QUANTIFYING THE EMISSIONS IMPACT OF REPURPOSED EV BATTERY PACKS IN RESIDENTIAL SETTINGS

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ABSTRACT
The market share of plug-in electric vehicles (PEVs) is growing, thanks to continuous improvements in battery efficiency, declining production costs, and sustained policy support. Concurrently, concerns are growing over the supply of decommissioned (or spent) PEV batteries. Following their service life, PEV batteries can maintain close to 80% of their original capacity, rendering them suboptimal for transport use, but viable for battery storage systems (BSSs). As a result, there has been a growing interest among researchers and the private sector to determine the utility of repurposing PEV batteries for energy storage. Previous work has optimized behind-the-meter (BTM) BSSs for self-sufficiency and energy arbitrage, but few have sought to use the system to lessen a home's electricity-related carbon footprint. This study uses high resolution 2018 electricity demand and grid feedstock data for energy-efficient homes in the Austin, Texas area to simulate the daily operations of a 6 kWh BTM BSS to minimize daily CO_{2e} emissions. Homes with rooftop solar could reduce on average 50% of total household emissions or 2.67 tons of CO_{2e} annually, while homes without rooftop solar could reduce just 2% of total household emissions or 0.12 tons of CO_{2e} annually. Adding BTM BSS to homes with rooftop solar increases average annual carbon savings by 64%. For BTM BSSs to be cost-effective for consumer use, the price of repurposed PEV batteries must fall to \$15/kWh or carbon pricing must rise to \$38.75 per ton of CO_{2e} for homeowners to reach breakeven at the end of the estimated 10-year lifespan of the BSS.

Keywords**:** battery storage; emission reduction; residential energy storage; battery repurposing

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1. Introduction

Vehicle electrification is an indispensable component in a suite of solutions designed to reduce transportation activities' greenhouse gas (GHG) emissions (Kockelman et al., 2008). Electric vehicles (EVs), or more generally, PEVs, are differentiated between plug-in hybrid electric vehicles (PHEVs), which have up to 40-mile all-electric range with a gasoline engine for range extension, and fully-electric battery electric vehicles (BEVs), which have a median range of 201 miles for non-Tesla, U.S. 2020 EVs (Hyatt and Ewing, 2020; U.S. Department of Energy, 2020). Increasing battery range and the deployment of additional public fast-charging infrastructure may lessen both range anxiety and long charging concerns, two common barriers to the adoption of EVs (Egbue and Long, 2012; Neubauer and Wood, 2014). Technology advancements have significantly improved since the first PEV models, and all-electric BEV vehicle sales now substantially outpace PHEVs (about 3:1 ratio in new sales), thanks to the development of popular models, like the Tesla Model 3 (Gohlke and Zhou, 2020). Fig. 1 depicts both the share of PEV sales broken down into PHEV and BEVs and the number of sales, with the noticeable divergence in sales starting in 2018 attributed to the Tesla Model 3. Market share for EVs continues to increase year-on-year, and U.S. EVs now make up 2% of domestic new light-duty vehicle sales, which is up from 0.7% in 2015 (Hertzke et al., 2019). By 2035, more than half of new U.S. passenger vehicle sales could be electric (Bloomberg New Energy Finance, 2020). But projections are dependent on a host of factors, including government incentives, vehicle turnover rates, consumer demand for EVs, and when purchase-price cost parity with conventionally-fueled vehicles is met (Lutsey and Nicholas, 2019; Slowik et al., 2019).

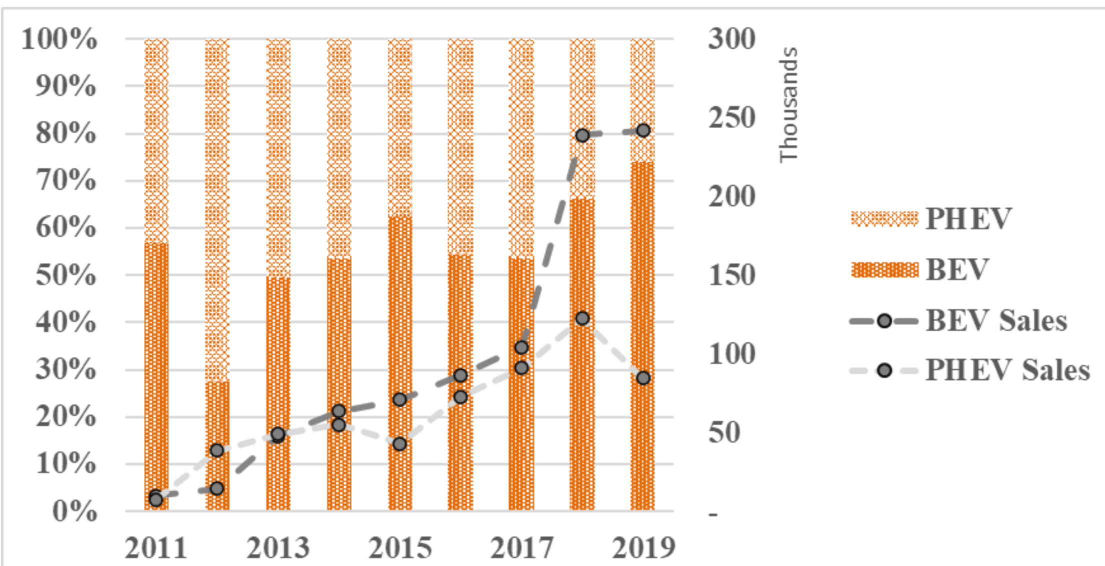

Fig. 1. Share and count of annual US PEV sales by type: BEV and PHEV
(Data from Argonne National Laboratory, 2020)

As a result of increased EV sales, the global stockpile of used PEV batteries may exceed 3.4 million by 2025, compared to just 55,000 in 2018 (IER, 2019). Moreover, a BNEF forecast of used PEV battery availability from 2016-2025 estimated 29 GWh of used PEV batteries by 2025 (P.V. Europe, 2016). Notwithstanding concerns about raw material sourcing for batteries and manufacturing-related GHG emissions (Elgowainy et al., 2016; Qiao et al., 2017; Wu et al., 2018), few life cycle assessments (LCAs) consider the extended environmental benefits of repurposing PEV battery packs for stationary battery storage systems (BSS) (Ahmadi et al., 2014, 2017; Bobba et al., 2018) before end-of-life recycling and waste disposal. In contrast to recycling, repurposing PEV batteries entails modest disassembly, battery health tests to assess degradation (and to redirect inferior packs to recycling), and assembling similarly rated and performing packs together by adding critical electrical, control, and safety parts (Cready et al., 2003; Ahmadi et al., 2014). Estimates on battery health show that used PEV battery capacities may still hold 60-80% of its design capacity (Malcho and Kelly, 2015), which under favorable conditions could provide up to 10 years of second-life stationary BSS (Neubauer et al., 2015) at an economic savings of up to 60% compared to new storage systems (P.V. Europe, 2016).

Repurposed BSS are dynamic, flexible power sources for storing and dispatching energy. For example, they can be programmed to store intermittent zero-carbon renewable energy to balance supply and demand or provide electricity load leveling by discharging electricity into the grid to ease localized power grid constraints. Utilizing repurposed batteries for behind-the-meter (BTM) energy storage has recently garnered attention as homeowners attain partial energy independence with rooftop solar/photovoltaic (PV) arrays (Fares and Webber, 2017). While residential buildings and appliances are becoming more energy efficient (Barbose et al., 2013; Mecrow and Jack, 2008), smaller residential carbon footprints (or net zero) can be achieved by transitioning to renewable energy paired with BSS (Casals et al., 2017). Integrating renewable energy generation sources with BSS provides several energy management tools, which can be finely adjusted for homeowners and power providers alike. Some of these tools include storing excess renewable energy which can be injected back into the grid during the evening peak, thus abating natural gas peaker power plants.

This paper presents a methodology to assess the environmental impact of BTM repurposed PEV BSS. The costs of a repurposed PEV battery pack are also explored under carbon pricing to perform a break-even analysis. High resolution (15-minute) household electricity consumption data of 45 homes in Austin, Texas, collected on a voluntary basis by Pecan Street in 2018, is paired with 15-minute electricity generation data from the region's independent system operator (ISO), the Electricity Reliability Council of Texas (ERCOT)[2]. The objective of the BTM BSS is set to minimize the household's carbon footprint by storing excess rooftop solar (if present) and low-carbon stored energy from the grid to minimize power draw from the grid during periods of carbon-intense power generation. The remaining sections of this paper are organized as follows: relevant BSS, repurposing PEV batteries, and residential BTM BSS literature is consolidated, the modeling framework is explained, the case study data is presented and results discussed, and concluding remarks are presented with implications for homeowners and utilities seeking untraditional decarbonization strategies.

2. Literature Review

Highly efficient, energy dense lithium-ion batteries (LIBs) have significantly contributed to making PEV's an economically viable and reliable source of intraregional transportation (Reid and Julve, 2016). Early studies suggested that PEV owners may let go of their battery once out of

[2] ERCOT serves almost three-fourths of the customers in Texas, accounting for around 90% of the state's electric load (US-EIA, n.d.)

warranty or after reaching 8 to 10 years of service life (Casals et al., 2017; Sathre et al., 2015). However, advanced batteries capable of withstanding more charge cycles (Liu et al., 2020) suggest that first-life use may follow the turnover of household vehicles of 10.5 years (Schipper, 2018). Advances in battery design may even allow for residual capacities to remain relatively unchanged (or lessened only to 90%), even as batteries face more charge cycles (Lambert, 2018). With greater adoption of PEV's in recent years, due in part to steeper-than-expected price reductions of LIB packs (Henze, 2019), the supply of spent batteries for second use is expected to grow to between 112-227 GWh per year by 2030 (Engel et al., 2019).

The large supply of PEV batteries can be repurposed for utility-scale energy storage, often collocated with generational units to firm up capitally intensive assets, down to distributed energy storage (DER), often in BTM settings for individual utility customers. Given that the utility-scale LIB-storage demand is estimated at 183 GWh per year by 2030 and an opportunity to reduce costs of repurposing PEV packs with economies of scale, several existing repurposing PEV pilots are at utility-scale (POWER, 2018; Schmid, 2018; The Mobility House, 2019). Despite this, Burke (2009) suggested repurposed PEV batteries would only be helpful for BTM load leveling in residential and light commercial buildings or telecommunication backup applications, primarily due to barriers in sourcing used PEV batteries. Regardless of the eventual split between second life applications, both are plausible adopters for a repurposed PEV BSS. Lower costs of repurposed battery packs combined with increased demand for residential rooftop solar has made BSSs more attractive for households wishing to become more self-sufficient (Fares and Webber, 2017). Additionally, market-ready BSSs, such as the Tesla Powerwall and SonnenBatterie, have pushed some proactive residential and commercial consumers to protect themselves from potential grid outages, like the and public safety power shutoffs during 2019 wildfire seasons by California-based Pacific Gas and Electric (Alvarez, 2019) and electric grid failure caused by the 2021 winter storm in Texas (Doss-Gollin et al., 2021) which both left millions without power for several days. Although many studies have analyzed the practical and logistical side of using of BSSs (Bistline and Young, 2020; Bobba et al., 2018; Casals et al., 2017; Fares and Webber, 2017; Reid and Julve, 2016; Vejdan et al., 2019; Zheng et al., 2015), few have aimed to quantify the environmental impact of such technologies. Considering the urgency of decarbonization, it is imperative to assess the carbon intensity of these systems to determine the benefits and drawbacks of implementing BTM BSS over a broad geographic region.

Previous studies quantifying GHG impacts of using repurposed PEV batteries as BTM BSSs have shown that CO_2, NOx, and SO_2 emissions vary across the board based on the condition of a battery and context of use (Sathre et al., 2015; Vejdan et al., 2019). Estimates showing high emissions from BTM BSSs have power grids that rely primarily on non-renewables feedstocks (namely, coal and natural gas). However, many utilities are transitioning away from fossil fuels to renewable resources, with or without policy mandates or tax credits (Bistline and Young, 2020). Several initiatives are also currently underway by municipalities to address the climate crisis by encouraging BSS owners to charge from low-emission sources including (rooftop) solar and wind power, which are increasingly a larger feedstock share in the grid (Fisher and Apt, 2017). Since solar and wind energy sources emit zero GHG emissions at the source and continue to be supported by state policies through subsidies, these renewables are critical to lessen a BTM BSS user's electricity-caused carbon footprint (Fares and Webber, 2017; Fisher and Apt, 2017). However, the consensus among researchers is that the use of grid-connected BSSs results in increased emissions due to a variety of internal and external factors impacting batteries.

Most net positive emissions caused by BTM BSSs can be primarily attributed to round-trip inefficiencies (typically near 15%) generated during the use of BSS's (Fisher and Apt, 2017). Fisher and Apt (2017) found minor improvements in efficiency from 83% to 91% can reduce CO_2 emission rates by around 50%. Despite improvements in this technology, achieving a round-trip efficiency consistently greater than 90% may be difficult due to secondary losses caused by battery pack operation even when idle (Fares and Webber, 2017). For example, extreme ambient operating temperatures (high and low) can reduce PEV battery efficiency by greater than 20% (Yuksel and Michalek, 2015). In all, BTM BSS inefficiencies can increase annual energy consumption on average by 324–591 kWh, and emissions by 153–303 kg CO_2, 0.03–0.20 kg SO_2, and 0.04–0.26 kg NO_x annually for a Texas household (Fares and Webber, 2017).

Despite initial findings suggesting increased emissions, BTM BSS demand continues to grow as homeowners aim to reach energy independence by reducing their reliance on the grid (Fares and Webber, 2017; Reid and Julve, 2016). Partial grid isolation provides resilience to homes during natural disasters (e.g., hurricanes, tornadoes, and wildfires) and times of load-shedding where the flow of electricity can be disturbed (Demand Side Analytics, 2019). BTM BSS also have the potential to be used for energy arbitrage to effectively control demand charges and frequency regulation (Fisher and Apt, 2017). Energy arbitrage can be implemented into BTM BSSs to store energy when electricity prices are low and utilize or sell the same energy when prices increase to benefit a homeowner (Reid and Julve, 2016). For example, four coincidental peak (4CP) reduction utilizes a form energy arbitrage where BSSs support and enable utility peak load reduction. During a 4CP event, customers with BSSs can take advantage of \$60/kW benefits while curtailing utility net transmission costs (Pecan Street, 2021). On the other hand, increased adoption of distributed PV arrays at residences tends to displace utility-scale PV investment (Carvallo et al., 2020), which is often the system-optimal investment. To ensure that these BSSs and PV arrays, also called distributed energy resources (DERs), do not impede utility investments in renewables, a centralized-coordinated dispatch strategy or decentralized strategy with a system-optimal goal may be of interest for utility operators, such as storing excess rooftop solar and abating the use of peaker power plants.

One key variable contributing to the extent of possible GHG savings for a home is the regional grid feedstock or energy-mix (Fisher and Apt, 2017). Although emission factors (EFs) vary by time of the day, they follow a similar daily pattern (with peaks at early-morning for western US states). Identifying and utilizing this pattern is fundamental to optimize GHG emissions, especially in regions where EFs vary significantly throughout the day. In this study, residences without rooftop solar are the main users of this optimization technique. While there is potential to minimize GHG emissions in this manner, several studies underscore how only adding BTM BSSs is unlikely to reduce GHG emissions due to increased energy usage and unfavorable roundtrip efficiency rates (Bistline and Young, 2020; Fares and Webber, 2017; Fisher and Apt, 2017; Yuksel and Michalek, 2015). Furthermore, previous work suggests the synergy of DERs (rooftop solar and BTM BSS) to serve as one of the primary catalysts to lowering residential GHG emissions.

3. Materials and Methods

3.1. Data Sources and Assumptions

To show how BSSs could lessen residential GHG emissions requires two data sources: residential energy consumption and distribution of electricity generation feedstocks. These sources, both collected at 15-minute intervals during the full year 2018, were obtained from Pecan Street and ERCOT, respectively. Since marginal EFs (MEFs) were not obtainable for this year, average EF by fuel type were used to approximate EFs.

Pecan Street collects household electricity usage data voluntarily from program participants using eGauges, down to the circuit level, across Texas, New York, and California energy markets. The load data, in kilowatts (kW), separates the household's electricity demand from solar production which can allow one to retrospectively assess periods where a homeowner added electricity to the grid. Due to the high upfront capital cost of solar panels and their multi-year payback period and the nature of voluntary participation in Pecan Street data collection efforts, the dataset likely biases upwards to wealthier households (Yu et al., 2018). Households from the dataset consumed on average 1.01 MWh per month, slightly below the state average of 1.18 MWh in 2018. However, the early adopters of residential BSS will likely have similar demographics, especially if these systems are composed of repurposed used EV batteries since many of these program participants also own EVs. An inherent assumption is that these households do not have already have BSS, which is reasonable given the niche market for BSS.

Pecan Street provided a subsample of their Austin, Texas data (n=45). The majority of the houses had solar panels (n=39). It is assumed this subsample is randomly sampled from the Texas pool such that the results from this subsample largely align with the full set. The normalized net power demand of these households and can be found in Appendix A. Electricity generation data by fuel type collected by ERCOT provides a broad understanding of how renewable and non-renewable resources are utilized to produce electricity for customers across the ISO throughout the day and across larger temporal periods (e.g., weeks, months, and seasons). Although some residential customers may be entirely served by baseload generational units out of proximity to power plants, assuming a household's electricity feedstock is equivalent to the wholesale generational data is appropriate absent information on transmission and distribution systems. Additionally, it is assumed that the BSS does not impact the dispatch problem for this Austin market, since the size of the system is small.

Previous studies on the application of repurposed PEV batteries as BTM BSSs have found a broad range of findings. Many of the assumptions listed in Table 1 vary significantly due to variability in testing procedure and conditions. Although high variability impacts confidence in findings, parameter values are based in the literature and scientific advances. For example, residual capacity is expected to be near 70-80%, but it expected to rise as improvements in battery chemistry over time will allow for greater quantity of charge-discharge cycles. Estimated lifespan of repurposed PEV batteries is expected to be near 8-10 years. Current battery roundtrip efficiency rates are expected to be near 90%. Finally, BTM BSSs are expected to reduce peak power demand by 10-32% depending upon rate of adoption.

Table 1 Summary of Repurposed PEV and BTM BSS Assumptions in the Literature

Variable	**Parameter**	**Study**
Residual Capacity	80%	Ahmadi et al. (2014)
	81.31%	Bobba et al. (2018)
	70-80%	Kamath et al., (2020a)
	70-80%	Sathre et al. (2015)
Estimated Lifespan for Second-Life Applications	10 years	Ahmadi et al. (2014)
	6-12 years	Casals et al. (2017)
Total Roundtrip Efficiency	80-85%	Ahmadi et al. (2017)
	91%	Bistline and Young. (2020)
	95%	Bobba et al. (2018)
	85%	Fares and Webber (2017)
	83-91%	Fisher and Apt. (2017)
	75-80%	Neubauer et al. (2015)
Potential Reductions in Peak Power Demand	10%	Vejdan et al. (2019)
	15-20%	Fisher and Apt. (2017)
	8-32%	Fares and Webber. (2017)

EF values shown in Table 2 were used along with grid-generation data to determine BSS charge and discharge times for the battery-grid component; EF values of 0 (lbs. of CO_{2e} per MWh) indicate 100% renewable energy use whereas all greater EF values indicate increased emissions. EF values of zero can only be found in the solar component of the optimization process. Grid generation EF values range from 400 to 1,250 lbs. of CO_{2e} per MWh. The quantity of carbon savings can be adjusted based on energy storage and use. Applying EF values in conjunction with cost estimates per pound of CO_{2e} saved provided a means to estimate the social cost of GHGs saved through optimization.

Table 2 Summary of Emission Factors Used During Optimization

Energy Source	**Emission Factor (lbs. CO_{2e}/MWh)**	**Source**
Coal	2,242	ERCOT (2018)
Gas	861	ERCOT (2018)
Natural Gas – Combined Cycle (CC)	783	Bell et al. (2011)
Biomass[1]	65	US-EIA, n.d.; US-EPA, n.d.
Renewables (including rooftop solar)	0	ERCOT (2018)

[1] Biomass is a weighted average according to generational output from Texas' biomass plants by feedstock type.

To determine an ideal battery BSS size across all homes, the correlation between the capacity of solar generation (kW) with the home square-footage was examined. Results showed the correlation between solar capacity and square-footage was very low, indicating additional parameters such as EV ownership and baseload electricity consumption are needed to hypothesize the capacity of future BSSs. To this end, several household solar generation capacities were analyzed to determine the capacity of a battery pack sufficient for storing all excess solar energy during the year. Limited by roundtrip efficiency, it was determined that a 6 kWh battery pack could capture up to 90% of excess solar energy during the year.

The BSS is also expected to inject power within a short period of time for both resilience purposes and to strategically discharge stored solar or stored grid electricity to use when the house relies on grid electricity that is carbon-intense (i.e., has a high EF measure). The BSS model contains fixed parameters that determine its capabilities: 6 kilowatt-hour (kWh) maximum energy capacity, 5 kilowatt (kW) maximum charge/discharge rate, and 90% roundtrip efficiency. Initial capital costs are assumed to be $100 per kWh of storage (Kamath et al., 2020a; Neubauer et al., 2012; Nykvist and Nilsson, 2015; Sun et al., 2018). Solar energy gathered in real-time is assumed to be 100% efficient, even though the Pecan Street data reveals the inverter yields a negative output at night. Carbon pricing values are derived from analysis of trends only across the United States, whereas carbon pricing in non-U.S. markets may vary based on enacted policies and expert recommendations: the lowest scenario represents the current pricing in Austin, Texas (Ryan Thornton, 2020), the moderate scenario represents the highest pricing implemented in the United States (Kennedy et al., 2015; World Bank and ECOFYS (Firm), 2015), and the aggressive scenario represents the suggested pricing according to national budget estimates (US-CBO, 2020).

Table 3 Summary of Tested BTM BSS Assumptions

Variable	**Parameter**
Battery Capacity	6 kWh
Max Charge/Discharge Rate	5 kW
Roundtrip Efficiency (Solar)	100%
Roundtrip Efficiency (Battery)	90%
BSS Capital Cost	$100/kWh
Carbon Pricing Scenarios	$4, 12, 27.56/ton CO_{2e}

3.2. Energy Modeling Framework

The environmental impact of residential BSS use is approximated through an integrated model combining household electricity use, rooftop solar generation (if present), and a BSS system to charge and discharge power to lower residential GHG emissions. The developed modeling framework conducts a continuous temporal analysis that optimizes the use of energy from both grid and local renewable sources. In this study, the optimization process occurs on a daily basis during the 2018 calendar year. The following sections detail the sequential processes and assumptions involved during model construction.

The developed optimization program model uses EFs alongside demand curve data as the foundation to simulate a BSS for the daily continuous sample period. Each home has its own BSS to store energy for future use, depending on the household's power generation and electricity demand. To minimize a household's carbon footprint, the model identifies periods of the day when EFs reach the daily minimum, and stores energy from the grid for use during peak EF times later in the day. Since no electricity is carried over to the next day, we assume the battery fully or partially charges and completely discharges during a single day. Efficiency rates shown in Fig. 2 are considered during the charge and discharge cycle. Based upon the varying levels of installed solar energy capacity (or lack thereof) present with households across the dataset, three separate operational components were identified for the home BSS to use and store electricity:

3.2.1. Battery-Grid. While incorporated into all simulations, the battery-grid component is the primary energy interaction for homes without solar panels to minimize GHG emissions through a peak-shaving approach. This scenario functions by extracting and storing grid energy in the BSS when EF values reach a local minimum. Consumption of the stored battery energy by the home occurs when EF values reach a local maximum. Since historical consumption data is used and assumed to be representative of typical demand patterns, the extrema may be considered global across a day. Although this direct interaction is used less frequently on homes with solar panels due to capacity constraints and the desirability of the battery to store 100% renewable solar for later use, this operational method offers the greatest benefit during times when solar energy generation is unreliable.

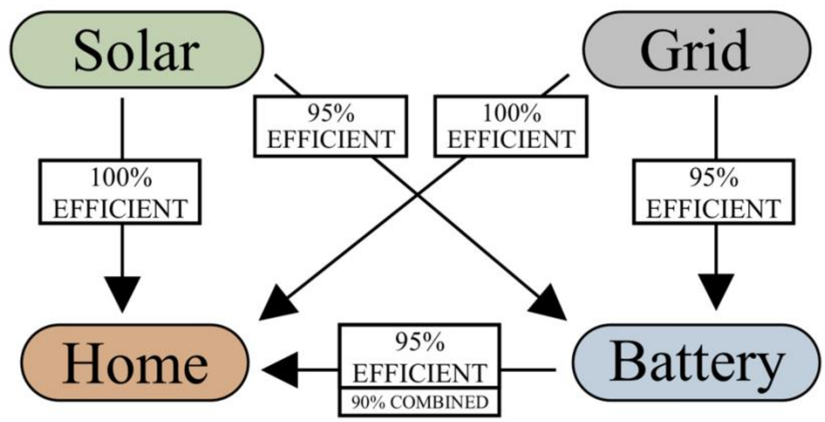

Fig. 2. Diagram of Solar-Battery and Battery-Grid Interactions

3.2.2. Solar-Home. The solar component captures the production of solar electricity and actively transfers this energy to the home for immediate use. Residences see direct GHG reduction by substituting grid electricity with 100% renewable energy for periods of the day when solar irradiance is high. Solar panels actively generate electricity for direct use and have an EF value of 0 (lbs of CO_{2e} emitted per kWh of energy) when stored. Since this study only accounts for household GHG savings, emission savings of excess solar generation are ignored in circumstances where the energy stored in the battery is at capacity and can no longer be transferred to the battery (i.e., net metering).

3.2.3. Solar-Battery. The solar-battery interaction (which is a combination of the Battery-Grid and Solar Components) allows for solar energy to be stored when the panels produce more energy than the household demands. Additionally, integrated battery-grid interactions allow for greater GHG savings when solar energy generation is suboptimal and battery conditions are met. For households residing in markets where net metering exists, the panels may be oversized relative to the household's demand to receive some credit for when excess solar is pushed to the grid. Residences in Austin, Texas can participate in the Value of Solar program that credits their bill with their generational output and allows for credits to carry over from solar rich months. This solar-battery component offers significant benefits over the battery-grid method because the stored solar power maintains an EF value near 0. The inefficiencies of the battery system discussed earlier are assumed to capture the energy demand of the inverter.

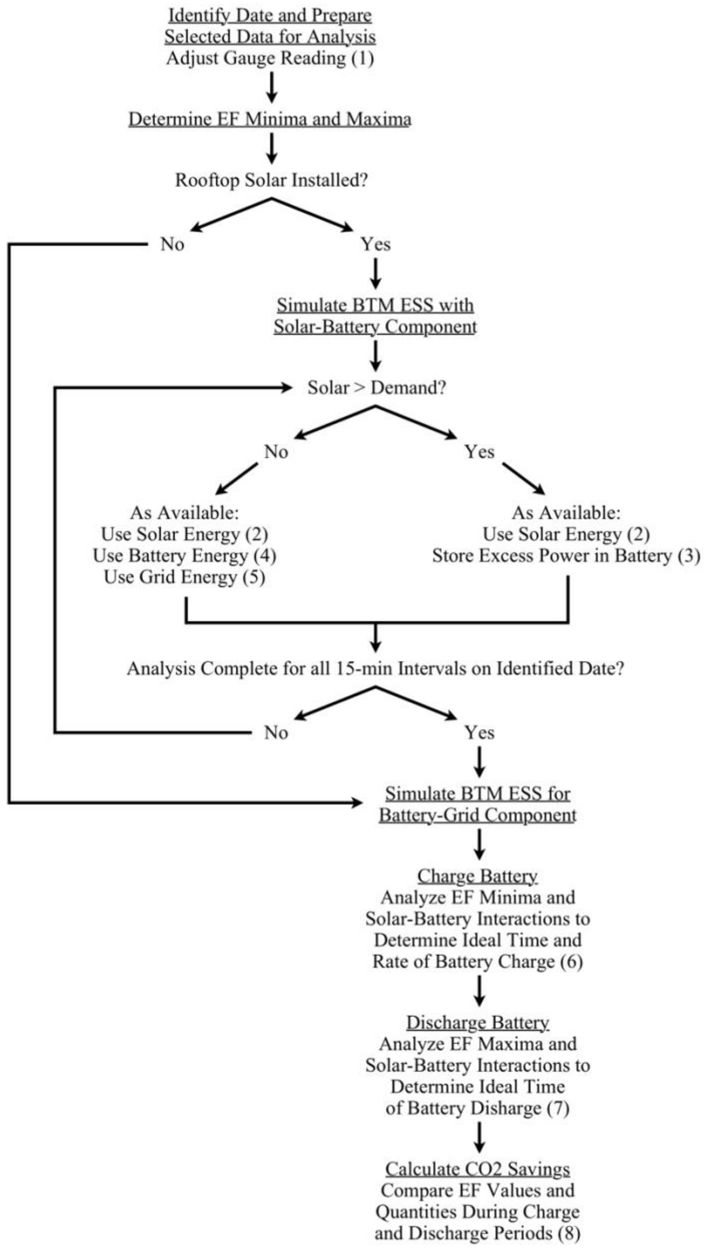

Fig. 3. Daily GHG Optimization Process

For the optimization model, simply using a renewable energy ratio value (i.e., renewable energy generated to total energy generated) was not an accurate measure to determine the ideal times for BSS (dis)charging since it did not consider the mix of non-renewable emission sources based on rate of emissions. Therefore, it was necessary to create an EF unique to each 15-minute interval that provided insight on the quantity of emissions generated relative to total electricity generated.

3.3. Calculations

A general outline of the optimization process is depicted in Fig. 3 along with the following equations. Before the optimization process was initiated, it was critical to convert energy values from eGauges to power readings for proper analysis using Eq. (1):

$$P_{transfer} = \frac{E_{gauge}}{4}, \tag{1}$$

where $P_{transfer}$ is the magnitude of power transfer (kW) calculated for each 15-minute interval measured from the E_{gauge} or energy reading (kWh) typically found on gauges near the electricity meter and inverter. Gauge readings measuring solar energy generation are classified under P_{solar} and demand measurements are assigned to P_{demand}.

The solar component part of the optimization model only considering interactions between home demand and solar panels is determined as shown in Eq. (2):

$$P_h = P_{solar} - P_{demand}, \tag{2}$$

where P_{demand} is actual home demand, P_{solar} is the direct injection of solar energy, and P_h is the magnitude of home demand remaining. Excess solar power is stored in the battery when P_h is a positive value as calculated in Eq. (3):

$$P_{battery} = P_h, \tag{3}$$

where $P_{battery}$ represents the inflow of power and increase of energy stored in the BTM BSS at any 15-minute interval.

Circumstances when P_h is negative warrants compensation of remaining demand from the battery (assuming the battery has a stored energy reading greater than 0) as calculated in Eq. (4) and/or directly from the grid as shown in Eq. (5):

$$P_{remain} = P_h - \eta P_{battery}, \tag{4}$$

where $P_{battery}$ is the power transferred from the battery to the home which is limited to 1.25 kW (relative to 5 kW maximum discharge rate) and does not exceed the remaining demand at any interval $\frac{P_h}{\eta}$. Roundtrip efficiency of the battery is assigned to η, which is static at 90% for this study. P_{remain} (always ≥ 0) represents remaining demand which is equivalent to the transfer of power from the grid to the home P_{grid} where solar and battery power are not sufficient to completely support home demand as related in Eq. (5).

$$P_{grid} = P_{remain} \tag{5}$$

Ideal charging time is calculated to be at the time(s) when EF reaches its daily minima. Rate of charge is determined according to the component of optimization as shown in Eq. (6).

$$P_{charge} = \frac{E_{max} - \max\left(\sum_{i=1}^{96} P_{bat}\right)}{k} \tag{6}$$

For the battery-grid option, charge rate (P_{charge}) is fixed at 1.25 kW while the solar-battery option has a variable charge rate (limited to 1.25 kW) and is calculated to be the difference between battery capacity (E_{max} fixed at 6 kWh) and maximum energy stored (max ($\sum_{i=1}^{96} P_{battery}$)) in the battery (from solar-battery interaction) divided by the number of intervals (k) necessary to charge the battery. The optimization process minimizes k to ensure energy extraction utilizes the smallest EF values to maximize future savings.

Battery discharging functions similarly, but aims to compare the largest EF values with (remaining) demand to ensure highest possible CO_{2e} savings by utilizing peak-shaving technique as calculated in Eq. (7):

$$P_{discharge} = \begin{cases} P_{demand} \text{ } if \text{ } E_{battery} \geq \frac{P_{demand}}{\eta} \\ E_{battery} \text{ } if \text{ } E_{battery} \leq \frac{P_{demand}}{\eta} \end{cases}, \quad (7)$$

where $E_{battery}$ is the energy in the battery at any given point in time, P_{demand} is the magnitude of home demand, and $P_{discharge}$ is the quantity of power discharge at any specific 15-minute interval. The equations for the charging and discharging functions (relating to the battery-grid component) run until certain parameters are met. The charging function will run until the battery as adequately or fully charged and the discharge function will run until the battery no longer holds any energy. Following the battery simulation process, final GHG savings are determined as shown in Eq. (8):

$$GHG_{savings} = P_{sol\ discharge} * EF + P_{bat\ discharge} * EF_{calc} - P_{bat\ charge} * EF, \quad (8)$$

where $GHG_{savings}$ is the CO_2 savings in pounds, $P_{sol\ discharge}$ and $P_{bat\ discharge}$ are the quantity of solar and battery power transferred to the home during discharge process, $P_{bat\ charge}$ is the quantity power (only associated with the battery-grid interaction) received and stored by the battery, EF is the precalculated dynamic energy factor, and EF_{calc} is the adjusted energy factor value which accounts for the magnitude and source of power.

All the previous general equations describe how results were calculated for one 15-minute interval. To calculate the values of these variables and simulate the functions of a BTM BSS over a full day, the subscript n, which is assigned to an integer, must be added to the general equation (Eq) and combined with the summation shown in Eq. (9) to represent the equation values associated with all 96, 15-minute intervals in a full day.

$$\sum_{i=1}^{96} (Eq)_n \quad (9)$$

4. Case Study Results

Running optimization analysis on the Battery-Grid and Solar-Battery components suggests the extent of EF variability and potential for solar-energy generation in Austin, Texas meets the threshold to reduce CO_2 emissions. Since these findings were consistent across 2018, BTM BSSs seem to be a viable method of reducing GHG emissions for homeowners under the ERCOT grid energy-mix. The simulated results discussed below suggest carbon emission savings through BSS can be achieved, but only in scenarios when emission factors vary enough on a daily basis (such as the summer peak days) to overcome battery efficiency limitations or with the installation of rooftop solar panels.

4.1. Battery-Grid Only Scenario

The Battery-Grid only scenario optimized carbon emissions from 6 homes and reduced on average 0.12 tons of CO_{2e} per household in 2018. Illustrated in Fig. 4, the household carbon savings range between an average minimum 12.3 pounds of CO_{2e} in September and an average maximum 30.9 pounds of CO_{2e} in March due to optimizing charging and discharging of the grid (even when accounting for an assumed 10% inefficiency). Furthermore, the high variation in CO_{2e} savings between summer/fall and winter/spring seasons is most likely attributed to (1) the near doubling of average household energy use during the summer season compared to winter season, and (2) the ERCOT grid dispatching inefficient power plants to meet the peak summer demand. The distribution of energy in ERCOT's grid energy-mix fluctuates between 11% and 68% renewable energy and averaged 32% renewable energy in 2018. Additional analysis of grid energy-mix variability indicates the percentage of renewable energy is lower for extended periods of time in the summer/fall season and higher for winter/spring season. These findings indicate grid energy-mix is the one of primary variables impacting the magnitude of monthly CO_{2e} savings. Considering similar electricity demand curves for tested households, CO_{2e} savings for the Battery-Grid only scenario remained close to the average due to uniform emission factor values and similar energy use patterns.

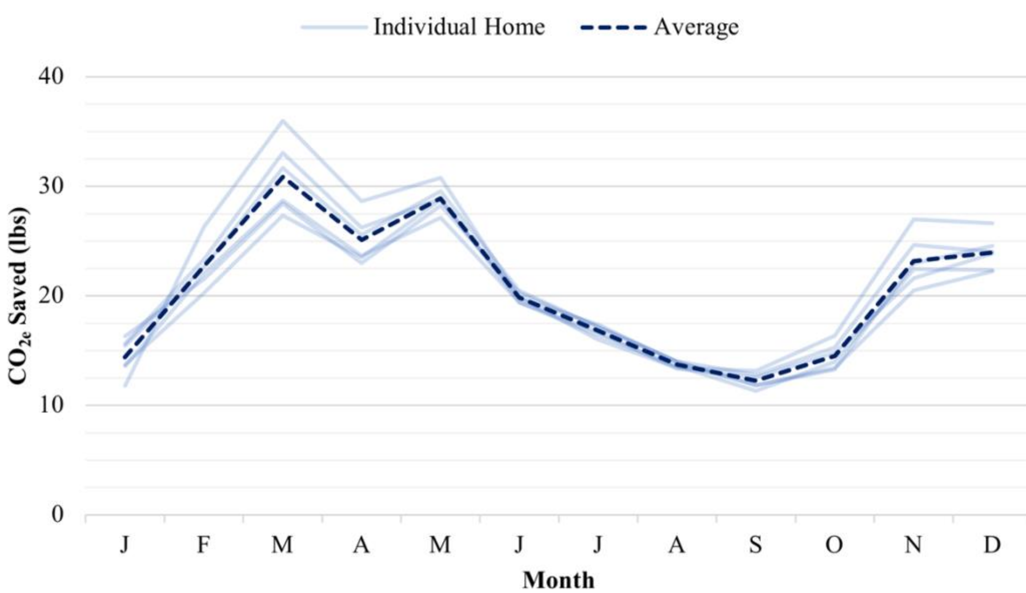

Fig. 4. Average CO_{2e} Savings Through Battery-Grid Optimization

4.2. Solar-Battery Only Scenario

The Solar-Battery only scenario optimized carbon emissions from 39 homes, and reduced on average 2.67 tons of CO_{2e} per household in 2018. Fig. 5 shows carbon emission savings calculated for Solar-Battery component vary significantly throughout the year ranging between an average minimum 231 pounds of CO_{2e} in February to an average maximum 727 pounds of CO_{2e} in July. This variation of CO_{2e} savings is especially prominent during the summertime as rooftop solar generation systems are prone to reach maximum solar production (values vary between homes due to array size and configuration). Similarly, a more consolidated carbon savings value is observed in the wintertime as rooftop solar panels may no longer achieve peak production due to suboptimal conditions. In contrast to household renewable energy generation patterns, grid energy-mix analysis revealed ERCOT's renewable energy generation sources sustainably yielded 8%-18% greater share of grid energy-mix in the winter season compared to the summer season. Assuming relatively similar usage patterns, households with rooftop solar panels achieve at least 9 times greater carbon savings throughout the year when compared to homes with standalone BTM BSS.

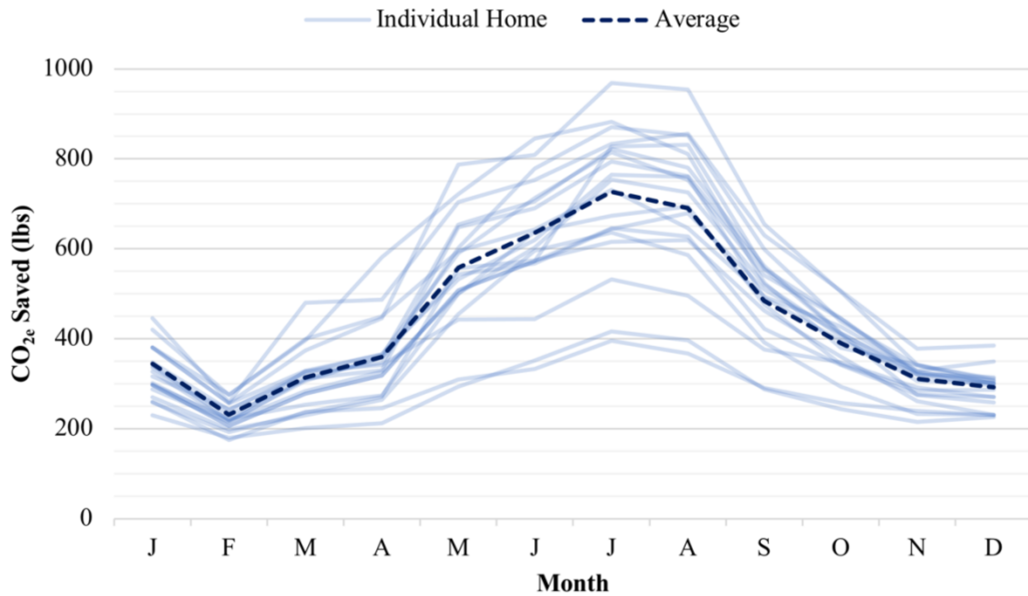

Fig. 5. Average CO_{2e} Savings Through Solar-Battery Optimization

4.3. Economic Analysis

While results indicate BSS systems can reduce carbon emissions, the expected maximum quantity of additional energy required due to efficiency losses is near 219 kW (for the Battery-Grid scenario) which would equate to an additional annual cost of $27.19 per household. This estimation includes fees and is calculated from values directly from Austin Energy assuming a home within Austin city limits consumes 1 MW per month (Austin Energy, n.d.).

Based on the emissions reduction results of this study, the potential value to the consumer is estimated assuming Austin households could be compensated under carbon pricing. As shown in Fig. 6, current (base), moderate, and aggressive pricing estimates of $4 per ton CO_{2e}, $12 per ton CO_{2e}, and $27.56 per ton CO_{2e} are used to calculate estimates. Under the current carbon pricing model an Austin homeowner with a BSS would receive an annual average compensation of $0.49 without rooftop solar or $10.67 with rooftop solar. Comparing electricity costs to carbon pricing benefits of the Battery-Grid scenario, even the aggressive carbon pricing estimate is not enough to offset the cost of electricity (an expected annual loss of $23.80). Meanwhile, the Solar-Battery scenario ensures positive returns under only a few carbon pricing scenarios as initial capital costs are a barrier for adoption. Break-even cost results presented in Table 4 underscore how the rapid decline of battery prices and fruition of carbon pricing policies can approach a tipping point where BTM BSSs may soon be desirable and add value to a home with rooftop solar. Assuming an annual discount rate of 3% on carbon pricing, BTM BSSs are profitable in few cases (as listed in Table 4) within the estimated BSS lifespan of 10 years.

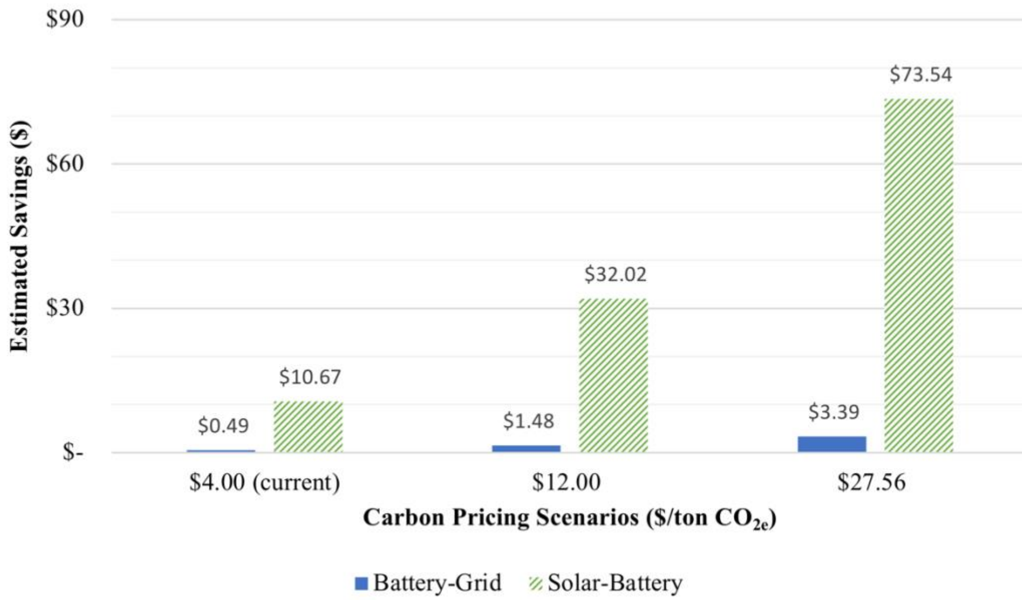

Fig. 6. Benefits Under Carbon Pricing Scenarios

Although carbon pricing may help offset electricity fees, it is imperative to also consider the cost of BSSs. According to studies, current costs of repurposed BSSs are typically 30% the cost of new batteries and lie between $38 to $147 per kWh (Cready et al., 2003; Neubauer et al., 2012). EV sector growth, market competition, and product availability will continue to play a key role in reducing the costs of repurposed BSSs. With these catalysts continuing to expand the capabilities of BSSs, we expect costs to continue to lower and market penetration to increase in the future.

Table 4 Cost Recovery Time of BSSs with Carbon Pricing for Solar-Battery Case

	Cost of Repurposed BSS		
Carbon Pricing	$147/kWh (maximum)	$100/kWh (estimated)	$38/kWh (minimum)
$4.00 per ton CO_{2e} (current)	infeasible	infeasible	34.7 years
$12.00 per ton CO_{2e} (moderate)	59.3 years	27.9 years	8.1 years (profitable)
$27.56 per ton CO_{2e} (aggressive)	15.1 years	9.5 years (profitable)	3.3 years (profitable)

While there is identified potential for BSSs to reduce carbon emissions, limitations of this study will impact how storage systems function in practical settings. This study uses perfect knowledge of energy demand, solar generation, and grid emissions. Therefore, optimization performance is likely to decline as historical data does not align with real world observations. In addition, BSSs may also require maintenance and additional costs associated with life cycle analysis (LCA) which are not considered as part of this study but should be evaluated in the future. Lastly, the small dataset of 45 homes provided by the energy provider is not a true random sample and does not represent all usage trends across the City of Austin.

5. Conclusion

5.1. Summary

In light of the transition to PEVs, this paper sought to answer how the benefits of PEVs could be extended by repurposing spent batteries for BTM BSS. The utility of this system is explored with the objective set to minimize a household's carbon footprint due to electricity. Battery storage can store excess renewable energy and discharge it to reduce the carbon footprint of energy consumed. Due to battery inefficiencies, homes without on-site renewables, such as rooftop solar, are unlikely to adopt a BSS for carbon reduction purposes. Although they may serve other functions like energy arbitrage and as backup power, BSS optimization for carbon reduction relies on the grid's carbon intensity to vary. Increased intermittent renewable energy without large-scale energy storage could allow for such systems to succeed since electricity will need to come from fast response power plants, often natural gas-fired, which could represent a large enough fluctuation in carbon intensity to overcome inefficiency loss. Homes with on-site renewables, PEVs, and communities served by microgrids are likely early adopters of this system. While early adopters may not prioritize carbon emission reduction, they could implement the function as a secondary objective when the feasibility of energy arbitrage and necessity for emergency energy storage are absent. This study of homes in Austin, Texas finds an annual savings of 2.67 tons of CO_{2e} per household with rooftop solar. Although the actual emission reductions are a function of array features (size and orientation), baseline energy consumption, weather (solar irradiance), and system set-up (knowledge of generation and demand, algorithm performance), BTM BSS with used PEV batteries may soon represent a long-term low hanging fruit in meeting climate change goals.

Under the current carbon pricing of \$4 per ton CO_{2e}, households with rooftop solar could expect \$10.67 in compensation annually. Annual compensation is capable of increasing to \$32.02 with \$12 per ton CO_{2e} and \$73.54 with \$27.56 per ton CO_{2e}. Additional cost-benefit analysis reveals BSS prices must fall to either \$15/kWh or carbon pricing must increase to \$38.75 per ton of CO_{2e} for homeowners to breakeven at the end of the estimated 10-year lifespan of the BSS. Therefore, unless governments pass higher carbon pricing legislation, falling repurposed PEV battery costs are expected to be the primary driver of feasibility for BTM BSSs as a medium for GHG reduction.

5.2. Limitations and Future Research Needs

This study estimates the potential GHG savings of BTM BSS with repurposed PEV batteries in residential settings. Estimates could be improved to include the life cycle GHG savings of this battery from principal use in transportation to secondary uses in energy storage. Additionally, this study assumes a process for regional collection of used PEV batteries (with sufficient supply of LIBs), industrialized repurposing methods exist, and these DERs can be installed by homeowners who are principally motivated by the opportunity to store rooftop solar and, perhaps, to lower their carbon footprint by interacting with the grid at advantageous times. Future work should study the impact of carbon pricing on household decisions to invest in these DERs and the economic implications to charge and discharge their batteries at different efficiency costs, time of use (TOU) electricity rates, and demand charges to lower their household's carbon footprint.

CRediT AUTHOR CONTRIBUTION STATEMENT

Alizer Khowaja: Methodology, Software, Formal Analysis, Writing – original draft, Visualization. Matthew D. Dean: Conceptualization, Methodology, Writing – original draft, Supervision. Kara M. Kockelman: Writing – review and editing, Project Administration.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A.1 ERCOT Grid Energy-Mix Data Summary

Month	**Average Renewable Energy (%)**	**Std. Dev. Renewable Energy (%)**	**Average EF (lbs CO_{2e} /MWh)**	**Std. Dev. EF (lbs CO_{2e} /MWh)**
Jan	35%	15%	928	172
Feb	37%	13%	825	164
Mar	40%	13%	742	144
Apr	39%	12%	828	152
May	35%	11%	842	113
Jun	31%	9%	890	97
Jul	22%	7%	963	93
Aug	25%	8%	947	93
Sep	24%	8%	995	98
Oct	29%	10%	970	119
Nov	35%	14%	925	157
Dec	34%	14%	903	162
Average	32%	11%	897	130

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