumed by building space heating and cooling, ventilation, water pumping, lighting, and so on. Among them, 30% of carbon emissions are related to HVAC (Heating, Ventilation, and Air Conditioning) equipment operation. The significant consumption and associated emissions have led to global concerns in terms of rapid climate change and the increasing frequency of power outages. Although there has been a notable shift towards renewable energy sources to gradually achieve net-zero carbon emissions of the grid, these sources operate intermittently and are not always

Aoyu Zou is a PhD student at Center for the Built Environment, University of California, Berkeley. **Carlos Duarte Roa** is an assistant professional researcher at Center for the Built Environment, University of California, Berkeley. **Stefano Schiavon** is a professor of Architecture and Civil and Environmental Engineering at Unversity of California, Berkeley and the associate director of the Center for Environmental Design Research.

available during peak demand. Specifically, at peak conditions, the marginal generator, often a gas plant, may be employed, resulting in substantially higher emissions (Callaway et al., 2018; Holland et al., 2022). This situation underscores the importance of accurately calculating the carbon emissions of electricity usage, particularly in the building industry. This is because the conventional average carbon emissions rate fails to capture the variability and dynamic nature of electricity generation, leading to a significant underestimation of the environmental impact, especially during peak times. The use of a marginal carbon emissions rate, which reflects the emissions of the additional electricity supply required to meet demand, provides a more accurate and realistic understanding of the carbon footprint associated with building energy consumption. One study shows that calculation using the average carbon emissions rate has significantly different indications from using the marginal emissions rate (Holland et al., 2022). However, this does not imply that the average emissions rate should not be used. For example, attributional studies that focus on carbon accounting such as life-cycle analysis, should use average time-dependent emissions. On the other hand, consequential studies that focus on emissions change due to system effects should apply marginal rates (Regett et al., 2018). However, demand management that emphasizes environmental impact commonly uses hourly average emissions rates or even constant values to assess (Braun et al., 2016; Lowry, 2018; Setlhaolo et al., 2017; Stoll et al., 2014; Vogler-Finck et al., 2018; Zeng et al., 2023). A few studies found in the literature incorporate marginal carbon emissions in load shifting (Fiorini and Aiello, 2020; Fleschutz et al., 2021; Kim et al., 2022; Péan et al., 2019), but there is generally a lack of attention for office buildings. Commercial buildings use about 30% of electricity and account for 16% of all CO_2 emissions equivalent in the US (U.S. Energy Information Administration (EIA), 2023). Therefore, recognizing the marginal emissions rate is crucial for developing more effective strategies for the commercial office building sector, aimed at reducing its carbon footprint and mitigating climate change.

Upgrading existing control logic can be a cost-efficient approach for most commercial buildings to reduce their operational carbon footprint. The advent of Advanced Metering Infrastructure (AMI) with 15-minute interval data collection and fast two-way communication capabilities is improving the interaction between buildings and the electrical grid (Sofos et al., 2020). This infrastructure facilitates advanced control strategies such as grid-interactive load shift control. Currently, the primary focus of load shift control strategies in building HVAC systems is to reduce energy costs by shifting consumption away from peak periods when electricity prices are higher (Jiang et al., 2021; Robillart et al., 2019; Rogers and Rasmussen, 2018; Turner et al., 2015). This cost-based load shifting helps mitigate peak demand charges and lower overall energy expenses while maintaining thermal comfort. However, there is a significant gap in understanding whether load shift control is also effective in reducing operational carbon emissions. On the one hand, emission-based load shifts can align energy consumption with the availability of cleaner energy sources, thereby minimizing the environmental impact. On the other hand, the intermittency of grid renewables and the availability of building flexible loads can limit its effect. We summarized the contribution of this study as follows:

1. Explore the significance of incorporating the marginal operational emissions rate (MOER) into electricity emissions calculations, arguing for its critical role in assessing consequential impact after an applied change in building operation;
2. Develop a rapid approach to assess the effectiveness of emission-based load shift strategy based on real measurements and use a case study building to demonstrate;
3. Use various grid MOER signals as thresholds to initiate load shift and compare corresponding results to understand the impact on energy and emissions.

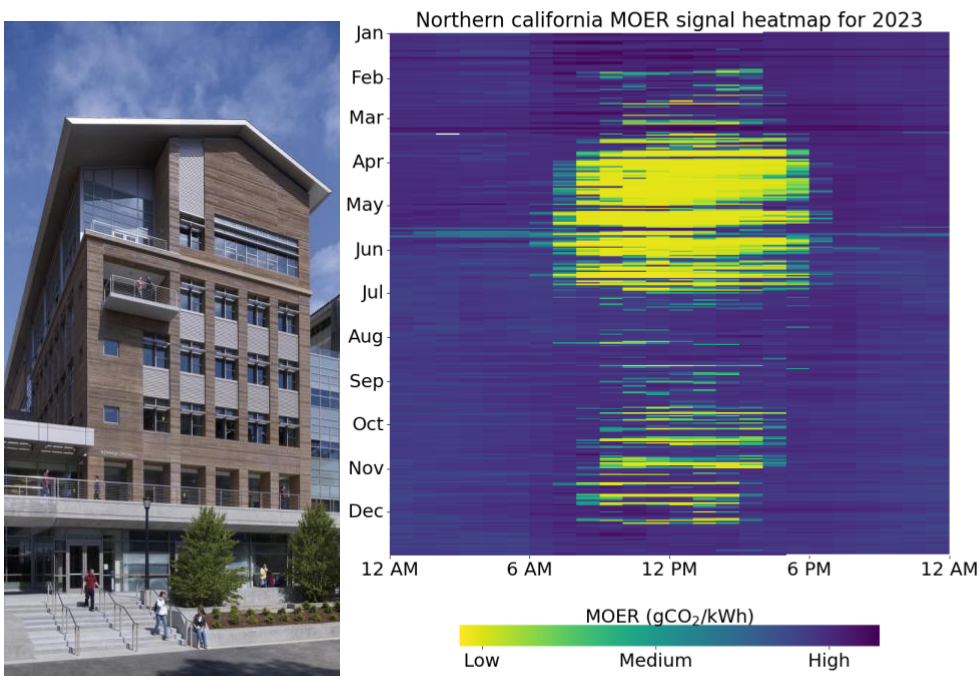
APPROACH

Case study building characteristics

The case study building, depicted in Figure 1 (a), is Sutardja Dai Hall (SDH), a seven-story campus office building at the University of California, Berkeley, built in 2001. The building spans 13,100 m² (140,000 ft²) and includes office units, classrooms, a nanofabrication laboratory, and an auditorium. SDH does not have an on-site boiler; instead, it relies on steam from the campus's cogeneration plant and a local heat exchanger to supply hot water for heating. Cooling is provided by two chillers: an absorption chiller (CH-1) and a centrifugal chiller (CH-2). CH-1 also uses steam from the campus cogeneration plant and alternates operation with CH-2, meaning only one chiller runs at a time. During summer, CH-1 typically operates, taking advantage of the campus's cogeneration plant's excess steam. When cooling demand exceeds CH-1's capacity during peak periods (i.e. with high outdoor temperatures), the building manager would disable CH-1 and activate CH-2. In winter and part of the shoulder season, CH-2 normally handles any cooling needs since most of the steam from the cogeneration plant is needed to provide heating. In this study, we focus on calculating HVAC electricity usage by investigating a scenario where the centrifugal chiller (CH-2) provides all cooling. This means when CH-1 operates, we predict the energy CH-2 would need to deliver the same thermal energy (i.e., same supply and return water temperature) and calculate the corresponding electricity usage to assess carbon emissions. We consider the most recent year 2023 to be the study period, and the measurements are extracted from the building automation system (BAS) shown in Table 1.

Grid marginal operating emissions rate

Marginal operating emissions rate (MOER) calculates the carbon emissions induced by an additional unit of electricity required from the grid (or avoided if less electricity is required). This means it calculates emissions more accurately than average emissions by assessing the impact of any operational change. For example, Figure 1 (b) shows the MOER heatmap of the Northern California grid in 2023. From March to June, the MOER is low during the daytime, this is because renewables generated (mostly solar) are sufficient to meet the region's electricity demand and hence avoid using fossil fuel peaker plants. However, from July to October, grid demand increases significantly during the daytime and requires occasionally switching on natural gas plants to meet peak demand. Therefore, consuming one additional unit of electricity over certain hours might lead to a much higher carbon footprint. A general solution for building operators to consider, which is also this study's focus, is to match the electricity load with the grid generation profile by shifting the electricity load to a time period when the grid has more available renewable plants to dispatch.



(a) (b)

Figure 1 (a) Case study building in Berkeley, CA. (b) Northern California grid 2023 MOER heatmap (low, medium and high MOER implies around 50, 250, and 450 gCO_2/kWh respectively).

Grid-interactive control

The grid-interactive control allows the building to access grid MOER in advance, normally using prediction from 1 day ahead up to 72 hours, and shift its electricity load to match grid low-emissions periods. We simulated the grid-interactive control under two main assumptions: 1) we only intend to shift the operation of the centrifugal chiller (CH-2), since in practice, only a fraction of the whole-building electricity load (typically encompassing HVAC operations) is able to shift; 2) to isolate the load shift impact on emissions, we intend to maintain an equal annual chiller energy consumption between the existing baseline control and the proposed load shift control. In general, this control strategy requires accessing the grid MOER signal one timestep before each control sequence and aims to encourage using more electricity generated from renewables by setting a lower supply water temperature for pre-cooling when the MOER is low. As a result, the building can reduce HVAC operating emissions by setting a higher water supply temperature when the MOER is high. Therefore, in order to simulate the strategy, we need to define two parameters: how much load is available to shift and when to shift.

We defined the first parameter by running a trial supply water temperature reset test in the case study building. After increasing the CH-2 supply water temperature setpoint by 4 °C (5 °F), we observed a 30% decrease in chiller power usage. Additionally, the airflow rate in the air handling unit (AHU) increased, but the associated fan energy change was negligible, and the supply air temperature remained stable. Based on these observations, we conclude that despite the chiller efficiency varies over time, it can increase/decrease power output by 30% without violating comfort conditions during a load-shift event. We also acknowledge that the value may vary across different buildings due to variations in their demand flexibility, a factor that will be explored in future studies.

We defined the second parameter using a grid emissions threshold, which is a pre-defined value by a building analyst to quantitatively consider whether the grid emissions rate is low and hence beneficial to use more electricity. As described in the figure below, when the one-step ahead MOER signal drops below the threshold (indicated as yellow shade), the control increases CH-2 power. After MOER exceeds the threshold (indicated as the purple shade), the control decreases CH-2 power to mobilize charged thermal mass. Figure 2 also implies by varying the threshold, the impact would be different even if the total consumed energy remains the same. To explore those effects, we simulated 5 scenarios with different load shift thresholds starting at 50 gCO_2/kWh with 100 gCO_2/kWh for every increment to 450 gCO_2/kWh.

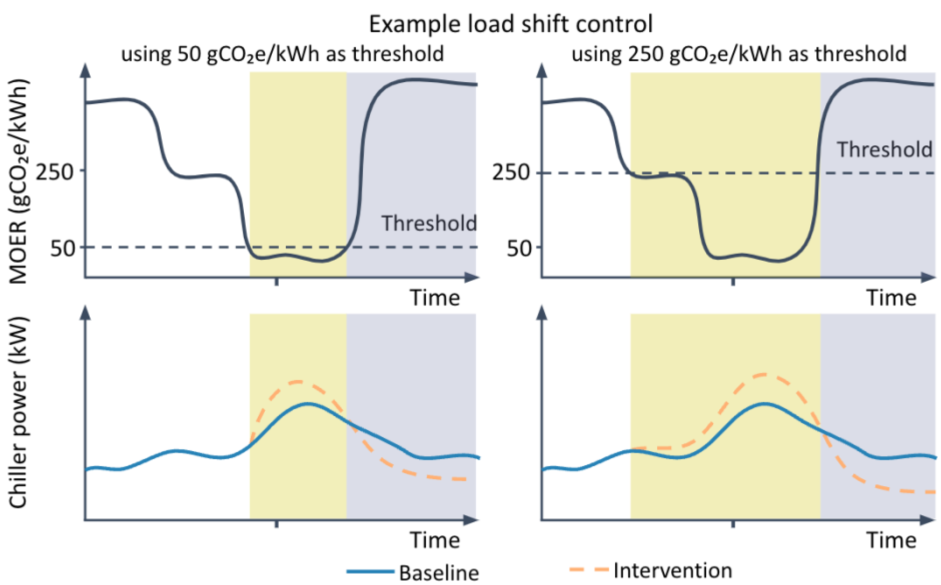


Figure 2 Two examples illustrating the load shift strategy developed (using 50 and 250 gCO_2/kWh as the intended load shift threshold respectively, blue line: baseline chiller power output, gold dashed line: chiller power output under load shift intervention, yellow shade: grid low emissions periods, purple shade: periods to avoid emissions).

DATASET

Table 1. Overview of the dataset[1]

Type	Source	Unit (SI | IP)	Resolution
CH-1 and CH-2 thermal energy rate	BAS	– | ton	15-minute
CH-2 electricity usage	BAS	kW | –	15-minute

[1] The data and analysis code are open source on GitHub (https://github.com/ZAY630/ls_sdh/tree/main) with a Binder link for automatically configuring the environment.

Outdoor drybulb temperature	NOAA	°C | °F	15-minute
Marginal operating emissions rate	WattTime	gCO_2/kWh | $lbsCO_2/MWh$	5-minute

As summarized in Table 1, we queried chiller thermal energy rate and CH-2 electricity usage measurements in 2023 from the case study building BAS, and site outdoor weather conditions from the National Weather Service (NOAA). As mentioned before, CH-1 and CH-2 operate alternatively but the queried thermal power measures regardless. We plotted the power with respect to measured outdoor weather conditions in subplot (a) and the hour of the day in subplot (b) of Figure 3 to show the fluctuations throughout the study period. Despite the cooling load from the nanofabrication lab for processes being independent of the outdoor temperature, we found the overall cooling load generally increases with the outdoor weather and peaks around noon.

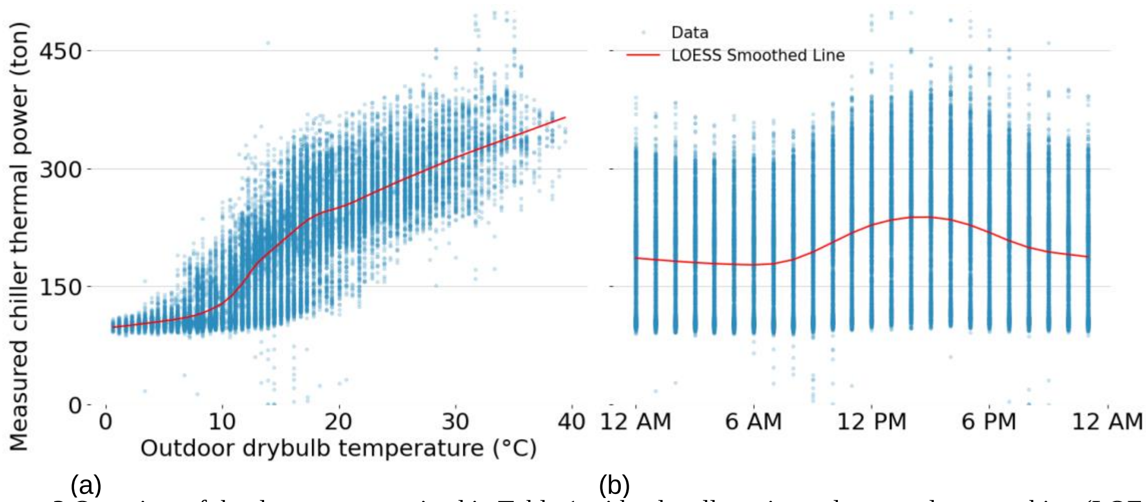


Figure 3 Overview of the dataset summarized in Table 1 with a locally estimated scatterplot smoothing (LOESS) function fitted; (a) chiller thermal power measured at different weather conditions; (b) chiller thermal power measured at each hour of the day.

The MOER signals which reflect the grid carbon intensity were queried from a non-profit organization called WattTime[2]. They provide high-resolution CO_2 estimation results associated with a region given the location of the site. We showed the measurements earlier in Figure 1 (b). Due to the less granular of the chiller power measurements, we consider 15-min as a timestep for the load shift control, and so the MOER data queried was further averaged to match the resolution.

RESULTS

Chiller electricity usage prediction

As described in the building characteristics, the study aims to assess a scenario where HVAC cooling is provided entirely by the centrifugal chiller CH-2. Given that thermal power is measured, we can obtain CH-2 electricity usage by modeling its operational efficiency. Specifically, we considered chiller cooling load and outdoor wetbulb temperature as independent variables (Blum et al., 2022; Wang et al., 2019), and CH-2 operational efficiency as the dependent variable assuming a linear relationship. We plotted the prediction results in subplot (a) of Figure 4 and the estimated electricity power using the predicted efficiency and measured thermal power in (b).

To validate the fitted model, we evaluated the modeling error and summarized in Figure 4 (a). The calculated CV(RMSE) satisfies the baseline energy model accuracy outlined in ASHRAE Guideline 14 (ASHRAE, 2014) and aligns with the results of a meta-study that compared different modeling accuracy across a variety of modeling

[2] WattTime: https://watttime.org

techniques and buildings (Granderson et al., 2016). Therefore, we believe the estimated electricity is acceptable for further analysis.

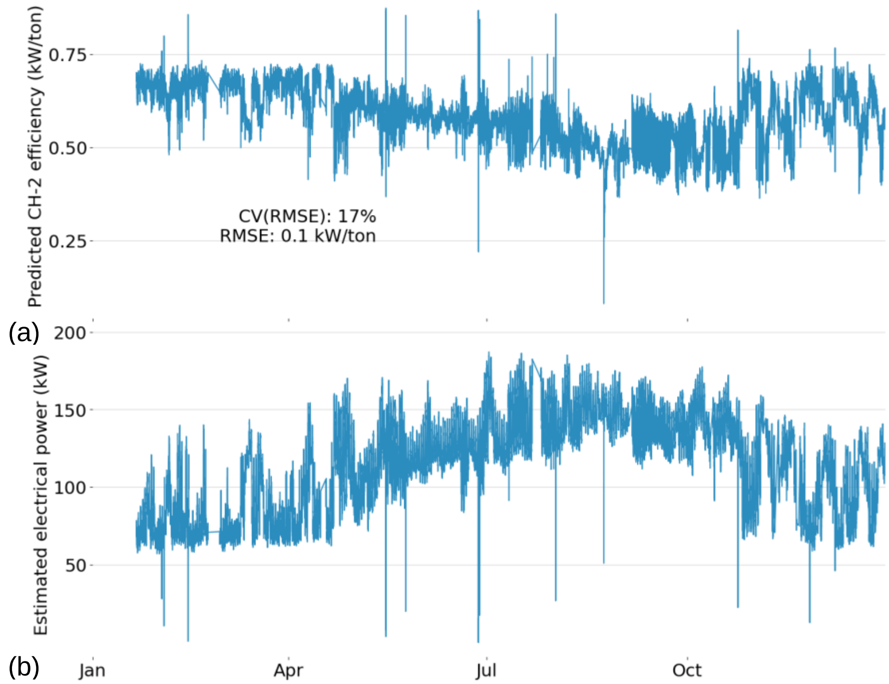


Figure 4 Predicted CH-2 operation over the study period; (a) CH-2 efficiency prediction results using a linear model; (b) estimated CH-2 power output based on predicted efficiency and measured thermal power.

Baseline marginal operating emissions

The consequential emissions impact of an applied change should be assessed using the marginal rate reflecting the amount of carbon emissions released if an additional unit of electricity is required (or avoided if the demand decreases). Figure 5 plots the calculated marginal operational carbon emissions hourly rate based on CH-2 prediction results and the color indicates different seasons. Similar to Figure 1 (b), during the spring season, the Northern California grid generally has low MOER, especially around noon, meaning most of the electricity used by the building's HVAC system is likely drawn from renewable sources (i.e. solar and wind). However, this is not the case in summer when the marginal emissions rates are generally high. Additionally, we also noticed hourly variations throughout the day, so we expect the proposed control strategy could shift CH-2 electricity usage to low emissions periods when triggered by a pre-defined threshold.

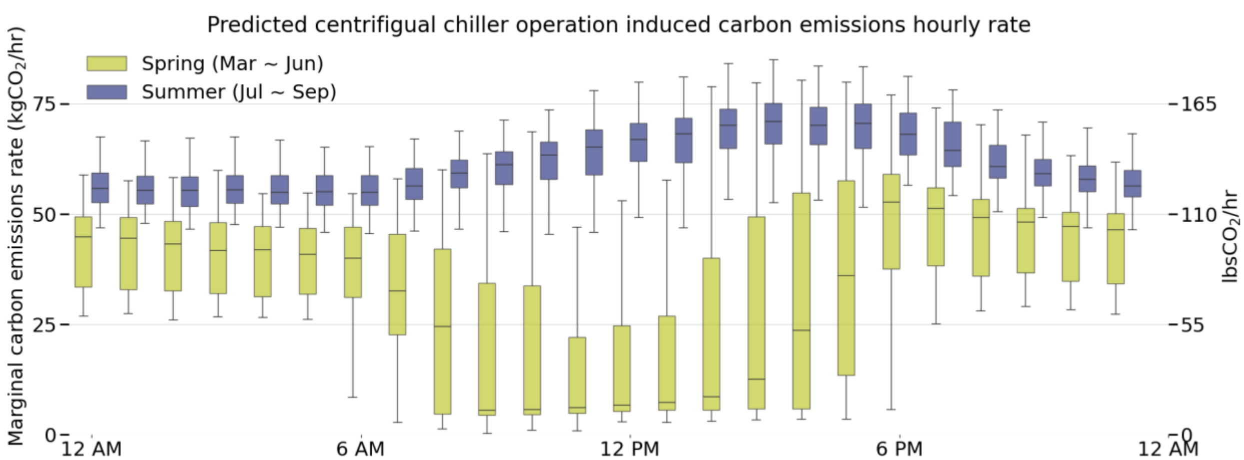


Figure 5 CH-2 marginal operating emissions hourly rate based on predicted electricity usage.

Avoided carbon emissions through load shift control

Figure 6 presents the estimated avoided carbon emissions resulting from the numerical simulation for 2023. The baseline (in blue) is defined by the carbon emissions from the existing HVAC operation, as calculated in Figure 5. Each column to the right of the baseline in Figure 6 corresponds to a threshold scenario outlined before. Subplot 6 (a) indicates that increasing the threshold value from 50 gCO_2/kWh to 350 gCO_2/kWh leads to more avoided operational emissions annually. However, this effect is relatively modest, with only 2% of avoided emissions compared to the baseline. Additionally, we observed that setting the threshold above 350 gCO_2/kWh could result in higher emissions than the baseline. This is because higher thresholds often prompt the HVAC system to pre-cool the space for longer periods and more often, which increase the risk of consuming more energy overall.

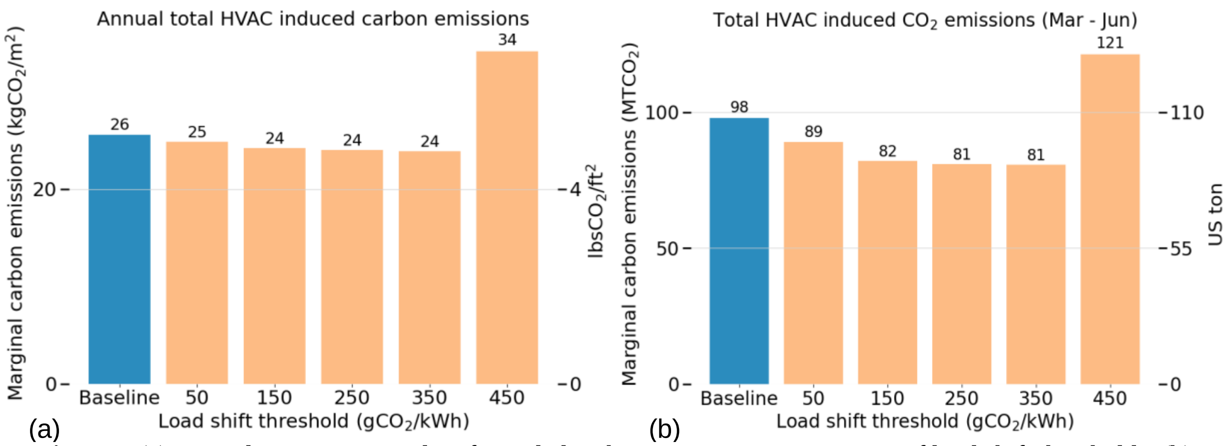


Figure 6 (a) Annual estimation results of avoided carbon emissions over a range of load shift thresholds. (b) Avoided carbon emissions estimation results through load shift control during the spring season over a range of load shift thresholds.

We infer that the non-significant annual effect of load shift can be attributed to large seasonal variations. In other words, most of the low-emissions time windows occur during the spring season, which explains why the overall effect appears diminished when assessed on an annual basis. Figure 6 (b) illustrates the avoided carbon emissions in metric tons (MT) (and US tons) during the spring season only. Unlike the annual results, Figure 6 (b) demonstrates a more substantial impact on avoiding operational carbon emissions. For instance, setting the threshold between 250 gCO_2/kWh and 300 gCO_2/kWh indicates an 18% of avoided emissions compared to the baseline. However, similar to the annual results, setting a higher threshold increases the risk of higher energy consumption.

DISCUSSION

Induced energy cost

Due to the largely available solar energy in California, the proposed grid-interactive control tends to shift the HVAC operation towards noon as shown in Figure 7. Although the total annual energy remains constant for most of the threshold cases (except when the load shift threshold is set to 450 gCO_2/kWh), the energy cost could still vary depending on the building's utility structure. For example, if the peak utility rate period matches the electricity peak load shown in Figure 7, then the building owner might pay for a higher energy bill annually. Or if there is a demand charge, then the building owner is likely to notice a significant increase in the energy bill after implementing the load shift control. This finding indicates that emission-based load shift could be limited in the real world if the control overlooks the energy and cost impacts emphasizing the significance of more sustainable and comprehensive future energy policy development. We plan to focus future studies on exploring practical ways to combine energy-saving control sequences of operation (e.g. ASHRAE Guideline 36) with emission-based load shift and test in real commercial buildings.

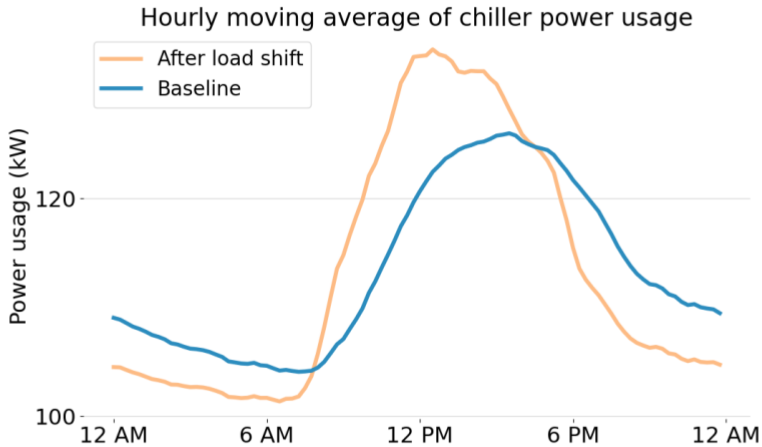


Figure 7 Hourly moving average of power usage before and after load shift.

Generalizability

This study explores load shift control in Northern California for the year 2023, focusing on grid marginal operating emissions intensity. As a result, the findings may be somewhat limited. For instance, the effect observed in the spring season mostly aligns with California's electricity generation characteristics (i.e. predominantly solar energy). In contrast, grid regions with a higher share of wind, such as in Texas, might exhibit markedly different results. Additionally, future grid conditions, which could impose greater penalties on fossil fuel use or consider increased building electrification, might reveal more significant annual effects from load shift control.

Despite these regional and temporal limitations, the analytical approach used in this study is generalizable to various scenarios. As an example, this method can be implemented using the Brick metadata schema, a recent development that standardizes and makes machine-readable the semantics of data points generated from the BAS (Balaji et al., 2018, 2016). This means an analyst can quickly evaluate the load shift control effects over a range of thresholds by querying electricity measurements from any building's BAS and applying the corresponding MOER signal from the local grid.

CONCLUSION

We developed an emission-based load shift control strategy for the HVAC system in a case study building located in Berkeley, California, and quantified its impact using the marginal operating emissions rate (MOER) from the local grid. This control strategy aims to shift chiller operation to periods when the grid has lower MOER, indicating a higher availability of renewable energy. To achieve that, the proposed HVAC control works as a grid-interactive pre-cooling strategy, which is enabled when the grid MOER falls below a predefined threshold, and in this study, we simulated various threshold scenarios. Our results indicate that the amount of avoided carbon emissions increases with higher thresholds, but this also raises the risk of increased energy consumption. The optimal threshold for the Northern California grid region was found to be between 250 and 300 gCO_2/kWh, resulting in an estimated 18% reduction in HVAC-related carbon emissions during the spring season. However, due to significant seasonal variations, the overall annual estimation only shows a 2% avoided operational emissions. The case study highlights that building operational emissions exhibit substantial temporal variations proving the importance of marginal vs. average emission, and load shifting alone is insufficient for reducing commercial building operational carbon footprint. Furthermore, investigating the economic and environmental implications of emission-based load shift control is essential for developing practical approaches to implement on a larger scale.

ACKNOWLEDGEMENTS

This research was funded by the industry consortium members of the Center for the Built Environment (CBE), University of California, Berkeley.

REFERENCES

ASHRAE, 2014. ASHRAE Guideline 14 -2014: Measurement of Energy, Demand and Water Savings.

Balaji, B., Bhattacharya, A., Fierro, G., Gao, J., Gluck, J., Hong, D., Johansen, A., Koh, J., Ploennigs, J., Agarwal, Y., Berges, M., Culler, D., Gupta, R., Kjærgaard, M.B., Srivastava, M., Whitehouse, K., 2016. Brick: Towards a Unified Metadata Schema For Buildings, in: Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments, BuildSys '16. Association for Computing Machinery, pp. 41–50. https://doi.org/10.1145/2993422.2993577

Balaji, B., Bhattacharya, A., Fierro, G., Gao, J., Gluck, J., Hong, D., Johansen, A., Koh, J., Ploennigs, J., Agarwal, Y., Bergés, M., Culler, D., Gupta, R.K., Kjærgaard, M.B., Srivastava, M., Whitehouse, K., 2018. Brick : Metadata schema for portable smart building applications. Appl. Energy 226, 1273–1292. https://doi.org/10.1016/j.apenergy.2018.02.091

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. Appl. Energy 318, 119104. https://doi.org/10.1016/j.apenergy.2022.119104

Braun, M., Dengiz, T., Mauser, I., Schmeck, H., 2016. Comparison of Multi-objective Evolutionary Optimization in Smart Building Scenarios, in: Squillero, G., Burelli, P. (Eds.), Applications of Evolutionary Computation. Springer International Publishing, Cham, pp. 443–458. https://doi.org/10.1007/978-3-319-31204-0_29

Callaway, D.S., Fowlie, M., McCormick, G., 2018. Location, Location, Location: The Variable Value of Renewable Energy and Demand-Side Efficiency Resources. J. Assoc. Environ. Resour. Econ. https://doi.org/10.1086/694179

Fiorini, L., Aiello, M., 2020. Predictive Multi-Objective Scheduling with Dynamic Prices and Marginal CO2-Emission Intensities, in: Proceedings of the Eleventh ACM International Conference on Future Energy Systems, E-Energy '20. Association for Computing Machinery, New York, NY, USA, pp. 196–207. https://doi.org/10.1145/3396851.3397732

Fleschutz, M., Bohlayer, M., Braun, M., Henze, G., Murphy, M.D., 2021. The effect of price-based demand response on carbon emissions in European electricity markets: The importance of adequate carbon prices. Appl. Energy 295, 117040. https://doi.org/10.1016/j.apenergy.2021.117040

Granderson, J., Touzani, S., Custodio, C., Sohn, M.D., Jump, D., Fernandes, S., 2016. Accuracy of Automated Measurement and Verification (M&V) Techniques for Energy Savings in Commercial Buildings. Appl. Energy 173, 296–308. https://doi.org/10.1016/j.apenergy.2016.04.049

Holland, S.P., Kotchen, M.J., Mansur, E.T., Yates, A.J., 2022. Why marginal CO2 emissions are not decreasing for US electricity: Estimates and implications for climate policy. Proc. Natl. Acad. Sci. 119, e2116632119. https://doi.org/10.1073/pnas.2116632119

Jiang, Z., Risbeck, M.J., Ramamurti, V., Murugesan, S., Amores, J., Zhang, C., Lee, Y.M., Drees, K.H., 2021. Building HVAC control with reinforcement learning for reduction of energy cost and demand charge. Energy Build. 239, 110833. https://doi.org/10.1016/j.enbuild.2021.110833

Kim, D., Wang, Z., Brugger, J., Blum, D., Wetter, M., Hong, T., Piette, M.A., 2022. Site demonstration and performance evaluation of MPC for a large chiller plant with TES for renewable energy integration and grid decarbonization. Appl. Energy 321, 119343. https://doi.org/10.1016/j.apenergy.2022.119343

Lowry, G., 2018. Day-ahead forecasting of grid carbon intensity in support of heating, ventilation and air-conditioning plant demand response decision-making to reduce carbon emissions. Build. Serv. Eng. Res. Technol. 39, 749–760. https://doi.org/10.1177/0143624418774738

Péan, T., Costa-Castelló, R., Salom, J., 2019. Price and carbon-based energy flexibility of residential heating and cooling loads using model predictive control. Sustain. Cities Soc. 50, 101579. https://doi.org/10.1016/j.scs.2019.101579

Regett, A., Boing, F., Conrad, J., Fattler, S., Kranner, C., 2018. Emission Assessment of Electricity: Mix vs. Marginal Power Plant Method, in: 2018 15th International Conference on the European Energy Market (EEM). Presented at the 2018 15th International Conference on the European Energy Market (EEM), IEEE, Lodz, pp. 1–5. https://doi.org/10.1109/EEM.2018.8469940

Robillart, M., Schalbart, P., Chaplais, F., Peuportier, B., 2019. Model reduction and model predictive control of energy-efficient buildings for electrical heating load shifting. J. Process Control, Efficient energy management 74, 23–34. https://doi.org/10.1016/j.jprocont.2018.03.007

Rogers, A.P., Rasmussen, B.P., 2018. Opportunities for consumer-driven load shifting in commercial and industrial buildings. Sustain. Energy Grids Netw. 16, 243–258. https://doi.org/10.1016/j.segan.2018.08.004

Setlhaolo, D., Sichilalu, S., Zhang, J., 2017. Residential load management in an energy hub with heat pump water

heater. Appl. Energy 208, 551–560. https://doi.org/10.1016/j.apenergy.2017.09.099
Sofos, M., Langevin, J.T., Deru, M., Gupta, E., Benne, K.S., Blum, D., Bohn, T., Fares, R., Fernandez, N., Fink, G., Frank, S., Gerbi, J., Granderson, J., Hoffmeyer, D., Hong, T., Jiron, A., Johnson, S., Katipamula, S., Kuruganti, T., Langevin, J., Livingood, W.C., Muehleisen, R., Neukomm, M., Nubbe, V., Phelan, P., Piette, M., Reyna, J., Roth, A., Satre-Meloy, A., Specian, M., Vrabie, D., Wetter, M., Widergren, S., 2020. Innovations in Sensors and Controls for Building Energy Management: Research and Development Opportunities Report for Emerging Technologies (No. NREL/TP-5500-75601; DOE/GO-102019-5234). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1601591
Stoll, P., Brandt, N., Nordström, L., 2014. Including dynamic CO2 intensity with demand response. Energy Policy 65, 490–500. https://doi.org/10.1016/j.enpol.2013.10.044
Turner, W.J.N., Walker, I.S., Roux, J., 2015. Peak load reductions: Electric load shifting with mechanical pre-cooling of residential buildings with low thermal mass. Energy 82, 1057–1067. https://doi.org/10.1016/j.energy.2015.02.011
U.S. Energy Information Administration (EIA), 2023. Annual Energy Outlook 2023 - U.S. Energy Information Administration (EIA).
Vogler-Finck, P.J.C., Wisniewski, R., Popovski, P., 2018. Reducing the carbon footprint of house heating through model predictive control – A simulation study in Danish conditions. Sustain. Cities Soc. 42, 558–573. https://doi.org/10.1016/j.scs.2018.07.027
Wang, L., Lee, E.W.M., Yuen, R.K.K., Feng, W., 2019. Cooling load forecasting-based predictive optimisation for chiller plants. Energy Build. 198, 261–274. https://doi.org/10.1016/j.enbuild.2019.06.016
Zeng, H., Shao, B., Dai, H., Tian, N., Zhao, W., 2023. Incentive-based demand response strategies for natural gas considering carbon emissions and load volatility. Appl. Energy 348, 121541. https://doi.org/10.1016/j.apenergy.2023.121541