

# Quantifying the Decarbonization Potential of Flexible Loads in Residential Buildings

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## ABSTRACT

The impact of human activity on the climate is a major global challenge that affects human well-being. Buildings are a major source of energy consumption and carbon emissions worldwide, especially in advanced economies such as the United States. As a result, making grids and buildings sustainable by reducing their carbon emissions is emerging as an important step toward societal decarbonization and improving overall human well-being. While prior work on demand response methods in power grids and buildings has targeted peak shaving and price arbitrage in response to price signals, it has not explicitly targeted carbon emission reductions.

In this paper, we analyze the flexibility of building loads to quantify the upper limit on their potential to reduce carbon emissions, assuming perfect knowledge of future demand and carbon intensity. Our analysis leverages real-world demand patterns from 1000+ buildings and carbon-intensity traces from multiple regions. It shows that by manipulating the demand patterns of electric vehicles, heating, ventilation, and cooling (HVAC) systems, and battery storage, we can reduce carbon emissions by 26.93% on average and by 54.90% at maximum. Our work advances the understanding of sustainable infrastructure by highlighting the potential for infrastructure design and interventions to significantly reduce carbon footprints, benefiting human well-being.

## CCS CONCEPTS

• Information systems → Data analytics; • Hardware → Impact on the environment; Energy metering.

## KEYWORDS

Decarbonization, optimization, social and health impact of climate.

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## 1 INTRODUCTION

Increasing concerns about greenhouse gas (GHG) emissions and their impact on climate change are motivating an intense focus on reducing society's carbon emissions. The residential energy sector accounts for 16% of energy consumption and 18.9% of GHG emissions in the United States [13]. Further, as the transition towards electric vehicles (EVs) accelerates, a significant fraction of the transportation sector's energy consumption (37%) and GHG emissions (37%) will shift to the residential sector. As a result, reducing the carbon footprint of electricity usage inside the built environments will be a key step toward societal decarbonization. Additionally, climate change is not just an environmental issue; it is increasingly being recognized as a social and health issue and part of the Environmental Social Governance (ESG) [2, 19, 21].

There are two broad pathways to decarbonization: supply-side and demand-side. The supply-side approach aims to decrease the carbon intensity of electricity by increasing the percentage of low-carbon energy sources, such as solar, wind, hydro, and nuclear. The demand-side approaches modulate energy demand to reduce energy consumption when electricity's carbon intensity is high and shift consumption to a time when carbon intensity is low. The decarbonization potential of demand-side approaches depends on the *flexibility* versus *efficacy* tradeoff afforded by electricity's demand in buildings. That is, the greater the *flexibility* to alter electricity's demand patterns while maintaining *efficacy* by producing consumers' desired outcome, the greater the decarbonization potential.

In the power grid and buildings domain, significant prior work has focused on leveraging flexible loads and energy storage to optimize electric grid operations using demand response programs or pricing mechanisms [4, 9, 18, 20]. The objective of this work has been to either shave the peak power consumption or perform price arbitrage rather than explicitly and directly minimize the carbon emissions of electricity demand. However, in peak shaving, the frequency of demand response is around once per day during peak hours or a few times a season during the peak summer/winter season. In contrast, the carbon intensity of electricity changes continuously, and thus, unlike prior DR approaches, carbon-aware demand-side methods will also need to operate continuously.

There is also recent work in cloud computing and datacenter scheduling that reduces carbon emissions by exploiting the high temporal and spatial flexibility of computing workloads by moving

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them to periods or regions, respectively, with low carbon intensity [5]. However, unlike computing, building loads have significantly less temporal flexibility and almost no spatial flexibility. For example, a toaster oven may only be delayed by a few minutes, and washing machine loads cannot be shifted to another region. Nevertheless, new types of building loads, such as EV charging at home, network-connected thermostats and water heaters, and home battery storage, offer greater temporal flexibility.

A key question is determining how much flexibility exists for these controllable and programmable loads and how much carbon emissions can be reduced by using carbon-aware time shifting or modulation of these flexible loads. Existing DR approaches for buildings have not been applied to reduce carbon emissions, and thus the efficacy of applying similar carbon reduction approaches from computing to building loads is unclear. Thus, there is a need for new analyses that quantify the degree of flexibility in buildings and the potential for reducing carbon emissions that can be achieved by time-shifting and modulating flexible loads.

In conducting our analysis, we make the following contributions.

- We formulate an optimization problem that, assuming accurate future knowledge of energy demand and carbon intensity, quantifies the potential to reduce carbon emissions by modulating the demand for flexible loads in buildings.
- We conduct a large-scale, upper-bound analysis of carbon saving potential using real-world demand traces from 1000+ buildings in a small city in the Northeast United States and carbon-intensity data from 3 different geographical regions. Our results demonstrate that we can reduce carbon emissions by 26.93% on average and by 54.90% at maximum.
- We analyze the impact of demand modulation on the electric load at the home-level. We find that the peak load can increase by up to 60% after carbon-aware modulation.

## 2 BACKGROUND

In this section, we present background on flexible loads in buildings and the carbon-intensity signal of the electric grid.

### 2.1 Flexible Building Loads

A typical building contains dozens of electric loads that can be broadly classified into two categories: interactive loads and background loads [4]. Interactive loads include lights, kitchen appliances, entertainment appliances, and miscellaneous devices like vacuums. Such loads do not offer any flexibility, as modulation of their demand impacts their efficacy. Contrarily, background loads, such as heating, ventilation, and cooling (HVAC) systems, permit bounded flexibility to modulate their demand. Additional background loads, such as electric vehicles (EVs) and battery storage, have also become available in recent years. While the number of background loads is small, they often contribute a large fraction of the overall energy consumption. Prior work has shown that, for a representative home, background loads may only comprise 7.5% of all loads, so they can consume as much as 59% of a home's total energy [4].

Importantly, the ubiquity of low-cost Internet of Things (IoT) devices means that background loads can increasingly be controlled remotely and programmatically. This allows for the use of such flexible loads in demand response programs for grid optimizations

and utility- or consumer-driven energy or carbon-saving initiatives. This paper focuses on three major flexible background loads: electric vehicles (EVs), battery storage, and HVAC systems.

**2.1.1 Electric vehicle (EV) charging at home.** The adoption of EVs has increased recently due to increasing gas prices, carbon emissions concerns, and their higher performance. EV charging can be divided into three categories: Levels 1, 2, and 3. Level 1 charging is the slowest and uses a standard 120V household outlet. Level 2 can be charged at 240V but requires installing dedicated charging equipment. Finally, Level 3 or “supercharging” charges at a high voltage of 400–800V and uses direct current, which is usually not available in residential locations. Therefore, residential EV charging is generally either Level 1 or Level 2 and typically happens at night. We analyze the EV charging pattern from a community of 1,006 homes. The charging usually occurs from 6 PM to 8 AM when the homeowners are home. We use insights from this dataset to configure the demand patterns of EVs in our analysis.

**2.1.2 Battery storage.** The residential battery energy storage market has been growing due to the declining cost of batteries [24], especially at places where solar net-metering incentives are non-existent or limited [3]. Batteries are often used for price arbitrage [20], peak shaving [9, 18], or storing excess solar energy for nighttime use. This paper uses battery storage as one of the three loads for explicit and direct decarbonization of buildings.

**2.1.3 HVAC.** HVAC accounts for 12% of the home energy consumption in the United States [12]. The energy consumption of an HVAC system is a function of its setpoint temperature, the ambient outdoor temperature, and a building's insulation. An HVAC system saves energy by deviating from the setpoint or pre-heating/cooling a building when energy's low carbon intensity. This paper only focuses on the first approach toward emission reduction.

### 2.2 Grid Carbon Intensity

Grid electricity comes from various energy sources with different carbon emissions. The carbon intensity of the grid's electricity is measured in two ways: average carbon intensity and marginal carbon intensity. Average carbon intensity indicates the CO<sub>2</sub> emitted per unit of electricity consumed, spread across total emissions and energy demand. Marginal carbon intensity measures the CO<sub>2</sub> emissions for the next unit of energy consumed. Both values are expressed in g-CO<sub>2</sub>eq/kWh. We currently use average carbon intensity and plan to consider marginal emissions in our future work.

Figure 1 shows the average carbon-intensity of the three regions that we use in our analysis. As shown, the carbon intensity of the different regions varies significantly depending on their energy mix. Ontario has a low carbon-intensity with high variability due to its reliance on renewable energy sources. Both Delhi and Quebec have almost constant carbon intensity, but have high and low carbon emissions due to their reliance on coal and nuclear, respectively.

## 3 DECARBONIZATION PROBLEM

In this section, we present our problem statement, the different models used in our problem formulation, and the optimization problem we define to determine an upper-bound on decarbonization.

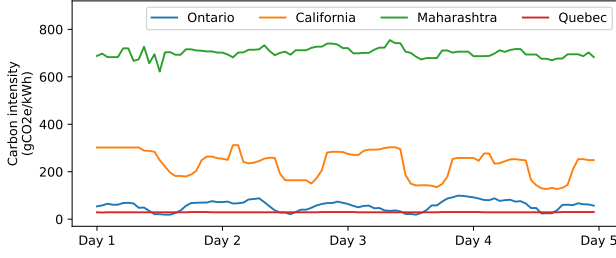


Figure 1: Sample carbon intensity across different regions.

### 3.1 Models

We first present analytical models for the three flexible loads in our problem formulation: home battery storage, EVs, and HVAC.

**3.1.1 Battery storage.** Let  $C(t)$  denote the amount of charge in the battery at the beginning of time slot  $t$ . The total power discharged from the battery,  $p_d^{\text{batt}}(t)$ , during time slot  $t$  should be less than or equal to the initial state of charge of the battery,

$$p_d^{\text{batt}}(t) \times t \leq C(t). \quad (1)$$

The power discharged from the battery and battery charge rate cannot exceed the maximum allowed discharge rate  $p_{d,\text{max}}^{\text{batt}}$  and charge rate  $p_{c,\text{max}}^{\text{batt}}$ , respectively,

$$p_d^{\text{batt}}(t) \leq p_{d,\text{max}}^{\text{batt}}, \quad p_c^{\text{batt}}(t) \leq p_{c,\text{max}}^{\text{batt}}(t). \quad (2)$$

The rate of discharge from the battery  $p_d^{\text{batt}}(t)$ , should be less than or equal to the electricity demand during time slot  $t$ ,  $L(t)$ .

$$p_d^{\text{batt}}(t) \leq L(t) \quad (3)$$

Let  $C^{\text{batt}}$  denote the energy capacity of the battery (e.g., 13.5kWh for Tesla power wall). The total charge in the battery at the end of time slot  $t$  should not exceed the battery capacity.

$$p_c^{\text{batt}}(t) \times t \leq C^{\text{batt}} - C(t) \quad (4)$$

**3.1.2 Electrical vehicle.** The model for the battery of an EV is same as a normal battery storage and is omitted for brevity.

However, EVs have an additional constraint to reach a pre-defined charge level before a deadline  $\tau$ . If the charge level of the EV at time  $t$  is  $C^{\text{ev}}(t)$  and the desired charge level is  $C_{\text{des}}^{\text{ev}}$ ,

$$C^{\text{ev}}(\tau) \geq C_{\text{des}}^{\text{ev}}. \quad (5)$$

**3.1.3 HVAC.** If the power demand of the HVAC system at time  $t$  is  $p^{\text{hvac}}(t)$  is a function of desired thermal setpoint  $T_{\text{set}}$ , ambient temperature  $T_{\text{amb}}(t)$ , and building insulation parameters  $\eta$ ,

$$p^{\text{hvac}}(t) = f(T_{\text{set}}, T_{\text{amb}}, \eta). \quad (6)$$

The savings in carbon emissions are a result of deviating from the setpoint by  $\Delta T(t)$ . In each time slot, we either deviate from the setpoint by  $\Delta T_{\text{max}}$  or do not deviate at all, such that,

$$\Delta T(t) \in \{\Delta T_{\text{max}}, 0\} \quad (7)$$

As the deviation from the setpoint causes thermal discomfort, we allow deviating from the setpoint by a maximum of  $k$  times. To avoid wasting energy in switching between setpoints and deviation, we require the selected time slots for deviation to be contiguous.

$$\Delta T(t) = \Delta T_{\text{max}} \rightarrow \Delta T(i) = \Delta T_{\text{max}}, \quad \forall i \leq t + k \quad (8)$$

### 3.2 Optimization Problem

We next present the individual optimization problems for each load and a combined optimization problem for all the loads. **Battery optimization:** Our goal is to minimize total carbon emissions by modulating load over a 24 hour period using battery storage. The temporal resolution of the optimization problem is hourly. If  $CI(t)$  is the carbon intensity at time  $t$ , the optimization becomes,

$$\min \sum_{t=1}^{24} [L(t) + p_c^{\text{batt}}(t) - p_d^{\text{batt}}(t)] \times CI(t).$$

**EV optimization:** Our goal is to minimize total carbon emissions from EV charging by scheduling its charging. If  $P_c^{\text{ev}}(t)$  is the EV charging rate at time  $t$ , the optimization problem can be written as,

$$\min \sum_{t=1}^{24} P_c^{\text{ev}}(t) \times CI(t).$$

**HVAC optimization:** Our goal is to minimize total carbon emissions from HVAC by deciding  $k$  contiguous slots for deviation. If  $p^{\text{hvac}}(t)$  is the HVAC power at time  $t$ , the optimization problem is,

$$\min \sum_{t=1}^{24} p^{\text{hvac}}(t) \times CI(t).$$

**Combined optimization:** The combined optimization problem is,

$$\min \sum_{t=1}^{24} [L(t) + p_c^{\text{batt}}(t) - p_d^{\text{batt}}(t) + p^{\text{hvac}}(t) + P_c^{\text{ev}}(t)] \times CI(t).$$

We solve this problem as Mixed Integer Linear Program (MILP) assuming perfect knowledge of  $CI(t)$ ,  $L(t)$ , and  $T_{\text{amb}}(t)$  over the optimization horizon (24hrs in this case).

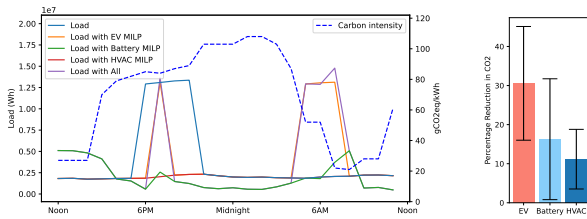
## 4 EVALUATION

**Setup.** We quantify the decarbonization potential of flexible loads, individually and in combination, using real-world electric usage data from 1,000+ homes, provided at 5-minute granularity, from a small city in an economically-advantaged country. The household's average daily electricity consumption is 82kWh.

For the battery, we assume each home has a Tesla Powerwall battery, with a capacity of 13.5kWh, and maximum charging or discharging rate of 3.3kW [17]. For the EV, we assume each home has a Tesla Model 3 Long Range battery capacity of 82kWh [16]. The in-home charger has a level 2 charger. We assume the car owner uses a max of 44kWh (or 192 miles) in a day, which translates to 192 miles of range for the Tesla Model 3 and represents the round-trip distance from this town to the nearest major city. EVs can only be charged directly from the grid.

The heating ventilation and cooling (HVAC) system modeling requires three configuration variables: (i) the size of the house from our dataset, (ii) the estimated value for insulation based on the year built [22], and (iii) the ambient temperature from the Darksky API [14]. We feed this data into an HVAC design and calculation tool called CoolSelector [15], which outputs hourly load values for the HVAC system. We subtract these values from the household demand to compute the non-HVAC component of the load. In our combined scenario, the battery can serve the HVAC demand.

Finally, we collect the carbon-intensity values, measured in grams of carbon dioxide equivalent per kilowatt-hours (g-CO2eq/kWh), at an hourly granularity using electricityMap [1].



**Figure 2: Illustration of carbon-aware flexible loads modulation in Ontario on July 21-22, 2022 (left) and the percentage savings for each flexible load over the course of a year (right).**

#### 4.1 Carbon-aware Load Modulation in Action

Figure 2(left) demonstrates the temporal shifting of flexible loads in household electricity demand. The carbon intensity (dashed blue) varies significantly over 24 hrs, from 22 to 110, being higher during the day than at night. Demand modulation is achieved through three flexibility types: *scaling up*, *scaling down*, and *shifting demand*. Carbon-aware EV charging *scales up* charging, fulfilling demand in a shorter window, slotted into least carbon-intense slots (7pm-10pm, 12am-1am) for higher carbon savings. The HVAC system *scales down* demand, ensuring discomfort within acceptable bounds, mainly at high carbon-intensive slots (6am-8am). Batteries *shift* demand to low carbon-intensity periods across time.

Figure 2(right) shows the reductions in carbon emissions for each individual flexible load over a year. The *scale up* flexibility of EVs provides the most benefits, 30.56%. Home batteries provide high savings as they *shift* the loads in the most carbon-intense slots to the least carbon-intense periods. Since the peak carbon intensity can be as high as 5 $\times$  the minimum value, home batteries provide a significant opportunity for savings. Finally, HVAC optimization cannot cause significant discomfort and yields smaller savings.

**Key takeaways.** EV charging leverages dips in carbon intensity (30.56%), batteries migrate load between carbon-intensity extremes (16.27%), and HVAC avoids bursts of high carbon intensity, but is bounded by a thermal discomfort threshold (11.16%).

#### 4.2 Impact of Regional Carbon Intensity

As shown in Figure 1, carbon intensity can vary significantly across space and time, depending on the energy generation mix. Figure 3 shows carbon emission reductions for four locations: Ontario (low average, high variations), California (high average, high variations), India (high average, low variations), and Quebec (low average, low variations). Unless you move to a location with low average carbon intensity, you need temporal variations in carbon intensity to achieve savings. Furthermore, given temporal variations, low (ON, 26%) and high average regions (CA, 10%) can reduce emissions with variations in savings across days and homes. While Quebec is not an ideal candidate for carbon-aware load modulation, its carbon emissions are quite low. India has one of the highest average carbon intensities in the world and provides no opportunity for carbon arbitrage. Unfortunately, it is also one of the most densely populated regions in the world and necessitates transitioning to either ultra-low carbon energy generation like Quebec or a mix of renewables and fossil fuels like California.

**Key takeaways.** Both high variations in, and low averages of, carbon intensity can yield a reduced carbon footprint of buildings. High variability alone can decrease carbon emissions by up to 55%.

#### 4.3 Impact of Seasonal Variations

Figure 3 shows that savings also vary across different seasons for various flexible loads. There are two key observations from this result: first, summer gives the most savings as batteries save the most in summer, and second, savings are the smallest during the spring. The high summer savings are due to a higher fraction of power generation from solar power, which leads to significant variations within a day and across days. A higher difference between the two extreme carbon-intensity values leads to 12% savings from battery, whereas all the other seasons have 5% or less savings. The savings during the Spring season are low as most of the demand is fulfilled by nuclear power, which does not have any variations [8].

**Key takeaways.** The changes in electricity generation mix over time leads to variations in savings, 12% in Spring versus 36% in Summer. However, the order of loads by savings does not change across seasons.

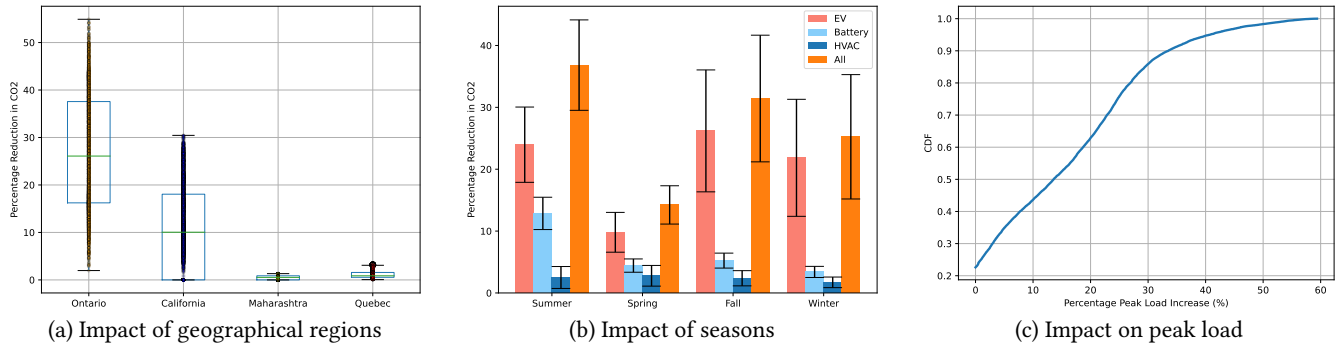
#### 4.4 Impact on Daily Peak Electricity Load

The higher-level goal for optimization is to shift the load from high carbon-intensity time slots to low carbon-intensity slots. However, if a significant amount of load is shifted, it can create a new peak during low carbon-intensity periods. While this may be desirable from a decarbonization perspective, it could trigger transformer and cable upgrades in the grid. To investigate the impact of our carbon-aware load modulation, we look at the increase in peak load post-modulation in Figure 3(c). The peak load does not increase for 25% of the days across all the homes; it increases by only up to 27% for 80% of the homes. The impact of such an increase in peak load depends on the status of the grid. If the grid is over-provisioned, this increase in peak load would not trigger any updates. In contrast, it may require immediate upgrades if it is already operating at peak capacity. Future work should look at configuring load modulation parameters such that the peak does not increase.

**Key takeaways.** Carbon-aware load modulation can increase the home-level peak load of the grid by up to 60%. Future work should investigate configuring load modulation to limit peak load increase.

### 5 RELATED WORK

Prior research has explored using energy resources to reduce peak demand at both home and grid levels. Grid-owned battery energy storage systems are commonly employed for peak shaving [11, 23]. Household energy resources like batteries [27], electric vehicles [25], HVACs [10], or a combination of these resources [7] have shown potential for peak load reduction. However, these approaches do not explicitly minimize carbon emissions from electricity demand. Previous work on reducing household carbon emissions considers one load at a time [20], such as aiming to lower carbon emissions while maintaining thermal comfort [6], and quantifies carbon savings from home retrofitting [26]. To the best of our knowledge, no prior research has specifically investigated the upper limit of using flexible loads for explicit carbon reduction.



**Figure 3: Carbon emissions reductions for (a) different geographical regions and (b) different seasons in Ontario. (c) Cumulative distribution of increase in peak demand when all flexible loads are optimized for carbon emissions in Ontario.**

## 6 CONCLUSIONS

In this paper, we investigate the upper-bound on the potential for reducing carbon emissions by exploiting flexibility present in building loads such as EVs, storage and HVACs, given the perfect knowledge of demand pattern and carbon intensity information. Our analysis, comprising of 1000+ homes shows that by co-optimizing battery storage, EVs, and HVAC systems, carbon emissions can be reduced by 26.93% on average and 54.9% at max. In future, we plan to relax the assumptions on future knowledge and demand behaviors to develop a practical online building flexible load modulation approach.

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