Demand-side Management Under Real-time Greenhouse Gas Emission Factor for Electricity

Gulai Shen[1], Hongling Li[2], Gurpreet Singh[1], Amir Behjat[1], Gerald Toge[1], Souroush Senemmar[2], Cong Feng[3], Jie Zhang[2], Ali Mehmani[1]

[1] Research and Development, Nantum AI
[2]The University of Texas at Dallas
[3]National Renewable Energy Laboratory (NREL)

ABSTRACT

Electric power generation contributes to the second largest share of greenhouse gas (GHG) emissions in the US. The direct and indirect carbon emissions created from generating electricity vary from resources of generation, and power plant efficiency. Approximately 60% of the electricity comes from burning fossil fuels, mostly coal and natural gas, emitting more than 1500 million metric Tons of CO_2 per year. Depending on regions and time of day, the cleanness of electricity significantly varies as more and more intermittent renewable energy resources, such as solar and wind, being added into the grid. With the growing awareness and regulations on GHG emissions, the need for accurate carbon measurement and technologies that reduces GHG for both the supply and demand side is ever-increasing. To optimally control demand-side users such as buildings, balance supply and demand, and incorporate energy storage technologies to reduce overall GHG emissions, the real-time emission factor and its predictions play critical roles. Here, we use the open-source real-time electricity GHG Emission Factor that covers all states in the US and four sample buildings' demand data from Nantum OS across different regions to propose an optimization framework for potential emission reduction through load shifting. This study highlights the importance to raise awareness, monitor, and account for real-time GHG emissions. Furthermore, it proves the viability to control buildings with electric energy storage system to reduce carbon emissions for demand-side users.

Introduction

Electricity generation contributes to over 37% of US energy demand (EIA 2024). As the trend of electrification continues in major sectors including buildings, transportation, etc., the US annual electricity generation is expected to grow another 25% to 4,000 terawatt-hours by 2050 (Statistica 2022). Further, electricity generation contributes to around a quarter of the Greenhouse Gas (GHG) emissions in the US (EIA 2020). Electricity can be generated from different types of resources including nonrenewable ones like natural gas, renewable ones like solar, wind, hydro, etc., and carbon-free ones like nuclear. As of 2023, merely 22% of US electricity generation comes from renewable resources (EIA 2023). With the objective for the US to be net-zero by 2050 and 100% carbon-free electricity by 2035 (White House 2021 and DoE 2023), it is necessary to accurately measure the carbon and develop actionable plans and technologies from both the supply and demand side of electricity.

[1] Corresponding Author: amehmani@prescriptivedata.io

In general, each unit of electricity generated will have carbon emissions associated with it. Life-cycle assessment (LCA) carbon emission considers the whole life cycle of the power plant for electricity generation while an operational carbon emission only considers the emission during the generation (NREL 2021). Thus, while renewable resources like wind and hydro might have negligible operational carbon, they still embed some carbon when considering LCA intensity. Based on extensive studies, which provide continuous measurements and calculations of the embodied carbon from different generations, a real-time varying emission factor is made possible (IPCC 2014). As the generation of electricity comes from a mixture of different resources in real-time, depending on weather, availability of power plant, and demand, the electricity generated and delivered to users consists of a mix of these resources, leading to a time-varying emission factor.

Specifically for demand-side users like buildings, a major portion of their GHG emissions is resulted from secondary energy like electricity. Governments and companies who have set ambitious carbon-neutral goals need to reduce their building portfolios' emissions associated with electricity use (UN2020). Further, building owners are now subjected to laws and penalties that limit on their GHG emissions such as the Local Law 97 in New York City (NYC Sustainable Buildings 2019). All these lead to the need for methods and new technologies to reduce emissions associated with electricity. Demand-side management (DSM) is an effective GHG reduction method, which changes the energy consumption profiles by managing the demand-side users' activities (Gellings1985). DSM has been applied to building controls extensively over the recent years. The main objectives of DSM include reduce energy consumption or increase energy efficiency (Shen 2021) and manage energy demand profile or demand response programs. However, a direct focus on minimizing GHG emissions based on the time-varying emission factor is lacking.

In this article, we utilize the GHG Emission Factor API (GHGAPI 2024) that provides the real-time emission factor and example building with electricity demand data provided by Nantum AI (Nantum AI 2024) to propose a potential DSM opportunity to minimize its total emission through a battery system.

Method

To demonstrate how an individual demand-side user, like a building with an electric energy storage system, can reduce its GHG emissions by shifting its load throughout the day, we propose an optimization model. This model aims to minimize total GHG emissions through load shifting based on real-time average emissions data.

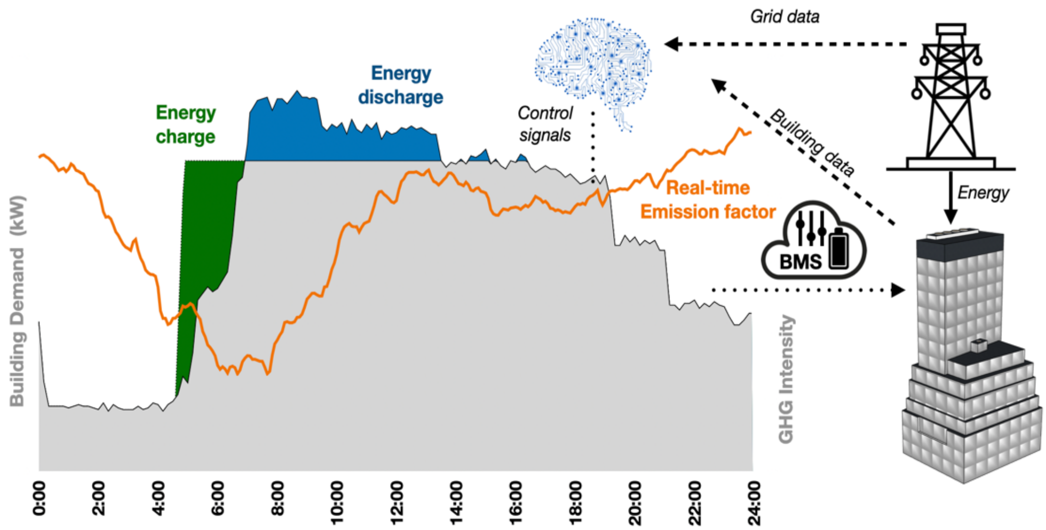

Figure 1. Example visualization for the desired system layout and results.

As shown in Figure 1, the proposed system should be able to optimally control battery charge and discharge throughout the day depending on the real-time emission factor to minimize the overall emission from using the delivered electricity from the grid.

For each day, the battery will be fully charged at the beginning of the day and return to fully charged by the end of the day, limiting the shift of load within 24 hours, and allowing continuous operation of such a system. The simplified battery model consists of losses of electrical energy both when charging and recharging to represent the round-trip efficiency. The energy loss can be caused by heat conversion, temperature regulation, and transmission loss. Further, battery degradation, charging/discharging speed, ambient temperature, etc. can all impact the significance of energy losses (Apostolaki-Iosifidou 2017). The optimization is formulated as follows:

$$\min \sum_{i=1}^{N} (d_i + x_i) * I_i$$

$$s.t. \sum_{i=1}^{N} x_i = 0$$

$$x_{discharge} \leq x_i \leq x_{charge}$$

$$SOC\_i = \begin{cases} X_{battery} & if\ i = 0, N \\ SOC_{i-1} + \left(X_{i,charge} * \eta_{charge}\right) & if\ x_i \leq 0 \\ SOC_{i-1} + \left(\dfrac{X_{i,discharge}}{\eta_{discharge}}\right) & if x_i > 0 \end{cases}$$

$$0 \leq SOC_i \leq X_{battery}$$

where d_i is the electricity total demand at each time step i, x_i is the rate of discharge and charge from an energy storage system at each time step i, which is positive when extra energy from the grid is used to charge the battery and negative when the battery is discharged to meet the building's demand. In addition, I_i is the GHG emission factor at each time step i. Lastly in the objective function, N is the number of timesteps considered as the optimization window. In this paper, $N = 24$ and the optimization is performed over hourly building data, and the planning horizon is one day from midnight to midnight of the next day.

For the first equality constraint, it enforces that the total electricity consumption of the building should be met by using energy from the grid and the battery. The second constraint is an inequality constraint that characterizes the charge and discharge rate. Third, the battery state of charge (SOC) is enforced to be at full capacity at the beginning and end of the planning horizon. SOC can be calculated based on the design variable and the specified efficiency during the intermediate time steps. The last constraint incorporates the battery size limit to ensure at any time, the battery holds a charge between 0 and its capacity. For the simplified battery model based on (Meinrenken and Mehmani 2019), two critical parameters are required: the capacity of the battery and the rate of charge/discharge of the battery. Since the example buildings provided vary in size, occupancy, and mechanical equipment, the battery size is set to be 5% of its average daily consumption, and the rate of charge/discharge is set to be 25% of its average daily peak demand for a fair comparison between different buildings at different regions.

Particle swarm optimization (PSO) is used to solve this optimization problem with soft constraints associated with penalties adjusted into the objective function. This allows robustness and flexibility, allowing more complex prediction and battery models to be implemented in the future for control purposes.

Result

To investigate the potential of the proposed demand-side management based on emission factors in real-world problems, we utilized commercial building electric demand data provided by Nantum AI for this analysis. Different buildings might show distinct energy use patterns. In addition, buildings' electricity at different regions can be supplied by different Balancing Authorities (BA). BAs are typically utilities, Power Marketing Administrations (PMAs), Independent System Operators (ISO), and other authorities that manage the balance between supply and demand of electric grid. Thus, buildings can have different potentials for reducing their GHG emissions. The key information about each example building is summarized in Table 1 below:

Table 1. Example building meta information.

Building location	Building type	Building average daily consumption (kWh)	Building average daily peak (kW)	Load factor
CA	Commercial	18,702	853	0.94
NY	Commercial	78,186	4,529	0.54
TX	Commercial	26,502	1,295	0.82
FL	Commercial	5,638	338	0.70

It is important to note that commercial buildings are typically occupied during the day while staying vacant overnight. Some buildings might completely switch off their heating, ventilation, and air conditioning (HVAC) systems overnight, while others might be in an overnight setback mode, representing the load factor shown in Table 1. A higher load factor indicates a higher building base load and vice versa.

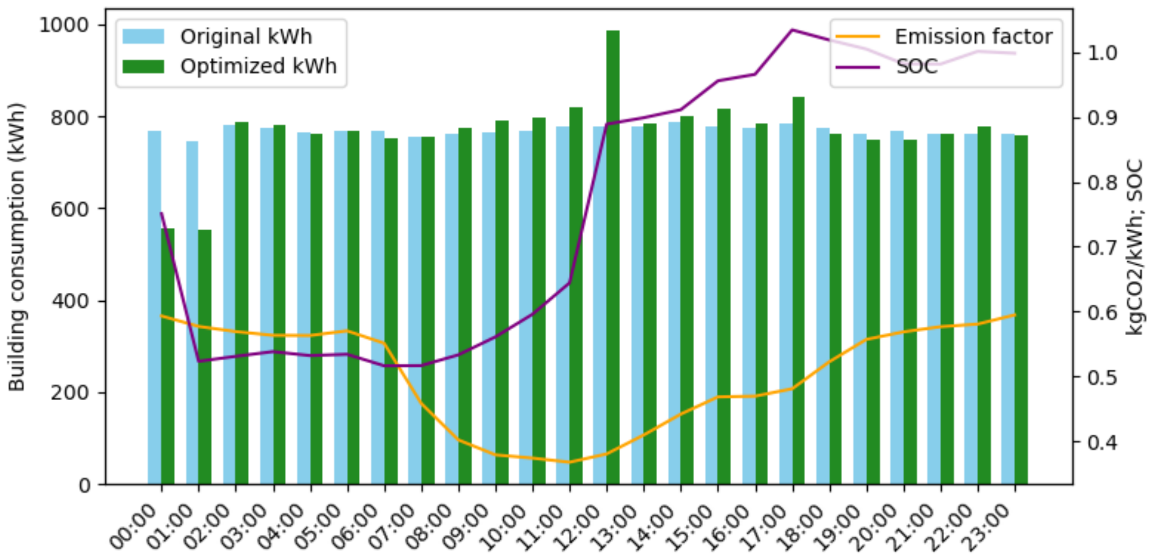

Figure 2. Optimal control for the example building in California on a typical summer day. The optimization resulted in 142.18 $kg\ CO_2e$ reduction, around 1.54% of the day.

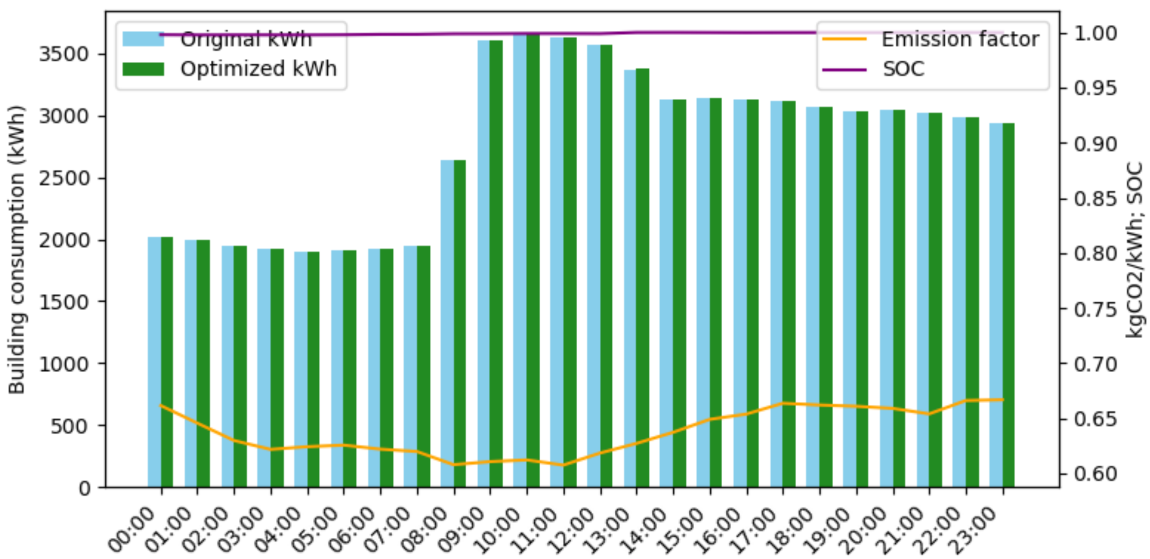

Figure 3. Optimal control for the example building in New York on a typical summer day. The result suggests almost no actions for the battery throughout the day, resulting a 0.41 $kg\ CO_2e$ reduction.

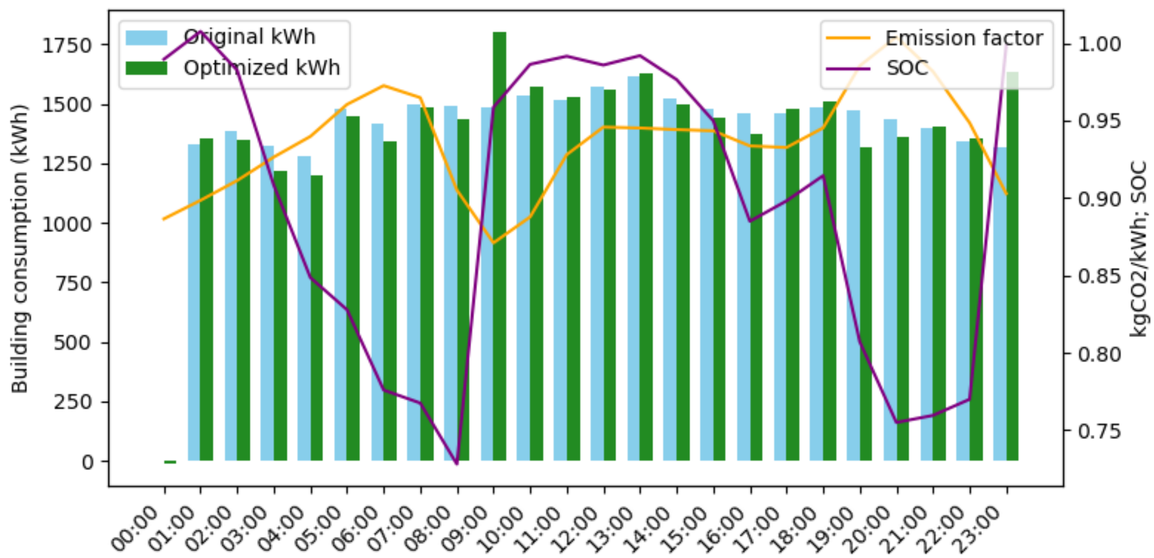

Figure 4. Optimal control for the example building in Texas on a typical summer day. The optimization resulted in 68.97 $kg\ CO_2e$ reduction, around 0.22% of the day.

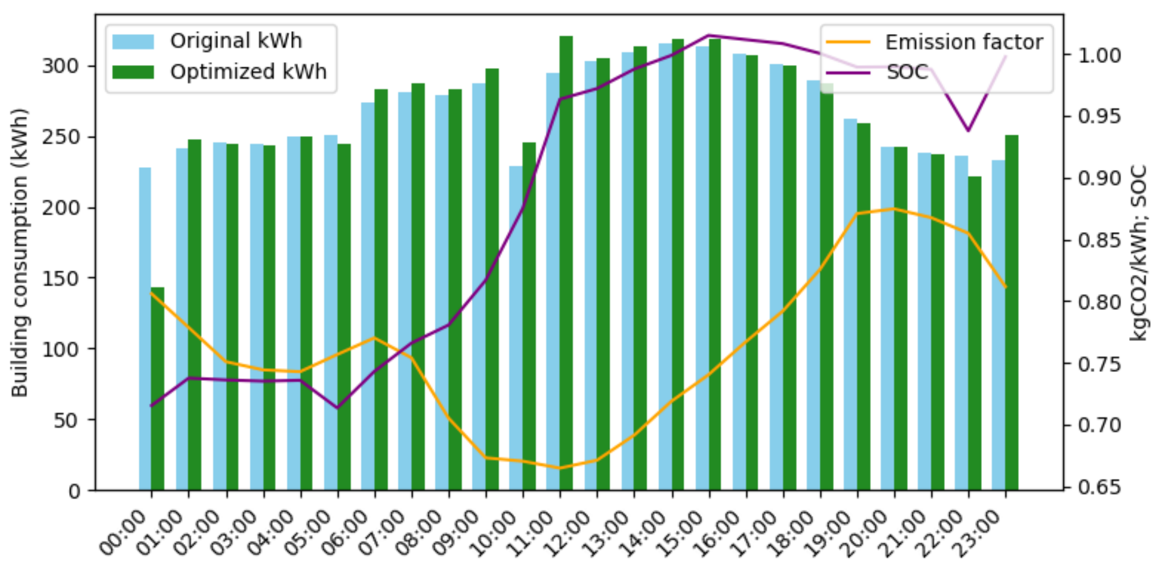

Figure 5. Optimal control for the example building in Florida on a typical summer day. The optimization resulted in 10.38 $kg\ CO_2e$ reduction, around 0.15% of the day.

Figures 2 to 5 show the example buildings' optimized behaviors for a typical summer day. While the original building kWh data is used, the optimized kWh is the potential the building could achieved. The $kg\ CO_2e$ represents the GHG emissions in kilograms of carbon dioxide equivalence. With the prominent renewable energy resource being solar, California's emission factor is noticeably lower during the day compared to evening. Such characteristic results in a pattern of battery discharge early in the morning and charge over mid of the day. Similar behaviors can be observed from the example building in Texas. The savings from New York and Florida are relatively small on the day, as shown in the example, as both regions have lower fluctuations in renewable energy. Further, the emission factors are relatively higher in the second half of the day, causing the battery to be unable to recharge if discharge happens in the mornings. Thus, savings can be potentially greater if the window of optimization can be flexible to start and end from the middle of the day.

Table 2. Yearly potential CO_2e reductions based on 2022 generation and building demand data.

Building location	Battery capacity (kWh)	Battery charge/discharge rate limit (kW/h)	Daily min emission factor / max emission factor	Yearly CO_2e reduction (kg)	Yearly CO_2e reduction (%)
CA	935	213	0.56	37,231	1.32%
NY	3,909	1,132	0.87	5,891	0.03%
TX	1,325	324	0.72	33,176	0.44%
FL	282	85	0.84	6,155	0.39%

Running the analysis over the whole year of 2022, the potential of CO_2e GHG emissions reduction for the example buildings is summarized in Table 2. Significant amounts of carbon can be potentially avoided from emitting into the atmosphere, leading to both environmental and financial benefits for people and building owners. However, the potential percentage savings are largely dependent on the variation of the emission factor. If throughout the day, the variation of renewable resources is more significant, indicated by a low daily min-max ratio like California, there will be a higher potential for carbon reduction through load shifting. On the other hand, in regions like New York where the min-max ratio is high, the potential to reduce carbon through load shifting is minimal. Further, the sizes of buildings, indicated by the average daily kWh consumption and daily peak kW, can significantly impact amounts of CO_2e GHG emissions. For example, despite showing a low percentage reduction, the absolute GHG reduction remained significant for the building in Texas.

Admittedly, battery installation and maintenance, as well as space requirements, could lead to further costs. While local legislation on penalizing excessive GHG emissions for demand-side users like buildings has been rolled out, the financial viability of the proposed technology has not been fully explored. Furthermore, a more flexible optimization window selection can be applied to the formulation and control of the system to allow more potential reductions of GHG.

Conclusion

In summary, the variation of the real-time emission factor leads to the potential to reduce GHG emissions for individual demand-side users by shifting the load. In this paper, utilizing example building electricity data, we formulated an optimization framework to control a battery storage system connected to the building with the objective of minimizing GHG emissions. We proved that there are varying opportunities for demand-side users at different locations with different renewable generations and emission factors. For regions like California where solar is the prominent renewable resource and the daily emission variation ratio is low, there are higher saving potentials. For regions like New York, where renewables are more prominent overnight, and the daily emission variation ratio is high, the potential emission reductions are lower.

Insights can be gained to plan for the path to be 100% carbon-free for different regions. In New York, for example, more renewable generation needs to be added throughout the days, suggesting investments in more stable renewables such as hydro and geothermal. For regions like

California, battery systems paired with abundant solar generation seem promising for reducing the carbon in electricity use. However, smart and robust control systems play a critical role in ensuring an accurate prediction and optimal interaction between the supply and demand side of the energy.

Appendix: Calculating real-time average GHG emission factor

The real-time average GHG emission factor I at each time interval t is calculated as:

$$I_t = \sum_{r \in R} \frac{G_{r,t}}{\sum_{r \in R} G_{r,t}} * e_{r,t}$$

where $G_{r,t}$ is the absolute or relative amount of generation at time t. Further, the carbon intensity $e_{r,t}$ for each resource r in R can be calculated in multiple ways. First, an extensive life cycle analysis has been performed on different types of generation resources from different power plants and across different regions (WNA 2011, EIA 2023, EPA 2022). For best accuracy across the U.S., IPCC 2014 (IPCC, 2014) is used to assign a fixed value for each type of generation resource.

To improve accuracy, calibrations are made based on available data. For example, based on eGrid reported zone-level yearly average emission factor (EPA 2022) a calibration for $I_{r,t}$ is made based on the yearly average and the yearly generation history of electricity. Further, power plant efficiency data and model are used to calibrate for the most accurate emission factor, for regions where power plant data are available (EPA 2022).

Real-time GHG emission factors are also provided through the EIA API and EPA for historical datasets for both average and marginal emissions. Commercially available real-time data are provided by Singularity (Singularity 2024) and WattTime (WattTime 2024) with limited availability. While average GHG emissions refer to the total emissions produced divided by the total electricity generated, marginal GHG emissions refer to the emissions produced by the last unit of electricity generated to meet demand. The choice of average GHG emissions here rather than marginal is due to the target size of demand-side users. The change in electric demand for individual buildings is negligible for the whole grid. For analysis performed on a larger scale that has a more direct impact on the grid, marginal GHG emissions can more accurately represent the change in GHG emissions.

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