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Finding Carbon Breakeven: Induced Emissions from Economic Operation of Energy Storage in Renewables-Heavy Electricity Systems

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Finding Carbon Breakeven: Induced Emissions from Economic Operation of Energy Storage in Renewables-Heavy Electricity Systems

by

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Dedication

To Mom, Dad, Katherine *&* Harris

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Abstract

Finding Carbon Breakeven: Induced Emissions from Economic Operation of Energy Storage in Renewables-Heavy Electricity Systems

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Energy storage systems (ESS) have the potential to reconfigure how the electricity system is used, operated, and expanded. Most research on grid-connected ESS is focused on applications related to renewables integration and system reliability; much less is written on the current economic uses (e.g., peak shaving and energy arbitrage). While these latter applications may be profitable, current literature suggests they tend to increase grid emissions. This need not be the case.

In this paper, I explore varying system resource mixes and ESS operational modes that enable carbon-neutral, or carbon-reducing, usage. Specifically, I model the carbon emissions induced by energy storage operated in three ways – energy arbitrage (EA), demand charge management (DCM), and carbon minimization ($MinCO_2$) – in 16 simulated electricity systems where wind and solar assets generate 17% to 81% of annual energy. Dispatch of a 1MW/4MWh battery is simulated for each operational mode and in each resource scenario (for a total of 64 combinations).

I find that energy storage is carbon-neutral, or carbon-reducing, in systems generating 17% to 40% of annual energy from renewables, depending on operational mode. That said, carbon emissions vary significantly between operational modes and resource scenarios. In general, (1) DCM with a time-of-use energy rate increases emissions; (2) EA generally reduces emissions; and, (3) $MinCO_2$ and DCM with real-time energy pricing always reduce

emissions. Moreover, economic dispatch of ESS attains only a portion of the maximum achievable environmental benefits, with MinCO_2 reducing system emissions by an average of 494lbs/MWh-stored more than the next-lowest operational mode. In addition, I find that greater exposure to wholesale energy prices generally reduces induced emissions, and that retail rate designs encouraging price exposure can reduce the carbon footprint of ESS without eroding the benefits offered by storage. These results indicate that the emissions induced by ESS should alleviate themselves in the coming years, as regulators encourage more efficient energy consumption and as more renewables are added to the grid.

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Chapter 1: Introduction

1.1 Energy Storage as Panacea?

Energy storage has transformative potential. It has the potential to reconfigure how the electricity system is used, operated, and expanded. Energy storage can be used to integrate renewables, defer new capital projects, enhance reliability, and increase market efficiency through arbitrage. Energy storage systems (ESS) can do all these things because they are fundamentally different from the technologies that power the grid today. Storage is both a consumer and supplier of electricity. It can be sited behind-the-meter or in front. It can range in capacity by more than two orders of magnitude. This flexibility will let storage play a critical role in any transition towards a cleaner or more distributed grid. For all this potential, however, there is also great uncertainty. Regulators, utilities, and industry are just starting to explore how ESS can provide services to customers and to the grid. There is active investigation into what ESS technologies and applications would provide the most value, and how they would affect electricity prices, system reliability, and externalities.

At its core, energy storage provides a simple service: temporal arbitrage. Storage can be charged at one point in time and be discharged later. This attribute makes ESS unique in power systems. For many years, methods for splitting production from consumption were mostly hypothetical – energy storage was expensive, very large or very small, and geographically constrained. Advancements in electrochemical storage (batteries) have brought down capital costs and minimum capacity requirements for ESS. Between 2006 and 2014, lithium-ion battery costs fell by 75% (Nykvist and Nilsson, 2015) and this trend is expected to continue for the foreseeable future (GTM, 2016). Batteries have driven this era of storage optimism.[1] Where once storage took the form of pumped hydro reservoirs or batteries for

[1] While many conflate batteries with energy storage, the latter is a hugely diverse field. Energy storage can occur a variety of forms including chemical (batteries), gravitational potential (dams), electrical potential (capacitors), thermal (molten salt, pre-cooling) and kinetic (flywheels) (Luo et al, 2015). Each of these technologies has distinct power, capacity, duration, and cycling ability – not to mention cost and integration feasibility. High-power, low-duration power quality applications are well served by super capacitors, flywheels, and batteries (Dunn et al 2011, Fig 1). Super capacitors, for example, are very efficient and have a high power-to-

portable-electronics, electrochemical storage costs have fallen to the point where installations in the 10kW to 1MW size are feasible. These advancements have made certain ESS applications cost effective today, and declining costs will enable new applications in the years to come.

The benefits that storage provides to customers are embedded in the way that it is charged and discharged. Rocky Mountain Institute identified 13 possible services ESS could provide to the grid, utilities, and end-use customers (RMI 2015, 6; cf. Rastler & Kamath 2010). For example, storage could be used for energy arbitrage by buying electricity when power prices are low and selling when they are high. It could be used to defer system upgrades by reducing grid-consumption when the system is constrained (charging when demand is low and discharging when demand is high). Storage could be dispatched in ways that increase the value of renewables (Braff et al, 2016) which could, in turn, encourage more renewables and further reductions in carbon emissions (Martinez & Hughes, 2015).[2] Storage provides, either on a commercially operational or demonstration basis, all these kinds of services today. Many of these services can be "stacked" (co-optimized) to increase battery utilization and improve the overall economics of the storage device. Value-stacking is considered critical for widespread battery adoption and a problem that regulators and legislators must work to ensure (e.g., RMI, 2015; Lazard, 2016).

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duration ratio which allows for quick injections of power into the system but they also have a shorter lifespan. High-power, high-duration applications can be served through pumped hydro and compressed air energy storage. These technologies scale well and are relatively inexpensive but are less efficient and less responsive than batteries. In between are intraday load-shifting and peak shaving served using a variety of traditional and redox-flow batteries.

[2] The specific point when current systems can no longer effectively cope with increasing renewables without energy storage is subject to debate. Traditional electricity markets have demonstrated the ability to maintain reliability with reasonably high levels of renewable electricity – up to 40% of instantaneous supply in Texas (Andrade et al, 2016). Modeling efforts suggest 55% annual energy from renewables is feasible with improved transmission (MacDonald et al, 2016). More speculative modeling suggests systems could prove reliable even with 75% or more of energy is derived from renewable sources (e.g. Becker, S. et al 2014; Hart and Jacobson, 2014).

Storage is a very small part of the grid today but annual installed capacity is forecast to increase by up to 10x, rising from less than 200 MW in 2014 to 2,045 MW in 2021 (GTM 2016, p. 9). This boom is related both to declining costs and regulatory mandates. Three states have introduced energy storage mandates designed to subsidize ESS adoption in the short-term, with the hopes that increased volume will reduce long-term costs through the effects of economies-of-scale and learning-by-doing. The largest of these, California's 1.3 GW mandate, was developed to hasten a future where storage is a mature and competitive technology providing many electricity-related services. These mandates are also driven by the expectation that storage can offer environmental benefits either explicitly or through renewables integration: "energy storage has the potential to offer services needed as California seeks to maximize the value of its generation and transmission investments: optimizing the grid to avoid or defer investments in new fossil-power plants, integrating renewable power, and minimizing greenhouse emissions (CPUC 2013, 6).[3] At the federal level, regulators are working to ensure that storage can effectively participate in wholesale electricity markets and is fairly compensated for the services it provides (e.g. FERC Rulemaking RM 16-23-000).

For all the interest in renewables-focused application, it is important to recognize that market participants generally purchase storage for economic reasons such as market participation, economic arbitrage, and backup power for critical systems. The largest application of ESS today is in grid-scale frequency regulation – a reliability function. Demand Charge Management (DCM), a form of rate-design arbitrage, is a quickly growing market in California, New York, and Hawaii. Certain residential customers may purchase storage to pair with solar – for these customers, storage is generally an emotional sale not an economic one.[4] These customers are likely in the minority for the foreseeable future (GTM 2016, 9).

[3] The state supports its mandate by offering $126 million per year through its Self-Generation Incentive Program (SGIP). SGIP seeks to "identify distributed energy resources which will contribute to greenhouse gas reduction goals and to set appropriate incentive levels to encourage their adoption."

[4] The Tesla Powerwall website promotes three uses for their ESS: "use more of your solar", "your path off grid", and "backup your home" (Tesla, 2017).

1.2 Induced Carbon Emissions from Energy Storage

Despite the potential benefits of ESS, a small but growing literature quantifying the emissions impact of ESS has come to dispute the assumption that storage is a "green" asset. Studies have explored the emissions impact of storage offering different services using a variety of modeling techniques, study periods, and timeframes. Although the approaches are heterogeneous and difficult to directly compare, they offer directionally similar results: today, grid-connected energy storage tends to increase net emissions of CO_2 irrespective of offered service or storage location.

In wholesale markets, studies have indicated that storage would increase emissions by 228 lbs to 895 lbs per MWh stored. For example, Carson and Novan (2013) concluded that ESS used for energy arbitrage in the ERCOT market would increase daily CO_2emissions by 380 lbs/MWh. Similarly, Hittinger and Azevedo (2015), in an analysis of national scope, found that net emissions from the storage range from 228 to 895lbs per MWh of delivered energy depending on system efficiency and location.[5] Behind-the-meter storage is less studied than wholesale applications but here too, the literature suggests storage generally increases emissions. For example, Fisher and Apt (2016), found that behind-the-meter storage in the Northeastern U.S. co-optimized for energy arbitrage, demand charge reduction, and ancillary services would increase CO_2 emissions by 165 to 570 lbs/MWh-stored. Fares and Webber (2017) found that residential solar-plus-storage in Texas increases net system energy consumption by 338 to 572 kWh/year which, in turn, induces an additional 337-667 lbs CO_2, 0.06-0.44 lbs SO_2, and 0.08-0.57 lbs NO_2 per storage system annually.

1.3 Causes of Induced Emissions

The emissions associated with grid-connected energy storage can be decomposed into two sources: innate losses due to technological constraints and market effects:

$$Total\ Emissions_{Year\ N} = Emissions_{Battery\ Efficency} + Emissions_{Market\ Effects}$$

[5] ESS increases emissions in all studied regions if the round-trip efficiency is less than 90%. In five zones, emissions are slightly reduced at 100% efficiency (a sensitivity not technically possible). Even West Texas sees increased annual emissions despite very high levels of wind generation in the zone.

Losses are endemic to all storage technologies and induce emissions because more total generation is needed if storage is added to the electricity system. For example, an 85% efficient battery must purchase 1.17 MWh of electricity for every 1 MWh it returns.

Market effects, by contrast, depend on the carbon intensity of the marginal generator from which storage charges and into which it discharges. Unlike losses, the emission impact of market effects can be either positive or negative depending on what power plants are participating in the market. While it is easy to think that electricity is homogenous, the ways in which it is produced is not. In power markets, when an extra unit of power is required to balance demand and supply in real time, a single power plant is ramped up to satisfy demand. Similarly, when the market requires one unit less, an active power plant will be ramped down. The plants that are called upon to ramp up and down at different times of the day are not likely to be the same units.[6] These marginal units set the market price for electricity as well as its marginal carbon emissions. These marginal power plants dictate the emissions induced by market effects. If storage charges when wind or solar is on the margin and discharges when coal or gas is on the margin, then emissions would be decreased. If the reverse were true, storage would increase systems emissions. Market effects can amplify or offset the physical inefficiencies of storage.

Table 1 expands on this idea by depicting the emissions a battery could induce in a hypothetical system with three kinds of resources. The first two columns represent the market's marginal resource (and carbon intensity) when storage is charging; the second two columns represent the possible resources when discharging. The final columns represent sources of induced carbon emissions.

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[6] Which power plant will be called upon by the system operator to ramp up and down depends on many factors, some of which are discussed below in the ERCOT market design section.

Table 1: Carbon Impact of Different Resource Mixes

Charge		**Discharge**		**ESS Induced Emissions**			
Marginal Resource (A)	Marg CO_2 lbs / MWh (B)	Marginal Resource (C)	Marg CO_2 lbs / MWh (D)	Losses at Charge lbs / MWh (E)	Losses at Discharge lbs / MWh (F)	Grid Interaction lbs / MWh (G)	Net Emissions lbs / MWh (H)
Wind	0	Coal	2000	0	150	-2000	-1850
Wind	0	NGCC	1000	0	75	-1000	-925
Wind	0	Wind	0	0	0	0	0
NGCC	1000	Coal	2000	81	150	-1000	-769
NGCC	1000	NGCC	1000	81	75	0	156
NGCC	1000	Wind	0	81	0	1000	1081
Coal	2000	Coal	2000	162	150	0	312
Coal	2000	NGCC	1000	162	75	1000	1237
Coal	2000	Wind	0	162	0	2000	2162

Note: Storage is assumed to have a capacity of 1 MWh and is 85% efficient (one-way efficiency, $\eta_{one\text{-}way}$, is 92.5%). Carbon intensity of generators is stylized for conceptual simplicity. In actuality, different resources within the same class have different carbon intensities.

$$E = {}^{B}/_{\eta_{one-way}} - B$$

$$F = D - D \times \eta_{one-way}$$

$$G = B - D$$

$$H = E + F + G\,;also, H = {}^{B}/_{\eta_{one-way}} - D \times \eta_{one-way}$$

If a 1MWh battery were to charge when wind was on the margin and discharge when coal was, then system emissions would *decrease* by 1,850 lbs/MWh. Storage operating in this market could also *increase* net emissions by 2,162 lbs/MWh if it bought from coal and displaced wind. In scenarios where the charge and discharge technology are different, grid interactions outweigh emissions from losses. If a storage efficiency increases, then the share of emissions from losses is decreased: the battery needs to buy less electricity from the market for the same output. Table 1 depicts all possible induced emissions outcomes but it does not calculate the expected emissions. Certain resources are more likely to be on the margin when charging and others more likely to be on the margin when discharging.

Studies have argued that one or both factors drive emissions. The energy arbitrage studies argue that emissions increase because a simple "buy low, sell high" algorithm will purchase electricity during off-peak hours when coal tends to be the marginal fuel and sell on-peak when gas tends to be marginal fuel (gas generation has roughly one-half the carbon-intensity per MWh as coal). Fisher and Apt (2016), by contrast, attributes most induced emissions mostly to system efficiency. While studies differ in their attribution, they agree that ESS operational modes and system resource mixes make certain outcomes more likely than others. The way in which storage is operated, and the market in which it is operated, influences the induced emissions of ESS.

1.4 Motivating Question & Approach

Today, storage is thought to increase emissions because of increased utilization of fossil fuel power plants. In the long-run, storage could facilitate more investment in intermittent renewables. In a system powered entirely by non-emitting resources, ESS operation would never induce carbon emissions. There must be an inflection point between the short-run increase and the long-run reduction in net system carbon induced by energy storage. At this point (or frontier), the positive emissions from battery inefficiency are offset by market effects, yielding carbon neutral energy storage. This inflection point will vary depending on the system resource mix, battery efficiency, and operational mode. The question is, *under what resource mixes and operational modes, do induced emissions from energy storage equal zero?* In this paper, I model the carbon emissions of batteries used in three different ways across 16 simulated ERCOT markets (each with varying amounts of wind and solar capacity). ESS algorithms are developed for energy arbitrage, demand charge management, and carbon-minimization. These use-cases are complimentary as they provide insight into different applications, optimizing for different goals, and operating in different markets. The economics of these operational modes are not formally assessed given the speculative nature of this paper and the very multi-decade scale it takes.

Under energy arbitrage, a battery is charged and discharged to maximize profits from the wholesale energy sales. Energy arbitrage is widely studied and an obvious application of ESS. Power prices are insufficiently volatile to make energy arbitrage profitable today, but many expect this market to grow in the years to come. Demand charge management is a retail market operation that seeks to reduce a customer's peak consumption in a given period to lessen the associated demand charges. Demand charge management is a common retail application for storage today: companies such as Stem, Advanced Microgrid Solutions, and

Greencharge offer DCM products in markets across the country. Carbon-minimization, unlike the preceding applications, is modeled to provide a benchmark of maximum achievable reductions.

1.5 Structure of this Paper

The remainder of this paper is laid out as follows. Chapter 2 provides background on energy storage and the competitive markets in which they may participate. Chapter 3 provides methodology on production cost modeling used to generate different resource mixes as well as the exogenous battery models used to assess emissions for both operational modes. Chapter 4 presents results from the production cost modeling. Chapter 5 provides concluding remarks, discussion of model limitations, and suggestions for further work.

Chapter 2: Background on Power Markets

2.1 The ERCOT Market

The Electric Reliability Council of Texas (ERCOT) is the Independent System Operator (ISO) that manages the dispatch, transmission, and reliability of electricity provided to 24 million customers in Texas. In all, it spans 200,000 square miles and contains 550 generating units and 46,500 miles of high-voltage transmission lines.

ERCOT is one of the nation's three interconnection regions that, together, span the entire continental United States as well as portions of Canada and Mexico. While ERCOT is totally contained by Texas, not all of Texas is in ERCOT. Several regions including the El Paso area, the Panhandle, and eastern fringe of Texas are excluded from ERCOT's control. ERCOT, unlike Western Interconnect and the Eastern Interconnect, is electrically isolated from other parts of the United States, except for several DC ties. The lack of material cross-state transmission interconnection frees ERCOT from most Federal oversight.

In addition to maintaining reliability, ERCOT is also charged with ensuring nondiscriminatory access to transmission systems for the buyers and sellers of electricity. ERCOT is an energy-only market, meaning that it does not offer payments for capacity like ISO New England or the PJM Interconnection. There are ancillary services that compensate market participants for various products (reserves, frequency, and so on). ERCOT manages the settlement process among buyers and sellers of wholesale electricity.

2.2 Market Design

In the day-ahead market (DAM), electric power plants ("generators") offer bids that describe how much energy they are willing to produce at what price for the next day at each hour. Generator bids are aggregated into a offer stack of ascending price. This offer stack represents the supply curve. The market clearing price is set by the offer of the marginal unit dispatched by the ISO. In real time operations, the ISO may need generators or load to behave differently to balance the system. The market clearing price may be set by a different market participant than one in the bid stack from the day-ahead market. Because demand varies from moment to moment, so too does price. In addition to the DAM, energy is also traded in a real-time market which is settled every five minutes. The real-time market is predominantly used for reconciling actual and forecast demand.

For added market efficiency, ERCOT does the same operation for many locations on its system. There are thousands of these locations, known as nodes. Every five minutes, prices are recalculated at each node and ERCOT provides new information to generators about their desired level of output and, if necessary, loads for reducing consumption. In addition to prices, ERCOT's dispatch orders consider outages, congestions in parts of the grid, and other factors. The goal is to keep the lights on for the least cost. This process is known as security-constrained economic dispatch (SCED).

Electric power grids must maintain constant balance between system load and generation to prevent outages or damaged infrastructure. Because load is highly inelastic in the short term, markets to ensure this constant balance are operated on the supply side of the wholesale market. While specific ancillary services differ from ISO to ISO, the general needs remain constant. FERC identifies six types of ancillary services as well as their time scale (Table 2).

Table 2: Ancillary services defined by FERC and their associated time scales

Service	Time Scale
Scheduling, System Control, and Dispatch	Seconds to Hours
Reactive supply and voltage control	Seconds
Regulation and frequency response	~ 1 Minute
Energy Imbalance	Hourly
Operational reserves – Synchronized reserve	Seconds to < 10 Minutes
Operational reserves – Supplemental reserves	> 10 Minutes

Reproduced from Andrade et al (2016)

In ERCOT, the four main ancillary services are: regulation up (RU), regulation down (RD), responsive reserve service (RRS), and non-spinning reserve service (NSRS). Regulation, both up and down, is provided by generators that can make minor adjustments to their output to keep grid frequency within tight bounds around 60Hz. System reserves, by contrast, are used to materially increase or decrease load or make up lost load in the event of a contingency. Spinning reserves are provided by units that can quickly increase their output (within 10 minutes) while non-spinning reserves must be able to provide this same service over a longer timeframe (within 30 minutes).

The quantity of ancillary services procured by ERCOT for system reliability is mainly a function of total demand and load profile but also depends on other factors related to transmission constraints, expectation of future demand, and share of renewable generation. Specific requirements depend hourly as well as seasonally. It has been argued that increasing penetration of solar and wind generation will increase the need for ancillary services as these generator types lack the certainty in output provided by traditional thermal generators (e.g. ERCOT 2013). Some analysis has found that the way markets are structured have a bigger effect on procurement requirements than the addition of new capacity (Andrade et al, 2016).

Energy storage can provide some ancillary services. ERCOT's now moribund "Future Ancillary Services" working group explored how to enable storage and other distributed resources to effectively participate in ancillary service markets. Though not in Texas, energy storage has become an active participant in the AS markets of other ISOs. The PJM Interconnection, for instance, has 263 MW of grid-scale energy storage in providing fast-response regulation (Baker, 2016).

2.3 Retail Markets and Rate Design

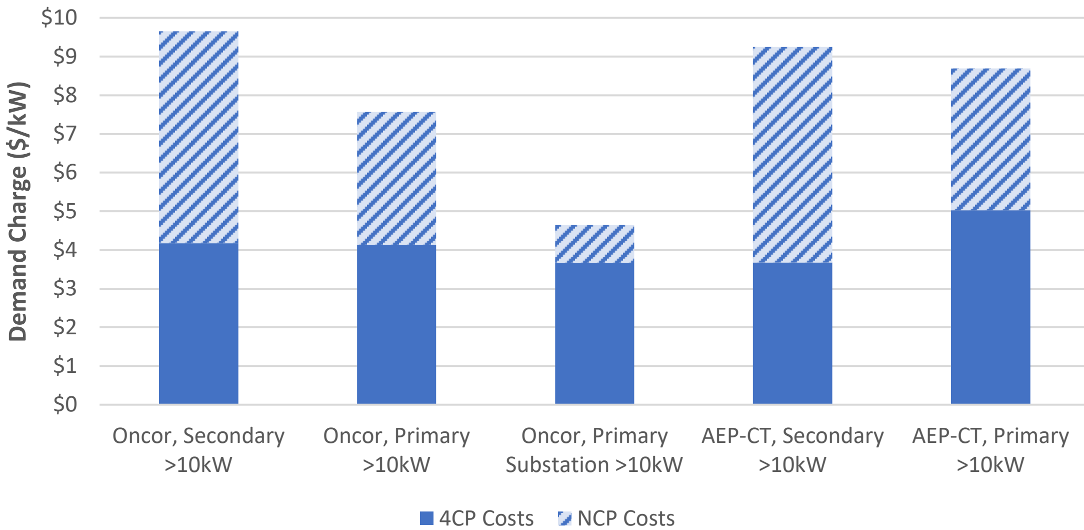
ERCOT coordinates market activities at the wholesale level, but two intermediaries sit between that market and retail consumers. Retail Electric Providers (REPs) design rate structures in the portions of the state with retail choice, purchase power from the wholesale market, and manage customer billing. Transmission and distribution (T&D) utilities, also known as "wires" companies, manage physical infrastructure – the poles, wires, and substations that connect generators to end customers. The wires companies are still regulated as natural monopolies. In areas of the state not subject to retail choice, municipal/cooperative utilities provide both services. A retail customer in Texas will have charges from both their REP and their T&D utility on their monthly bill.

Electricity rates have three possible components: energy charges, demand charges, and fixed charges. Fixed assets (e.g. meters, billing systems) have their costs recovered using a fixed charge on customer bills. Costs related maximum instantaneous usage (e.g. capacity, transmission and distribution infrastructure) are sometimes recovered using a demand charge measured in units of \$/kW. Finally, volumetric electricity (i.e., energy sales) is recovered through an energy rate measured in \$/MWh or ¢/kWh. Utilities in Texas recover their costs in different ways but, in general, TDUs have demand charges while REPs and municipal utilities use a combination of fixed charges and energy charges.

Energy and demand charges can be further tailored. Energy charges can be structured to vary with quantity (tiered rates that increase cost with overall usage instead of the same price for all units consumed) and with time (time-of-use and real-time rates charge higher rates during some times of the day than others, to approximate the costs seen on the wholesale level). The variety of rates offered in Texas is seemingly limitless. In 2016, 109 REPs offered 440 unique products for customers across ERCOT – nearly 100 products were 100% renewable offerings (PUCT 2017, 2).

In Texas, a commercial customer pays demand charges for both their coincident peak demand (CP) and their non-coincident peak demand (NCP). Coincident Peak represents share of demand a customer caused during when the whole ERCOT system peaks (irrespective of customer demand). Non-coincident Peak represents a customer's peak demand (irrespective of total demand in ERCOT). The former is used to recover transmission level costs (including wires, capacity payments, and ancillary services) while the latter is used to recover distribution costs. ERCOT allocates transmission costs by averaging a customer's share of system demand during the highest demand hour of June, July, August, and September – a measurement known as four coincident peak (4CP). A customer's distribution costs are measured using maximum monthly usage. This is known as non-coincident peak (NCP), because this maximum demand does not necessarily coincide with high demand conditions on the system. A customer's NCP and 4CP can occur at the same time, but needn't. Demand charges, and their constituent parts, vary from utility to utility. For AEP Central Texas and Oncor, two large TDUs, total demand charges vary from \$4.64/kW to \$9.65/kW depending on connection voltage and customer load (See Figure 1). 4CP costs range from 40% to 80% of all demand costs.

Figure 1: Demand Charges for Oncor and AEP Central Texas, 2017 ($/kW)



Price signals are embedded within retail rates are energy and demand. The free nights and weekend energy rates offered by some REPs encourage customers to shift usage later into the evening. Demand charges encourage customers to reduce their maximum usage – by not using multiple appliances simultaneously or turning on machines in sequence rather than simultaneously. Critical peak pricing (CPP) and Demand Response (DR) take this one step further by paying customers to reduce their demand during very expensive hours. 4CP demand charges encourage less usage specifically during peak times on the system (hot summer afternoons, for example) while NCP demand charges encourage reductions in demand generally.

Technological change has made responding to the price signals embedded in tariffs easier than ever before. Certain utilities have offered reduced cost of free Nest thermostats with the provision that the utility can "turn down" a customer's space conditioning when prices are high. Electric vehicles can be programmed to charge only during super-off-peak periods in the middle of the night. Energy storage has the potential to participate in similar ways but with added flexibility.

Chapter 3: Modeling Methodology

3.1 Framework for Calculating Induced Emissions

This chapter describes the approach used to model the system carbon emissions induced by the operation of an energy storage system (ESS). Carbon emissions induced by energy storage depend on where, how, and when a battery is used. A battery operating under different operational modes in the same market will induce different amounts of CO_2 depending on daily demand, resource availability, and other factors. Similarly, a battery with the same specifications located in different markets will induce different amounts of carbon emissions. At a high level, induced emissions are a function of:

1. The market in which the ESS is located (resource mix, system load, unit commitment)
2. Battery operational mode (how and when the battery decides to charge and discharge)
3. Physical attributes and constraints of the battery itself (power, duration, etc.)

My model addresses these factors in two separate halves. First, a production cost model is used to generate counterfactual market data for various high renewable scenarios. Second, battery dispatch algorithms are run on the simulated market data to assess emissions effects. By default, the battery is parametrized based on the attributes of a Tesla Powerpack, a lithium-ion battery commonly used for grid-scale storage.

As a general framework, the model assumes that small-scale energy arbitrage or demand charge management providers are engaged in Stackelberg competition (a leader-follower game). In this case, the ERCOT market is a leader that sets prices and the storage provider is the follower that can only react to those prices by changing quantity offered. The leader must know *ex ante* that the follower observes its actions – reasonable in the context of competitive wholesale markets. Throughout this paper, I assume that the energy storage system is unable to change the market's marginal unit – so it acts both as a price taker and a "carbon" taker. This assumption is common in the literature and is reasonable for the small units described but may not hold for larger installations.[7]

3.2 Energy Storage Operation

Three ESS dispatch algorithms are developed: wholesale carbon emissions minimization (MinCO_2); wholesale energy arbitrage (EA); and demand charge management (DCM). DCM is subdivided into demand charge management using a simple time-of-use energy rate (DCM-TOU) and DCM with a real-time-pricing energy rates (DCM-RT). A summary of these modes is provided in Table 3.[8]

Table 3: Summary of Operational Modes

Dispatch Mode	Dispatch Signals	Operational Constraints
Energy Arbitrage (EA)	Wholesale Energy Prices	None
Demand Charge Management with TOU Energy Rates (DCM-TOU)	Building Demand; Retail Energy Prices	Charge during off-peak; Discharge on-peak
Demand Charge Management with RT Energy Rates (DCM-RT)	Building Demand; Wholesale Energy Prices	Charge during off-peak; Discharge on-peak
Minimize CO2 Emissions (MinCO_2)	Marginal System Emissions	None

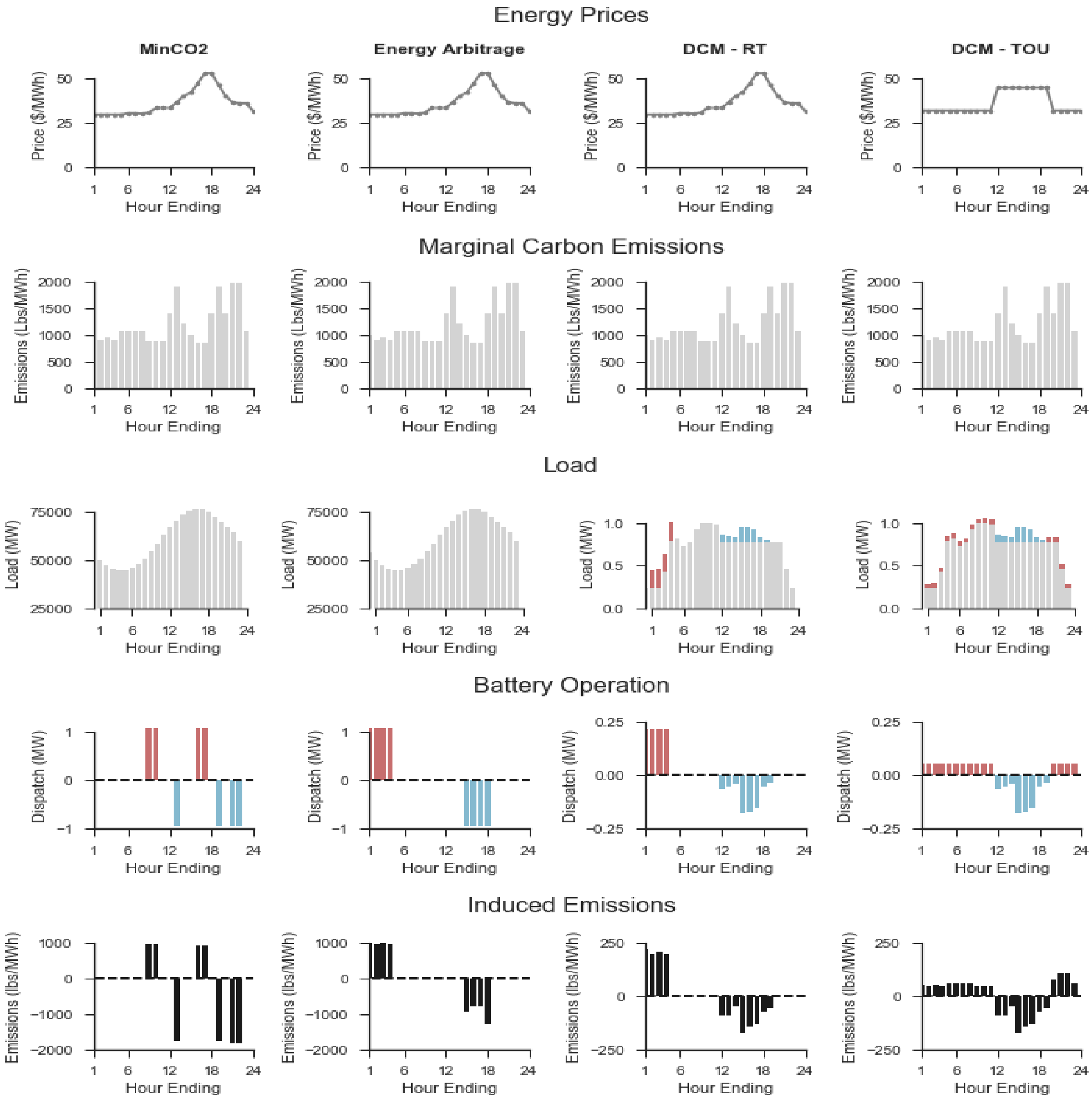
Energy arbitrage (EA) participates in wholesale markets and is dispatched to maximize energy profits by buying electricity when energy is inexpensive and selling it when it is more expensive. Demand charge management (DCM) is a retail function that reduces a commercial customer's peak demand over a specified time period. Informally, this process is known as "peak shaving" because the customer's peak is flattened. (Residential DCM is not modeled in this paper, nor is it a common application today.) Carbon minimization functions analogously to EA except it minimizes carbon emissions. Carbon-minimization is included as a benchmark for emissions reduction potential – not economic reasons.

[7] For example, some peaking or super-peaking power plants are as small as 50 MW so systems with large quantities of energy storage could easily change the offer stack. See Fares (2017) and Hittinger and Azevedo (2015).

[8] Battery dispatch is modeled in Python 2.7 using the Numpy, Scipy, and Pandas libraries for mathematical operations and data management.

A formal description of each operational mode is provided in subsequent sections, but the concept of each is illustrated in Figure 2. For each operational mode, this figure depicts the relevant energy prices, emissions, load, and battery operation.

Figure 2: Sample Day of ESS Operation by Dispatch Type



Notes: this chart depicts data from the base case for July 1, 2030. Other days and scenarios will have different energy prices and load profiles. For EA, the battery is assumed to be 1MW/4MWh and have 85% round-trip efficiency. Depicted prices and load are for the ERCOT system. Both DCM scenarios rely on an 8-hour peak period, load for a quick-service restaurant built before 1980, and a battery that is 0.2MW/0.8MWh (85% efficient).

For carbon-minimization (the left column), the ESS responds to the wholesale system's marginal emissions. The battery charges from the four hours when emissions are lowest (red) discharges (blue) when emissions are highest. On the depicted day, carbon minimization buys from very efficient NGCCs (~1000 lbs/MWh) and selling into coal units (~2000 lbs/MWh). Under carbon-minimization, the storage unit will pay whatever wholesale prices are required to minimize carbon. The ESS does not consider system load or when it makes buy/sell decisions.

Energy arbitrage (second from left column) responds to wholesale energy price signals. On the depicted day, the battery charges (red) in the early morning when prices are lowest and discharges in the mid-afternoon (blue) when prices are highest. In markets with large amounts of solar suppressing mid-day prices, ESS under EA may well charge mid-day and discharge in the evening when prices are higher. In markets with large amounts of wind, it will tend to charge during the evening and discharge mid-afternoon. Under EA, the ESS does not consider the marginal emissions induced by its operation or its effect on system load.

Demand charge management operates in a different market than the preceding cases and under different price signals. DCM is a retail product, not a wholesale product. For both demand charge management algorithms, the ESS is discharged to reduce a customer's peak load during the afternoon (when demand charges are assessed). They differ in when they are charged. DCM on a time-of-use energy rate is charged uniformly over the entire off-peak period because there is no price signal to charge it in one off-peak hour compared to another. By contrast, a battery subject to real-time pricing does have price exposure, so it will charge itself when wholesale energy prices are lowest. While real-time pricing is rare today, there is growing interest in moving sophisticated customers to these kinds of tariffs from flat or time-of-use rates. **In both DCM models, it is assumed that demand charges are high enough and energy charges are low enough that DCM is profitable.**[9]

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[9] This approach is complicated by the restructured Texas market. In ERCOT, demand charges are assessed by the TDSP while energy is provided by the REP. A customer of a TDSP will always be subject to the same demand tariff but could be subject to different energy tariffs depending on their REP.

All algorithms are both approximately 1-day myopic. Strong daily periodicity makes longer timeframes inessential. Actual market participants do not have perfect information but they do have very good information just over one day in advance. For energy arbitrage, day-ahead bids are submitted on the prior day's afternoon so a buyer has knowledge up to 32 hours in advance. For demand charge management without peak periods, there is some uncertainty regarding the timing of a coincident peak; however, if the customer always discharges the battery in the afternoon, the customer is playing it safe, since a CP demand charge should always occur in the afternoon in Texas. For DCM with specific peak periods, knowledge is certain: retail rates are set far in advance with rate schedules that can be easily assessed.

3.2.1 Variables & Parameterization

In the next three sections, models for specific ESS operational modes are formally developed. Table 4 summarizes all variables and parameters used in the analysis.

Table 4: Model Variables & Parameters

Name	Abbr.
Battery Parameters	
Maximum Charge Capability (MW)	K
Duration (MWh)	D
Charge / Discharge Rate	c-rate
Roundtrip Efficiency (%)	$\eta_{\text{round-trip}}$
One-way Efficiency (%)	η
Battery Dispatch Variables	
Quantity charged or discharged (MWh)	Q
Revenue ($)	R
Cost ($)	C
Charge probability (off-peak)	π_{charge}
Discharge probability (peak)	$\pi_{\text{discharge}}$
Market Parameters	
Wholesale Market Price($/MWh)	P
Wholesale Market Marginal Emissions (lbs/MWh)	E
DCM Parameters	
Building Demand – 1 hour load (MW)	δ
Set of Peak Period Hours	A
Set of Off-Peak Period Hours	B

3.2.2 Specific Storage Parameterization & Sensitivities

Throughout this paper I rely on a stylized battery that approximates the characteristics of lithium-ion batteries. Although there are a variety of battery chemistries that could be used for energy storage, Lithium-ion remains dominant and accounted for more than 90% of all deployed capacity in 2015 and 2016 (GTM 2016, 5). The stylized battery shares attributes with the commercially available Tesla Powerpack – a battery commonly used in commercial and utility applications (Tesla 2016). Eight operational characteristics are included as parameters.

Table 5: Battery Parameters

Name	Abbr.	Quantity	Sensitivity
Power (also, max charge)	K	1MW	N/A
Duration (quantity)	D	4MWh	2, 4, 8, 12 MWh
Charge/Discharge Rate	c-rate	1MW/Hour	N/A
Capacity	Q	K x D	N/A
Minimum Stable Capacity	Q_{min}	0MWh	N/A
Roundtrip Efficiency	$\eta_{round\text{-}trip}$	85%	75% - 100%
VO&M (Operating Cost)	VOM	$0	N/A
Fatigue	F	0%	N/A

Batteries are generally specified based on their power and duration. For example, a battery may be defined as "1-MW/4-MWh", meaning it has a maximum power rating of 1 MW and a total duration of 4MWh. A 1-MW/4-MWh battery can output a total of 1 MW of energy for four hours, 0.5 MW for 8 hours, and other lower power longer duration configurations.

All batteries incur losses when charging and discharging. Here, losses are assumed symmetric with equal losses occurring during charging and discharging. Thus,

$$\eta_{one-way} = \eta_{Buy} = \eta_{Sell} = 1 - \frac{\eta_{round-trip}}{2} \qquad (1)$$

In the base case where $\eta_{round\text{-}trip}$=0.85, so $\eta_{one\text{-}way}$=0.925. There are also losses associated with long-term storage of electricity but these are ignored given the daily cycling modeled. Assuming η equals 92.5%, then to have 1 MWh of energy stored, the ESS must buy 1.08 MWh (=1/η). Due to losses during discharge, only 0.925 MWh (=1η) of the stored energy is converted into useful energy.

This parameterization does not take into account discharge profiles or battery fatigue that occurs as the battery is repeatedly cycled. It also does not account for any minimum storage requirements or variable O&M costs.[10]

3.2.3 Energy Arbitrage

Under an energy arbitrage operational mode, an ESS seeks to maximize profits in an energy market by buying electricity when it is inexpensive and selling it at a later point in time when electricity is more expensive. The operational mode follows a simple "buy low, sell high" rule. More formally,

$$\max \sum_{d=1}^{365} \sum_{q=1}^{Q} R_t - C_{t-n} \qquad (Maximize\ Profit) \tag{2}$$

where:

$$R_t = \eta P_{t,Sell} Q_{Sell}$$

$$C_{t-n} = \frac{1}{\eta} P_{t-n,Buy} Q_{Buy}$$

Time t > t-n where n is an arbitrary number of time periods prior to t

Q is in integer quantities only

The objective function seeks to maximize annual profit. This is subject to two constraints. Revenues are equal to the efficiency adjusted quantity times price at time of discharge. Costs are calculated in the same manner, but here the quantity is multiplied by the reciprocal of efficiency. Because the battery is subject to constraints on maximum charge and discharge rates K, all buy periods are separate from one another as are all sell periods. This means that it cannot fully charge in a single low price period or discharge in a single high-priced period.

[10] If the reader desires a minimum storage requirement, this can be accomplished using a simple linear transformation by increasing the capacity of the battery and applying a minimum storage level. For example, a 1.25 MW battery with 80% useable energy is equivalent to a 1MW battery with 100% useable energy. This alternative configuration has the same environmental attributes as the modeled ESS. From an economic standpoint, a system with a minimum storage requirement erodes value because more battery is needed for the same effective output.

For computational simplicity, I assume that the ESS stores an integer quantity of energy so during charging it purchases $1/\eta$ units and during discharge it sells η units. I also assume that the system is approximately 1-day myopic. More specifically, it looks to maximize energy from the last sell hour of the prior day until the end of the current day. On average, the optimization period spans 26 hours. This period specification allows for charging late in the evening of the prior day.

The carbon intensity of energy arbitrage for each buy/sell pair is calculated after determining optimal purchase decisions using Equation 3:

$$Emissions_{Pair} = \frac{Q \times E_{T,Buy}}{\eta} - \eta \times Q \times E_{T,Sell} \tag{3}$$

Where Q is the nominal quantity procured (1MWh), E is the emissions rate of the marginal unit (measured in Lbs/MWh) and η is the one-way efficiency of the device. Equation 3 will be positive if the emissions incurred during charging are greater than the emissions abated at discharge; otherwise it will be negative. Buy/sell pairs are aggregated daily using Equation 4 and annually using Equation 5.

$$E[Emissions]_{Day} = \sum_{q=1}^{Q} E[Emissions_{Pair}] \tag{4}$$

$$E[Emissions]_{Annual} = \sum_{d=1}^{365} E\left[Emissions_{Day}\right] \tag{5}$$

3.2.4 Carbon Minimization

Carbon minimization is closely related to energy arbitrage algorithm in Equation 2, it replaces energy prices with system emissions. Put differently, carbon minimization switches the dependent and independent variables of energy arbitrage. As with EA, emissions induced by carbon minimization are aggregated daily and annually using Equations 4 and 5.

3.2.5 Demand Charge Management

The induced carbon emissions from ESS used for demand charge management depends on emissions in the wholesale market, a customer's retail rate schedule, and their building load shape. To model the discharge behavior of a DCM storage appliance, I use two hypothetical rate designs as well as simulated load data for 30 kinds of buildings in the city of Houston, TX. These elements, combined, yield the expected carbon by scenario, day, and building type. Emissions are calculated in three steps:

1. the probability of charging in a given off-peak hour and discharging in a given peak hour is assessed for all peak, off-peak hour pairs.
2. the carbon intensity of charging in a given off-peak hour and discharging in a given peak hour is calculated for all peak, off-peak hour pairs.
3. the carbon emissions calculated in (2) are weighted by the joint probabilities in (1) and then summed up by day.

Throughout, I assume that the building's gross load is invariant; that it will not change behavior with the addition of energy storage even though the net load of the building will.

The unique building load profiles are critical for assessing the emissions induced by demand charge management. Different buildings consume electricity differently. For example, fast-service restaurants have three peaks corresponding to meal-times; hotels have a bimodal distribution with peaks in the morning and evening; schools peak in the middle of the day. These individual peaks make sense given the ways we use physical space – restaurants use energy when making meals; hotels when people are staying in them; and schools during when pupils are in attendance. As induced emissions depend on when a battery is discharged, it stands to reason that different kinds of buildings may discharge their batteries differently when shaving their demand. Load data was developed in conjunction with the Department of Energy's *Commercial Reference Building Models of the National Building Stock* (methodology: Deru et al, 2011; data: OpenEI, 2016).[11] These reference building types are designed to represent 70% of the nation's commercial building stock including office buildings, strip malls, schools, restaurants, hotels, and apartment buildings.

[11] This data set consists of simulated load profiles (1998-2014, 30-minute profile) for commercial customers using the Pacific Northwest National Laboratory residential prototype building models and the US Department of Energy's commercial reference building models made for EnergyPlus simulation software (versions 8.4 and 8.5). These data make use of modeled weather data using the Physical Solar Model (PSM) downloaded from the National Renewable Energy Laboratory's National Solar Radiation Database for 15 sites in the continental US.

3.2.5.1 Charging Behavior

Charging a battery under DCM depends on a customer's energy tariff. Different kinds of tariffs will encourage different charging behavior. Hypothetical energy tariffs are designed to reflect common TOU and real-time attributes. Table 6 depicts a TOU Tariff structure with low energy prices off-peak and high energy prices on-peak. Table 7 depicts a RT tariff with prices that vary depending on ERCOT market conditions.

Table 6: Time-of-Use (TOU) Tariff Structure

Tariff Component	Off-Peak Period	Peak Period
Energy Charge	Low	High
Demand Charge	None	High

Table 7: Real-Time (RT) Tariff Structure

Tariff Component	Off-Peak Period	Peak Period
Energy Charge	Variable	Variable
Demand Charge	None	High

The periods in which demand charges are assessed are parameterized to allow for variation. In California, where DCM is most common, peak periods are as short as four hours while Texas generally has no peak period at all (i.e., charges are assessed based on NCP). For the base case, I split the difference, using a peak-period of 8-hours long and centered around the 4CP hours (HE16 and HE17). This peak-period duration is also a plausible middle ground between operating for minimizing 4CP costs and minimizing NCP costs. Peak-period durations between 2-hours and 12-hours, centered around HE16 and HE17 are assessed as sensitivities. The 12-hour peak period is functionally equivalent to a tariff where demand charges are assessed based on a building's non-coincident peak, because none of the assessed building load profiles peak outside of the period HE11 through HE22.

For a customer on a TOU energy tariff, the battery is assumed to charge slowly and uniformly over the entire off-peak period. This behavior is assumed because the TOU rate is a simple step function, the customer has no incentive to charge in one off-peak hour compared to another. For DCM with real-time energy rates, the charging pattern is different. Here, the battery will charge during the hours with the lowest energy prices. Because the modeled battery has a charge rate equal to its peak power, it will need D/K hours to fully charge. For a 1-MW/4-MWh battery, this means charging will occur uniformly over the 4 cheapest hours.

3.2.5.2 Calculating Peak Shaving and Battery Discharge Behavior

While charge behavior is the same for all building types on the same kind of energy tariff, discharge depends on the load shape of each building. Using the commercial building dataset, I calculate "typical day" discharge profiles for each month and each building type. The hourly gross load for a "typical" day is calculated as the simple average of all matching values in the dataset for that hour and month. There are 6,205 days in the dataset (more than 500 days for each month), each with 30 minute periods, so each hour of the typical day is developed using more than 1000 samples. The gross load for each building type is then normalized on a 0 to 1 scale to allow for standard comparison.

The stylized battery is assumed to be 20% of the building's annual peak load and have a 4-hour duration (same specification as Fisher and Apt, 2016). Hourly demand reduction for the typical day is calculated using a simple peak shaving algorithm that calculates the net ("shaved") demand for the peak period given the load shape, battery power and duration, and peak hours. Shaved demand can be calculated drawing a horizontal line tangent a building's peak load and then moving that line downward until the area contained between the line and the curve equals the battery's total capacity. This is subject to the constraint that the gross load shape cannot be reduced by more than the maximum instantaneous discharge rate of the battery itself. Formally, net demand for the peak period is calculated using the following equations:

$$\delta_{Max} = \max(\{f(i): i = A; where\ A\ is\ set\ of\ all\ peak\ hours\}) \tag{6}$$

$$\delta_{Net} = \arg\max\left(\delta_{Max} - K,\ \frac{\sum_{t = Peak\ Start}^{Peak\ End} \delta_t - KD}{t_{Peak\ End} - t_{Peak\ Start}}\right) \tag{7}$$

Equation 6 is simply the maximum gross demand during the peak period. Equation 7 sets net demand as the maximum of the two: technically feasible net demand and the ideal net demand. This calculation is conducted for each month and each building type. Discharge behavior is thus

$$Peak\ Discharge_j = \begin{cases} \delta_j - \delta_{Net} & if\ \ \delta_j > \delta_{Net} \\ 0 & if\ \ \delta_j \leq \delta_{Net} \end{cases} \tag{8}$$

$$f_{peak}(x) = \Pi_{peak}(\mathrm{X} = x_j) = \frac{Peak\ Discharge_j}{\sum_{j=1}^{J} Peak\ Discharge} \tag{9}$$

The discharge profile of the battery is defined in Equation 8 as gross load less net load for all hours. Using Equation 9, this discharge profile is normalized such that the sum of all discharge equals 1. This normalization allows for treating Π_{peak} as a probability distribution function.

3.2.5.3 Calculating Carbon Emissions Associated with Peak Shaving

Having established the likelihood of charging in a given off-peak hour (under a given tariff), and discharging in a given peak hour, and that the two events are probabilistically independent from one another, it is possible to calculate the joint probability for all charge/discharge pairs. Let $\Pi_{i,j}$ be the joint probability of charging in hour *i* and discharging in hour *j*.

$$\Pi_{i,j} = f_{peak}(x_i) \times f_{offpeak}(x_j) \ \ for\ all\ i\ and\ all\ j \tag{10}$$

$$i \in A; where\ A\ is\ the\ set\ of\ all\ peak\ hours$$

$$j \in B; where\ B\ is\ the\ set\ of all\ \ off\ peak\ hours$$

Using $f_{offpeak,TOU}(x)$ in Equation 10 provides the joint probability for DCM using a time-of-use energy tariff while using $f_{offpeak,RT}(x)$ in the equation provides the joint probability under real-time-pricing.

3.2.5.4 Pairwise Carbon Intensity

The net carbon associated with charging in one hour and discharging in another hour can be calculated simply using Equation 11 (reformulated from Equation 3, above). Using this equation, I calculate the pairwise net carbon for all possible charge and discharge pairs assuming the parameters found in Table 5.

$$Net\ Emissions_{i,j} = \frac{Q \times E_i}{\eta} - \eta \times Q \times E_j \tag{11}$$

As before, *i* is an element in the set of all off-peak hours and j is an element from the set of all peak hours. Note that these data are unweighted – they do not represent the likelihood that charging would occur in a given hour or discharging in another hour; they simply represent the net carbon that would result from charging/discharging in these hours.

3.2.5.5 Expected Carbon Emissions Induced from DCM Operation

Multiplying the unweighted carbon values by the pairwise weights yields the weighted, or "expected" carbon emissions for each hour pair (Equation 12). Summing across all pairs yields the daily expected carbon (Equation 13); summing across all days yields the annual expected carbon (Equation 14)

$$E[Emissions]_{i,j} = \Pi_{i,j} \times Net\ Emissions_{i,j} \quad (12)$$

$$E[Emissions]_{Day} = \sum_{i=1}^{N_{Peak}} \sum_{j=1}^{N_{Off-Peak}} E[Emissions]_{i,j} \quad (13)$$

$$E[Emissions]_{Annual} = \sum_{D=1}^{365} E[Emissions]_{Day} \quad (14)$$

Using this approach, I calculate induced emissions from energy storage used for DCM for each building type and for each day.

3.3 Dispatch Modeling

The ESS dispatch algorithms described in the preceding section make decisions based on prices or emissions. These data are generated using the production cost modeling program PLEXOS, and a dataset describing ERCOT under high wind and solar penetration rates.

This paper relies on a dispatch model initially developed to model ERCOT wholesale electricity prices for the year 2011 (Garrison, 2014). This model was revised as part of the University of Texas Energy Institute's Full Cost of Electricity Study (FCe-) to model ERCOT in 2030 (Mann et al, 2017). The FCe- model was developed to assess the ERCOT generation mix in 2030 based on current trends. The 2030 version, used in this paper, is benchmarked against three other simulations in Mann et al (2017).[12]

The base case of this paper represents ERCOT 2030 under current trends. In this model, peak demand is 81.2 GW, annual generation is 425 TWh, and the system generates approximately 17% of its energy from wind and solar resources. To depict ERCOT under even greater renewables penetration, fifteen other scenarios are developed. In these scenarios, I exogenously add an additional 25GW to 150GW wind and solar generation. This range in

[12] The 2011 version of the model is benchmarked in Garrison (2014) and has been used in several subsequent studies (e.g. Deetjen et al, 2016).

values is selected to allow for modeling a system with 50% of its annual energy from either wind or solar. Renewables were added to the system exogenously, rather than via a full capacity expansion. This simplification may change market prices, as sub-economic units are not retired. Given the emissions focus of this analysis, such changes are unlikely to materially alter results.

The PLEXOS model simulates security constrained economic dispatch for a zonal, day-ahead market using its short-term schedule optimization module (ST Schedule).[13] The short-term schedule uses short-run marginal costs (SRMC) to determine generator bids. This study uses a one-year planning horizon (8,760 hours) to account for seasonal variations. To simplify calculations, ancillary services markets for frequency regulation, spinning reserves and non-spinning reserves were not modeled. In this paper, ERCOT is simulated as a single zone without transmission constraints – a simplification from the Mann et al model that allows for investigation of changes in generation alone. As large quantities of wind and solar will be added to the modeled system, static transmission constraints would pose problems including highly differentiated prices and over generation (dump energy). The addition of gigawatts of new generation would be met with transmission expansion in the real-world.

3.3.1 Wind and Solar Resource Profiles

Wind and solar generation added to the PLEXOS model using composite resource profiles. These profiles assume that new generation is added proportionally the sum of existing generation and proposed in the ERCOT interconnection queue.[14] The wind profiles aggregate county-level profiles developed by ERCOT while the solar profiles rely on NREL's PV-Watts application. Detail on resource locations and profile calculation are provided in Appendix 1. Figure 3 depicts the normalized wind profile and Figure 4 depicts the normalized solar profile by hour and season.

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[13] PLEXOS solves this optimization using a combination of linear programming and mixed-integer programming techniques. In keeping with Mann et al, The Xpress-MP solver was used for all simulations.

[14] Actual from the 2016 EIA-923 (through November) and ERCOT's January 2017 Generator Interconnection Status Report (2017).

Figure 3: Wind Profile by Season

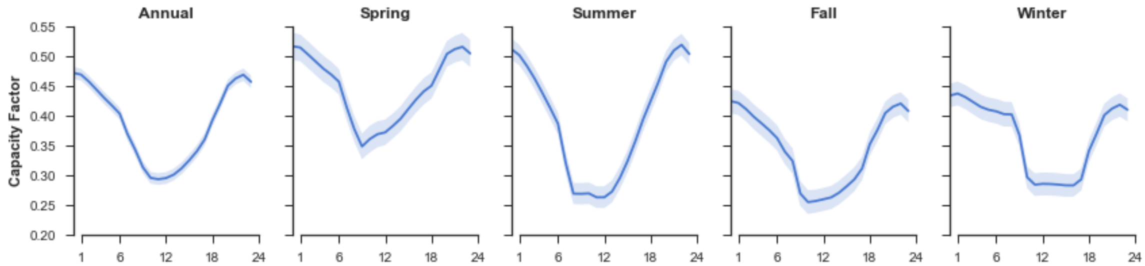
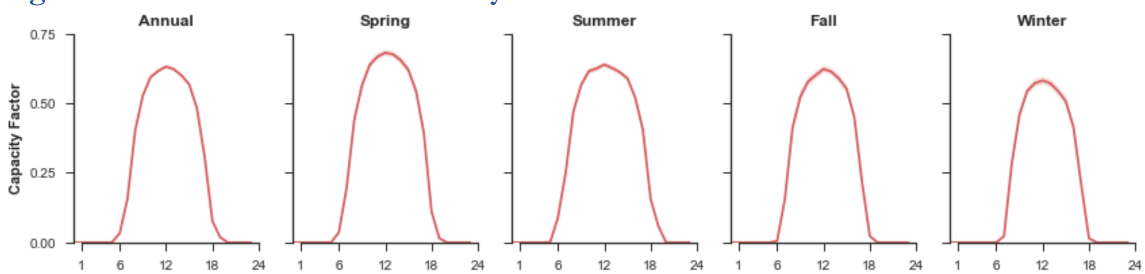


Figure 4: Normalized Solar Profile by Season



The composite profile for wind has substantial variation within each day and across the seasons. On an annual basis, the composite wind profile has a mean capacity factor of 39%. All seasons have a "U" shape where generation is higher in the evening than during the middle of the day. Generation drops by half of more between maximum and minimum output. The spring season has the highest capacity factor in all hours. The seasonal profile of solar exhibits far less variation. In the winter, capacity factors are lower because of the lower angle of the sun, reduced daylight hours, and increased cloud cover.

3.3.2: Production Cost Modeling Results for All Scenarios

Using the PLEXOS production cost model, described above, 16 high renewable scenarios were run. Table 8 summarizes key attributes by model run including the load-weighted average price, load-weighted average emissions, the share of generating coming from wind and solar assets, and the percentage of time renewables are curtailed.

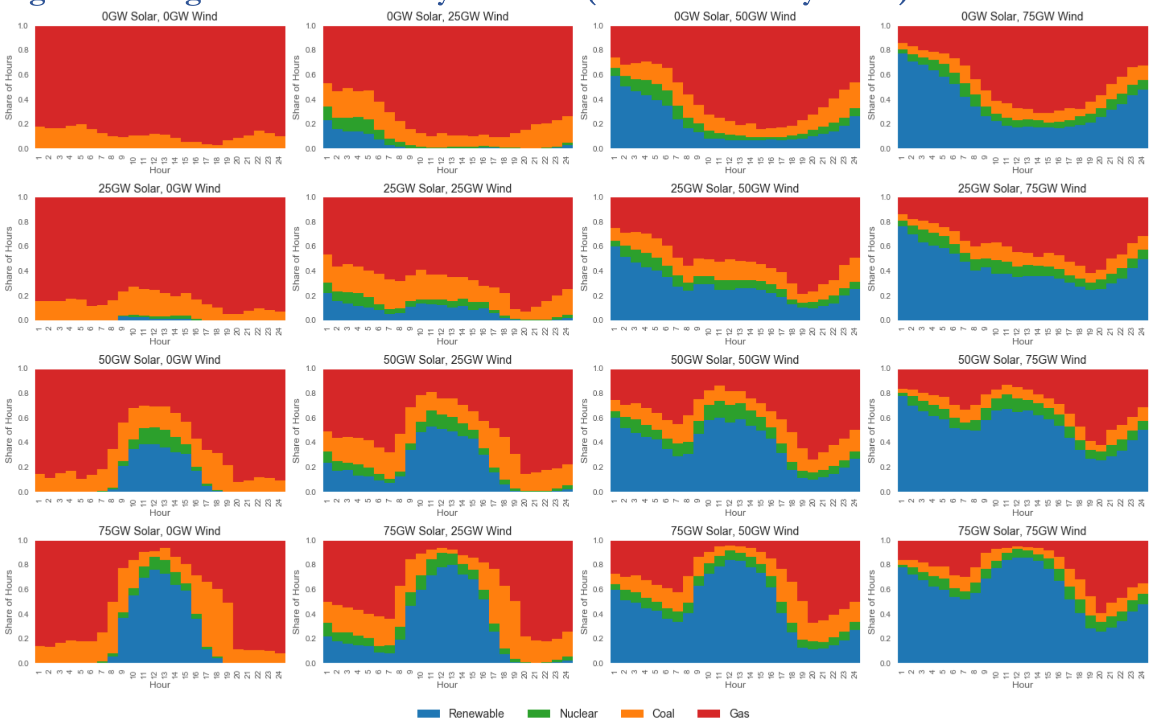
Table 8: Key Statistics by Scenario

Scenario	Load Wtd Price ($/MWh)	Load Weighted Emissions (lbs/MWh)	Resource Mix (%) Wind + Solar	Nucl.	Coal	NG	Other	Mean Curtailment Factor (%)
0GW Solar, 0GW Wind	34.00	1025	17.1	9.1	23.3	49.8	0.6	0
0GW Solar, 25GW Wind	30.77	764	36.8	8.9	18.5	35.2	0.6	0
0GW Solar, 50GW Wind	25.23	545	53.1	8	13.2	25.2	0.5	0.1
0GW Solar, 75GW Wind	20.20	398	64.2	7	9.3	19.1	0.4	0.3
25GW Solar, 0GW Wind	31.99	868	29.2	9.1	20.9	40.2	0.6	0.1
25GW Solar, 25GW Wind	28.14	610	48.3	8.7	15.5	26.9	0.6	0.2
25GW Solar, 50GW Wind	22.06	416	63.2	7.6	10.8	17.9	0.5	0.3
25GW Solar, 75GW Wind	17.14	289	72.9	6.5	7.3	12.9	0.4	0.5
50GW Solar, 0GW Wind	28.06	712	40	8.6	16.3	34.5	0.6	6.1
50GW Solar, 25GW Wind	24.04	494	57.1	8.1	12.4	21.9	0.5	4.3
50GW Solar, 50GW Wind	18.25	333	70	6.9	8.9	13.8	0.4	3.9
50GW Solar, 75GW Wind	13.78	225	78.3	5.9	5.9	9.5	0.3	3.6
75GW Solar, 0GW Wind	24.86	628	46.6	8.1	14.2	30.6	0.5	15.5
75GW Solar, 25GW Wind	21.07	871	61.9	7.5	11	19.1	0.5	14
75GW Solar, 50GW Wind	15.69	293	73.4	6.4	7.9	11.9	0.4	13.3
75GW Solar, 75GW Wind	11.61	195	81	5.5	5.2	8	0.3	12.7

Prices in these scenarios are generally lower than historic norms in ERCOT, but not as low as might be suspected given the 25 GW to 150 GW of incremental renewable capacity modeled. The average price in ERCOT was below $30/MWh in 2012, 2015, and 2016 (Potomac Economics, 2016, IV). Even prices in the low $20s have precedent, such as the winter of 2015/16 when natural gas prices fell below $2/MMBtu. In very low market price conditions, like those in the very high renewables scenarios, ERCOT may endure substantial resource realignment that would invalidate the presented results.

Beyond low but not inconceivable prices found, two trends dominate. First, as renewables penetration rates increase, so too does the percentage of the time that these resources are marginal (Figure 5). Second, carbon and price remain strongly and positively correlated through all cases (Figure 6). The incremental effect of wind and solar generation on the marginal generator are not commensurate. Figure 5 depicts the typical type of marginal generation by hour for 16 scenarios that add 0 to 75 GW of wind and solar to the system. In each subplot, the horizontal axis represents the hour of the day and the vertical axis represents the share hours with a given generation type on the margin (e.g. wind, gas, coal, or nuclear). The figure presents annual data, meaning that each "hour" depicts the proportion of the time a given fuel was marginal in each of the 365 days.

Figure 5: Marginal Generation by Scenario (Annual Share by Hour)



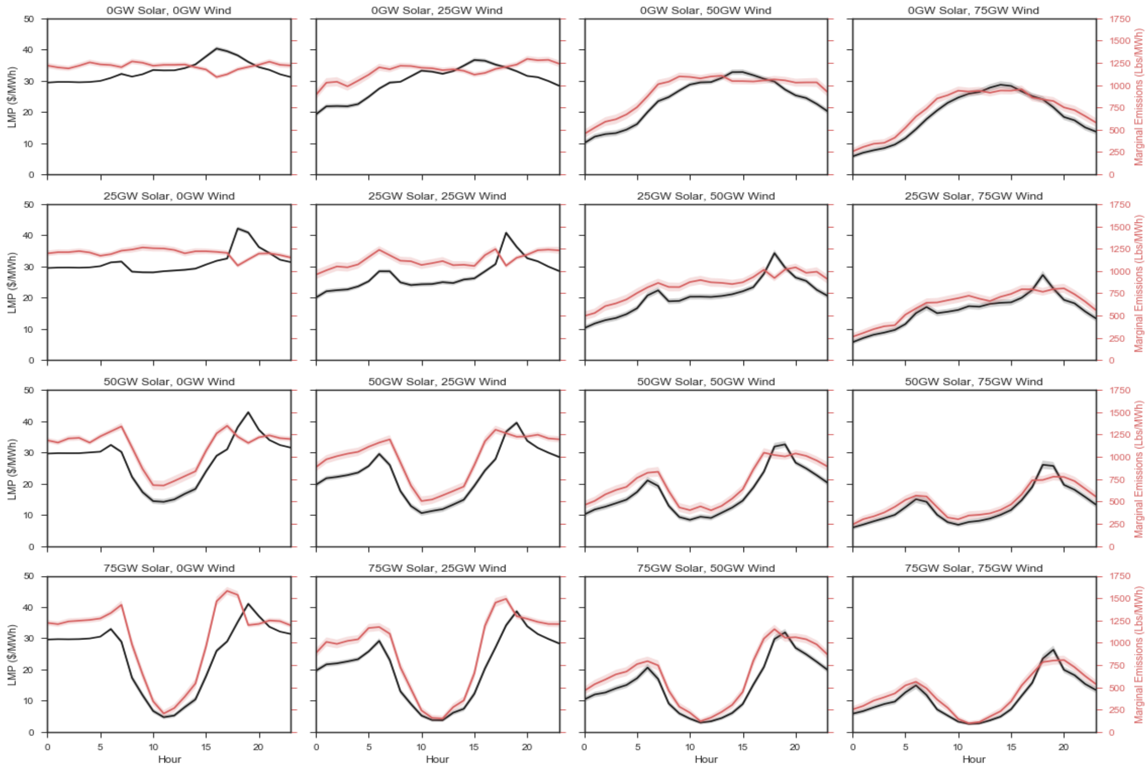
The top left plot in the figure represents the base case with no added wind or added solar. The top right represents the system with 75GW of wind added; the bottom left adds 75GW of solar; and the bottom right adds 75GW of both resources. Interior plots represent other pairwise combinations. In the base case, wind and solar are never on the margin while in the high renewables cases they are on the margin more than 80% of the time. In the high renewables cases, there is a significant amount of over-generation leading to curtailment by wind and solar.

When large amounts of solar are added to the system (bottom left) the evening hours continue to be served by gas and coal but the mid-day hours are met with increasing amounts of solar and nuclear. As solar is added to the system, more mid-day gross load is being met by those assets, cutting into the amount of coal and gas needed. Increases in wind penetration rates (upper right) likewise reduces the marginality of coal and gas assets, but in evening hours rather than mid-day. When solar is paired with wind (bottom right), renewables squeeze marginal gas and coal during both day and night. This has the effect of reducing marginal emissions, on average, across the day and of suppressing market prices.

The same capacity addition of wind yields more marginal wind hours than the same amount of solar because of wind's higher capacity factors and the shape of system load. Wind's capacity factor is nearly twice as high as solar's (39% vs 23%) so the same quantity of wind generation produces more energy. The generation profile of wind amplifies this effect: low load hours tend to be in the evening when solar generates no electricity but wind generates at its peak. By contrast, high load hours are when solar generates electricity; so, for solar to be on the margin, it needs relatively more installed capacity.

Adding wind and solar to the system suppresses marginal prices and marginal carbon. Scenarios with high amounts of renewables have lower prices and lower marginal carbon than those scenarios without added renewables. The price and marginal carbon profiles differ by the composition of resources added. Figure 6 depicts the relationship between marginal carbon and marginal price by hour. Marginal price is plotted in black and marginal carbon is plotted in red.

Figure 6: Correlation of Price and Carbon by Scenario (Annual Average Shapes)



In a market with gas frequently at the margin – like the base case – marginal carbon should be between the emissions rates of a natural gas combined cycle (~1000Lbs/MWh) and a natural gas combustion turbine (~1500lbs/MWh). When wind is added to the system, the off-peak hours should see price and carbon suppression. When solar is added to the system, mid-day prices and marginal carbon are suppressed, yielding something analogous to the "duck curve".[15] Systems with large amounts of solar and wind still exhibit the duck curve, but with lower magnitude, because of countercyclical generation profile. As wind rolls off in the morning, solar starts coming online; as evening falls, wind tends to pick up again.

[15] The CA duck curve is a load-based phenomenon due to high *behind-the-meter solar* reducing net load. Here, because all solar is *utility scale,* the curve manifests in price alone.

Chapter 4: Results

4.1 Summary of Results

Chapter 3 developed methods to assess how an energy storage system (ESS) is dispatched and the markets in which it could participate. In this chapter, induced carbon emissions from ESS are assessed for each operational mode and in each of the 16 simulated electricity systems. The base scenario represents an expectation of what the ERCOT generation mix will look like in 2030 – wind energy representing approximately 17% of energy, modest solar, and gas comprising much of the remainder. Baseline results rely on 186,000 simulated battery-days (3.5 million battery-days are simulated across all sensitivities).

The four modeled ESS use cases have dispatch signals that relate to energy prices, building demand, or system emissions. As a reminder, these modes are: wholesale energy arbitrage (EA); demand charge management using a simple time-of-use energy rate (DCM-TOU); and DCM with a real-time-pricing energy rates (DCM-RT); and, carbon-minimization ($MinCO_2$). Operational mode characteristics are summarized in Table 9.

Table 9: Summary of Operational Modes

Dispatch Mode	Dispatch Signals	Operational Constraints
Energy Arbitrage (EA)	Wholesale Energy Prices	None
Demand Charge Management with TOU Energy Rates (DCM-TOU)	Building Demand; Retail Energy Prices	Charge during off-peak; Discharge on-peak
Demand Charge Management with RT Energy Rates (DCM-RT)	Building Demand; Wholesale Energy Prices	Charge during off-peak; Discharge on-peak
Minimize CO2 Emissions ($MinCO_2$)	Marginal System Emissions	None

The different operational modes and resource scenarios yield five key results.

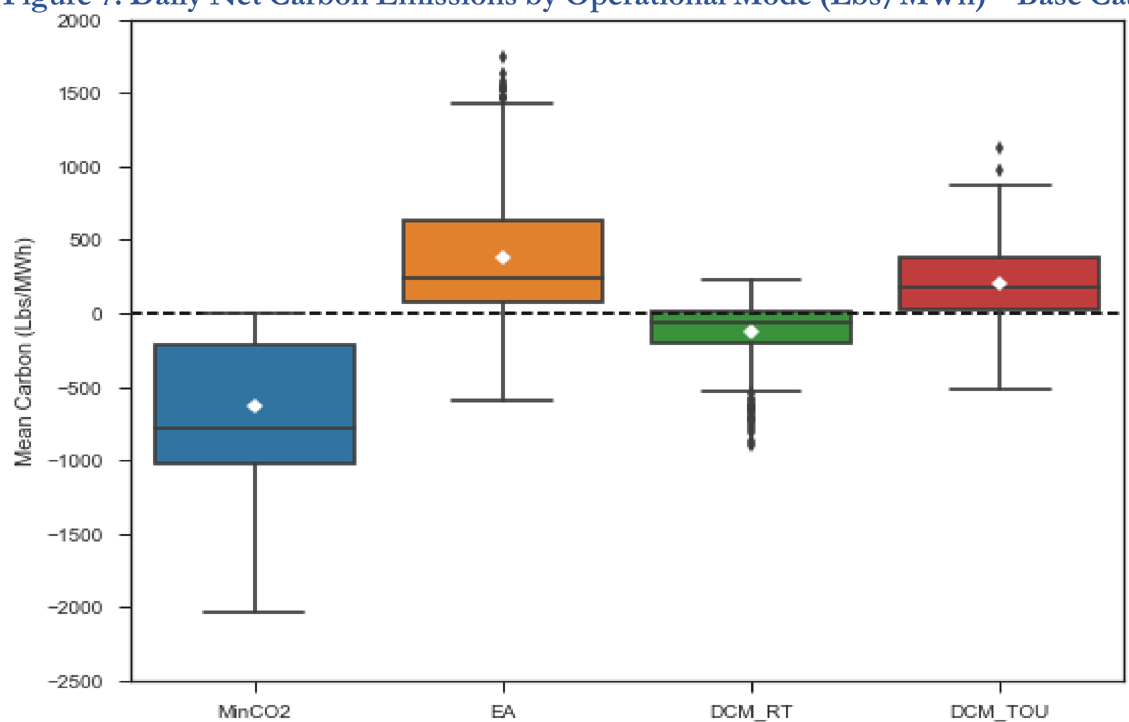
1. Different operational modes in the same resource scenario induce net carbon emissions that differ in magnitude and sign. The same operational mode in different resource scenarios induce different quantities of CO_2.
2. Energy storage is carbon neutral in systems generating 17% to 40% of annual energy from renewables, depending on operational mode.

3. Economic dispatch of ESS attains only a portion of the maximum achievable environmental benefits.
4. Greater exposure to ERCOT wholesale prices generally reduce carbon emissions
5. Cognizant rate design can encourage batteries to lessen their carbon footprint without a loss of economic benefit.

4.2 Different operational modes in the same resource scenario induce carbon emissions that differ in magnitude and sign. The same operational mode in different resource scenarios induce different quantities of CO_2.

Induced carbon depends on how storage is used and the generation mix in which the ESS is located. In the base-case, mean net emissions range from -500 to 500 lbs/MWh across scenarios. Two of the three economic operational modes increase emissions on average while one reduces emissions. Figure 7 depicts induced emissions by day for the base case.

Figure 7: Daily Net Carbon Emissions by Operational Mode (Lbs/MWh) – Base Case



The white diamond in each box denotes the mean response. This figure assumes a 1MW/4MWh battery that is 85% efficient. For the DCM scenarios, it depicts the "average" building and a peak period with a duration of 8 hours. Sensitivities on battery efficiency, battery duration, peak period duration, and specific building types are provided in Appendix 2.

In the base case, carbon-minimization induced mean emissions reductions of 626 lbs/MWh-stored. On average, energy arbitrage increased emissions by 384 lbs/MWh, DCM-TOU increased emissions by 197 lbs/MWh, and DCM-RT reduced emissions by 120 lbs/MWh. DCM results presented in Figure 7 are for "average" building (results for all 30 building types are presented in Appendix 2). The results for EA and DCM-TOU are comparable to, but on the low end of, and results for MinCO_2 and DCM-RT fall below the results found in the literature. This is unsurprising because our base case has renewables generating a larger share of energy than other studies. Extending these results to the 15 other resource scenarios, a more consistent pattern emerges. There is subtlety in the interaction between storage and the grid, but at its core: (1) DCM-TOU rate always increases emissions; (2) EA generally reduces emissions; (3) DCM-RT always reduces emissions to a modest extent; (4) MinCO_2 substantially reduces emissions. Table 10 depicts mean induced emissions by scenario and operational mode.

Table 10: Mean Induced Emissions by Mode & Scenario (Lbs/MWh)

Scenario	DCM-RT	DCM-TOU	EA	MinCO_2
0GW Solar, 0GW Wind	-121	197	384	-626
0GW Solar, 25GW Wind	-365	114	12	-963
0GW Solar, 50GW Wind	-579	-117	-502	-1247
0GW Solar, 75GW Wind	-601	-235	-703	-1300
25GW Solar, 0GW Wind	-169	164	337	-695
25GW Solar, 25GW Wind	-331	173	-125	-1034
25GW Solar, 50GW Wind	-448	-28	-529	-1231
25GW Solar, 75GW Wind	-463	-125	-718	-1309
50GW Solar, 0GW Wind	-336	398	-574	-1296
50GW Solar, 25GW Wind	-417	362	-810	-1412
50GW Solar, 50GW Wind	-382	159	-856	-1415
50GW Solar, 75GW Wind	-320	49	-833	-1327
75GW Solar, 0GW Wind	-400	596	-1007	-1609
75GW Solar, 25GW Wind	-375	518	-1100	-1628
75GW Solar, 50GW Wind	-319	280	-1020	-1531
75GW Solar, 75GW Wind	-232	163	-1020	-1531
Min	-601	-235	-1100	-1628
Max	-121	596	384	-626

Looking across the 16 resource scenarios, with MinCO_2, emissions are always reduced (by definition) and the mean emissions reduction ranges from 626 lbs/MWh to 1,628 lbs/MWh depending on scenario. Carbon minimization yields emissions reductions lower than, but comparable to, the environmental benefits seen in coal-to-gas substitution (on the low end) or coal-to-renewable substitution (on the high end).

EA exhibits the greatest range in emissions across scenarios for the economic operational modes. In three low-renewables scenarios, EA generates higher emissions than all other operational modes but as renewables are added to the system, EA reduces emissions more than either DCM mode. In the base case, EA increases system emissions by 384 lbs/MWh on average, but it can reduce emissions as much as 1,100 lbs/MWh in the additional 75-GW Solar, 25-GW Wind scenario. These directional results hold irrespective of battery duration and battery efficiency.

DCM-RT reduces emissions in all scenarios while DCM-TOU generally increases emissions. DCM-RT reduces emissions by 121 bs/MWh to 601 lbs/MWh; DCM-TOU ranges from +596 lbs/MWh to -235 lbs/MWh. While the specific emissions of these two modes differ by scenario, the relative positioning of the two means remains consistent. DCM-TOU induces an average of 532 lbs/MWh more CO_2 than DCM-RT. DCM is sensitive to peak-period durations, with different periods changing both the direction and magnitude of environmental impacts. Also important, different building types generate different environmental effects, especially in high-solar scenarios.

Unexpectedly, more renewables are not always better. For certain operational modes, higher renewable penetration rates do not monotonically reduce storage-induced carbon emissions. For EA and MinCO_2, more renewable capacity reduces emissions irrespective of its type. For EA, this makes sense because higher rates of renewables allow these resources to be on the margin more of the time, which, in turn, allows for more purchasing from zero carbon resources.

DCM, however, benefits more from wind than from solar. DCM-TOU, increases net system emissions when solar is added to the system but reduces emissions when wind is added. DCM-RT, reduces emissions in both cases but more so from wind than from solar. Demand charge management wants to charge when building demand is low and discharge when demand is high. Because of wind's night-peaking resource profile, when wind is added to the system, demand charge management is more likely to charge from wind (See Figure 5). Wind resources are unlikely to be marginal when battery is discharged according to DCM. Thus, in a wind-heavy resource mix, DCM will tend to charge from wind and displace coal – reducing net system emissions. Solar inverts this relationship. When solar is added to the system, a battery is likely to be charged from coal or gas but displace marginal solar resources. In effect, DCM in a high-solar world will tend to transport high carbon fuels generated off-peak to low-carbon peak periods, *increasing* net system emissions. DCM-RT can ameliorate this effect through more selective charging (it is more likely to charge from wind than DCM-TOU). Cognizant integration of storage requires the acknowledgement that there are deep interactions between portfolio and operational mode and it is hard to make universal statements about what works well or what does not.

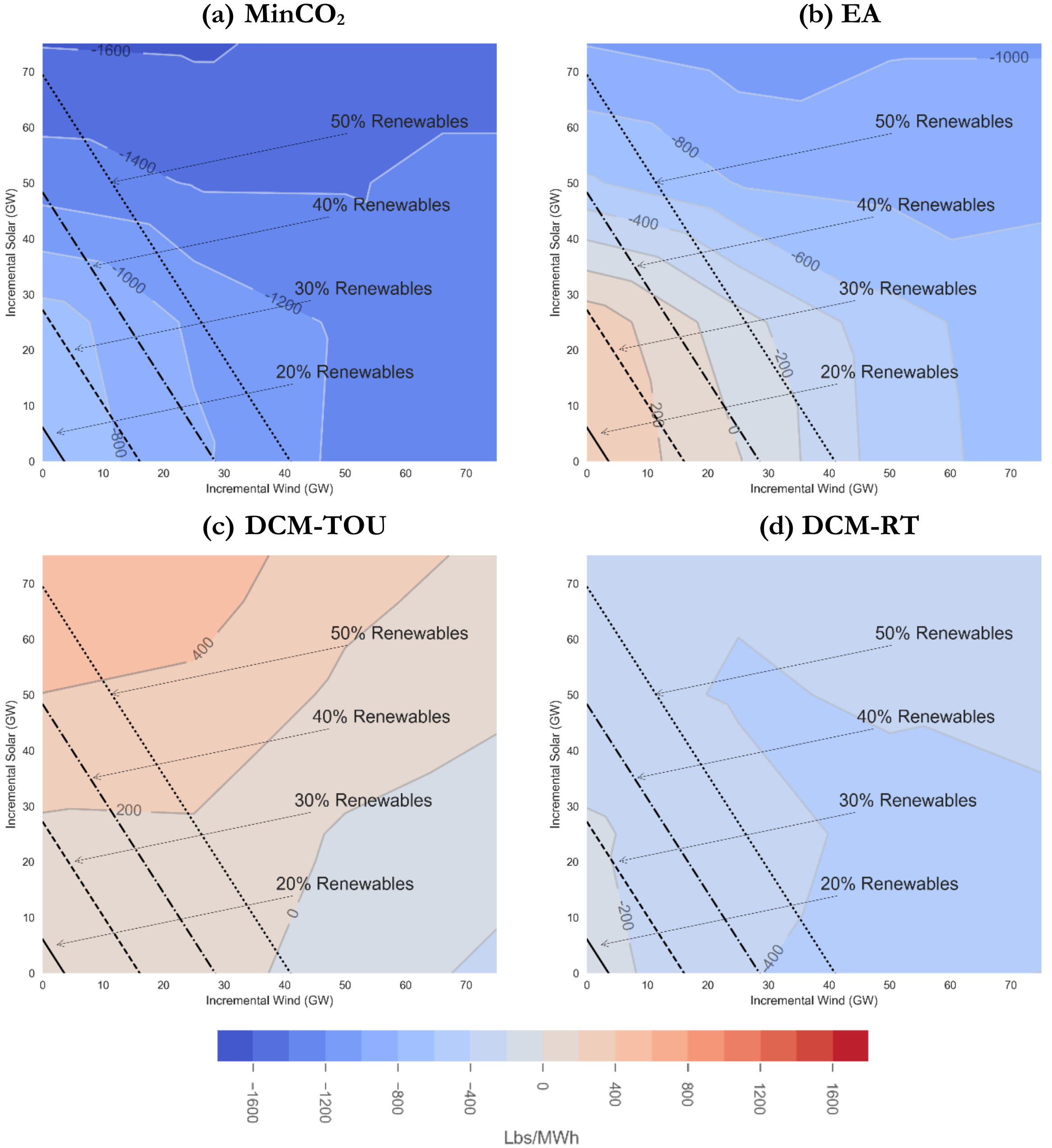
4.3 Energy storage is carbon neutral in systems generating 17% to 40% of annual energy from renewables, depending on operational mode.

The results derived in this chapter give insight into when storage may shift from being a net carbon emitter to a net carbon reducer. Two of the four operational modes, MinCO_2 and DCM-RT, reduce system emissions in the base case. EA reduces system emissions when renewables generate between 35% and 45% of annual energy. DCM-TOU is unlikely to reduce system emissions.

Figure 8 depicts four surface contour plots – one for each operational mode, which connect the mean induced carbon emissions by resource mix. The contour maps shade areas of increased emissions in red and emissions reductions in blue (the darker the color, the greater the magnitude of the response). The superimposed diagonal lines represent portfolios of wind and solar that would be required to generate a given amount of system energy from renewable resources.[16] In each plot, resource mixes closer to the origin (bottom left) are more likely to occur than those up and to the right.

[16] These calculations assume average capacity factors for wind and solar derived in Chapter 3 and no curtailment.

Figure 8: Mean Daily Induced Emissions by Generation Mix and Operational Mode (Lbs/MWh)



ESS used for carbon minimization reduces system emissions in all studied portfolios. Reductions are monotonic for both solar and wind additions over the study range. In a system with 50% of energy from renewables, emissions would range from -1,100 lbs/MWh down to

-1,500 lbs/MWh. These reductions are more substantial per unit than the reductions offered through coal-to-gas substitution.

EA reduces emissions in many plausible future ERCOT scenarios. Adding approximately 25 GW of wind to the baseline 20GW yields carbon neutral operation while it takes nearly 35 GW of solar to reach the same inflection point. If all of the proposed wind resources in the early-2017 ERCOT interconnection queue get built, then storage will reach breakeven. In such a future, Texas would be generating nearly 35% of its energy from wind on an annual basis (assuming the base-case load of 425 TWh). This is roughly five times more energy than is currently supplied by wind, but this inflection point conceivable.

DCM can always increase or always reduce net system emissions depending on the energy prices to which it is subject. Consider the two subplots: DCM-TOU is mostly red while DCM-RT is all blue. Based on the modeling work, DCM-RT would reduce system emissions before 2030 while DCM-TOU pricing never will. In this suboptimal operational mode, only portfolios with wind generating 60% of system energy see storage reducing system carbon (an unlikely edge case). While these DCM plots depict results for the *average* building, it is worth noting that none of the 30 simulated buildings reach breakeven in any modeled buildout scenario.

For DCM-RT, emissions are always negative but they are relatively invariant over the studied portfolios. DCM-RT reduces emissions by 0-200 lbs/MWh for the base case; further renewables additions will reduce emissions by another 200 lbs/MWh. DCM-RT will generate reductions sooner than EA, but will never generate the large reductions EA could induce in high-renewable futures.

4.4 Economic dispatch of ESS attains only a portion of the maximum achievable environmental benefits.

There is a substantial gap in emissions induced from MinCO_2 and the other modes. The magnitude of the gap is significant: the induced emissions from the least emittive economic operational mode is still 494 lbs/MWh to 721 lbs/MWh higher than MinCO_2 (See Figure 8). This is unsurprising because MinCO_2 reduces emissions by design while the economic modes may incidentally reduce emissions due to market configuration. Nevertheless, this result suggests that ESS dispatch could be cooptimized for economic and environmental benefits.

It is also worth noting that the reductions that occur in the three economic operational modes are a product of relationships that happen to hold in ERCOT but need not in all markets. ESS profit maximization tends to reduce emissions in ERCOT because of the positive correlation between system price and carbon emissions. In systems with baseload coal (inexpensive) and peaking gas (expensive) the opposite result would likely occur. This argument has been made elsewhere before but it bears repeating (e.g., Hittinger and Azevedo, 2015). MinCO_2 would perform similarly, however, because environmental benefits of gas displacing coal are approximately as large as the benefits of wind displacing gas (See Table 1.1).

4.5 Greater exposure to ERCOT wholesale prices generally reduce carbon emissions

In the preceding two sections, it has been shown that economic modes tend to reduce emissions more when they are offered greater exposure to price. EA tends to induce the greatest reductions in system net carbon while DCM-TOU yields the least. The relationship between induced carbon emissions and operational mode can most easily be considered in terms of constraints on optimization.

EA has no restrictions on charge or discharge timing while DCM-TOU has the most. DCM-TOU, with uniform off-peak charging and load-shape defined peak discharging, does not have flexibility regarding charging or discharging. Its behavior is fixed irrespective of the system's marginal price or marginal carbon. DCM-RT has a fixed discharge profile but a variable charge profile. It can optimize one half of the equation but not the other: peak shaving must occur when a building requires it while charging behavior can be modified to seek out lower carbon periods. A DCM tariff that uses a fixed "super off-peak" period to encourage charging in fixed off-peak hours would presumably lay between the two DCM modes modeled. Such a tariff would not capture day-to-day variation but would capture monthly or seasonal trends.

4.6 Cognizant rate design *can* encourage batteries to lessen their carbon footprint without a loss of economic benefit.

DCM-RT reduces system emissions while DCM-TOU tends to increase system emissions. The difference between the two DCM models highlights a critical fact: cognizant rate design *can* encourage batteries to lessen their carbon footprint without eroding the benefits offered through ESS operation. Simple TOU rates are common in the industry because they satisfy longstanding rate-design principles of economic efficiency, understandability, and equity (See Chapter 2.3). But batteries are more sophisticated than the standard ratepayer – they are complex computer controlled devices designed to arbitrage energy and exploit price signals embedded in rates. While real-time energy rates reduce understandability, it also reduces costs, reduces emissions, and provides the same net benefit to the storage operator. For batteries operating under retail rates, a focus on energy prices yields better (Pareto efficient) outcomes.

Chapter 5: Conclusions

5.1 Key Conclusions

In this report, the induced carbon emissions from energy storage are assessed for four operational modes and in 16 different high-renewable resource portfolios for a 1-MW/4-MWh battery. Three economic operational modes represent plausible ESS operations on a commercial or utility scale. The resource mixes depict futures in which wind and solar resources are a significant portion of the overall electric mix. In the base case, renewables generate 17% of annual energy; in the highest case they produce 81%. This paper is intended to provide directional results on induced emissions from ESS operation, and does not evaluate commercial or physical viability of either ESS or high-levels of renewable generation.

Induced carbon emissions are a function of the market in which the ESS is located (resource mix, system load, unit commitment); battery operational mode (and the energy tariffs to which it is subject); and, the physical attributes and constraints of the battery itself (power, duration, etc.). All three of these inputs are rapidly changing today and will continue to do so for the foreseeable future. Given the requisite inputs and the modeling framework, it is essential to note that this work is fundamentally speculative. Regulators may revise market rules to encourage ESS to participate in ways that differ from today; market resource mixes may evolve along axes other than just more-or-fewer renewables. Nevertheless, the results generated in this paper provide insight into many plausible futures.

While grid-connected energy storage will likely induce increases in carbon emissions today, it can also enable deep decarbonization in the long-run. Based on current projections, some economic and environmental applications of energy storage generate net reductions by 2030 if not sooner. Other applications induce a reduction in net system emissions after 30% to 40% of system energy is provided by renewable resources. Importantly, energy arbitrage and demand charge management provide these environmental dividends as an incidental benefit: EA is profit maximizing, not emissions minimizing; DCM is cost reducing, not emissions reducing. Nevertheless, when enough renewables are on the system, these economic uses of ESS provide incidental environmental benefits to society.

5.2 Limitations & Extensions

The results presented in this paper are subject to the specific limitations embedded in the model and its underlying assumptions. These limitations relate to how storage participates in markets, what those markets are, and how storage is dispatched. These limitations also provide opportunities for further work.

First, the model is limited by its assumption that ESS engages in Stackelberg competition – that it is both a price/carbon taker and that it is unable to change the market. In a high renewable future, storage will be participating in ways that *do* influence the market. For example, California has nearly 80 gigawatts of installed generation capacity – adding 1.3 GW of energy storage will increase capacity by 1.6%. Texas has neither the economic nor regulatory impetus to install storage in such quantities but it is easy to imagine several hundred megawatts of storage installed in the coming years – more than enough to change marginal units during periods of peak demand. As storage becomes an active participant, it will begin to shape wholesale prices and wholesale load. Storage used for energy arbitrage will reduce the likelihood of scarcity pricing and will, more generally, reduce the differential between peak and off-peak prices. Storage used for demand charge management will increase the system load factor by reducing peak demand and increase consumption other times. As with arbitrage, this will change system prices, the marginal unit, and the induced emissions from energy storage. Understanding how induced emissions change as a function of installed storage capacity would be the most useful extension of this paper.

Second, the limited scope of this paper – energy storage in ERCOT – does not provide direct guidance on its impact in other markets. ERCOT is an energy-only competitive market with retail choice. Texas has favorable resource endowments – wind, sun, fossil fuels – that yield a very particular set of market conditions. The modest amounts of coal in the system reduces possible environmental benefits induced by storage, its cheap natural gas and substantial resource availability limits storage from some of the economic benefits found in more constrained markets. Low prices also limit the benefits of behind-the-meter generation resources – ERCOT expects most solar in the state to be installed on a utility-scale. This enables renewable curtailment and influences how wholesale markets will function. Put simply, what happens in ERCOT may not happen in other systems/markets. Understanding how induced emissions depend by market would help ensure regulators make cognizant choices about where and how to encourage storage.

Third, single use storage dispatch does not represent how storage will actually be dispatched in the market. This takes two forms. First, the lack of economic analysis hinders the ability to suggest most likely outcomes. The results presented should be considered representations of a range of possible outcomes – not the ones most likely to occur given a specific market. Second, the ESS dispatch algorithms are single-use only. As RMI (2015) and Lazard (2016) make clear, a storage owner will likely use it for a combination of applications such as demand charge reduction, energy arbitrage, utility system deferral, and ancillary services. Co-optimization of ESS used for multiple applications will result in different ESS charge/discharge profiles and different quantities of induced carbon emissions.

5.3 Final Thoughts

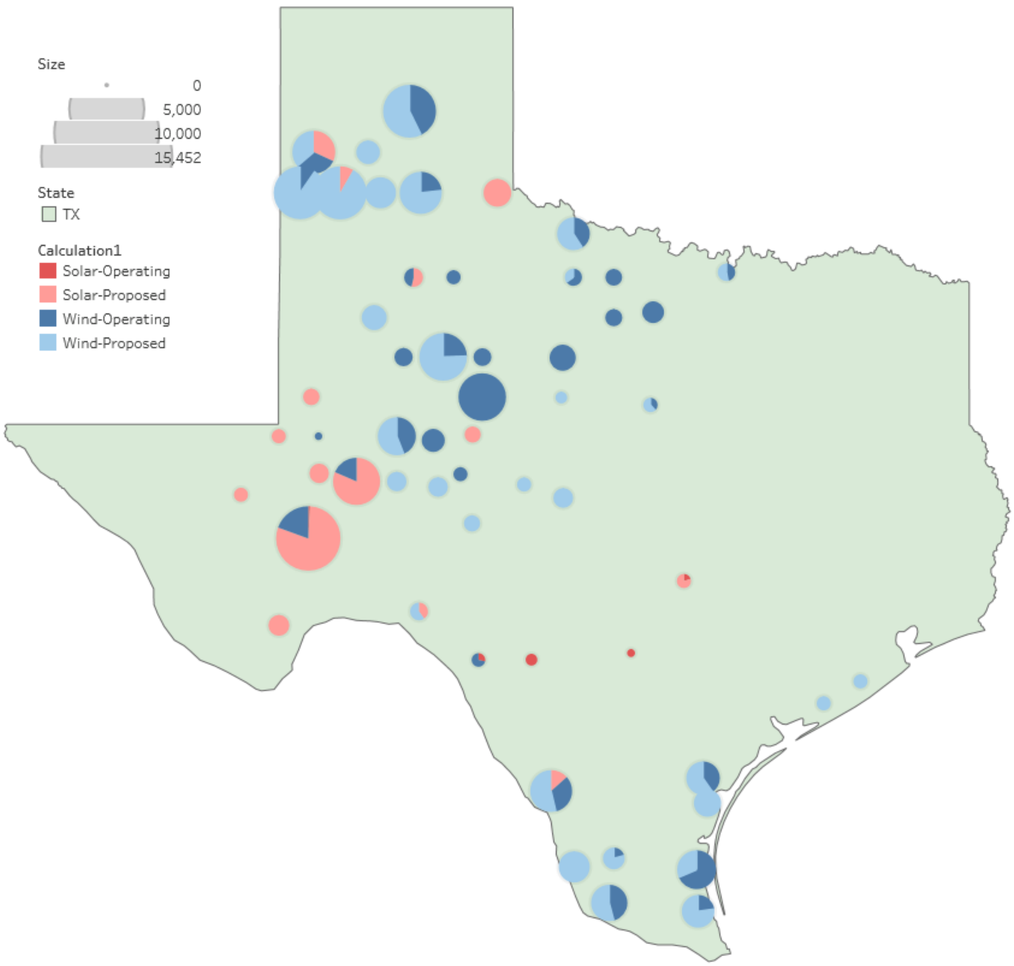
Despite these limitations, this paper successfully assesses some of the environmental implications of grid-connected energy storage. It confirms that storage today will likely increase system emissions today but also suggests that storage will likely reduce system emissions in the years to come. In this context, the key result of this paper are quietly optimistic. Current concerns about storage operation should alleviate themselves overtime as the regulators encourage more efficient energy consumption and as the system gets greener.

Appendix 1: Wind & Solar Resource Profiles

The production cost modeling work developed in this paper required the development of wind and solar resource profiles. The base model, developed in Mann et al (2017), incorporated a significant amount of renewable resources with resource profiles developed on a county-by-county basis. Given the large amount of renewables being assessed in this paper, a simpler approach was required. For both asset types, capacity is added proportional to the sum of existing generation and proposed in the ERCOT interconnection queue.[17] County-level resource profiles were then aggregated into an ERCOT-wide composite. Existing and proposed renewable capacity is heavily biased towards the West zone. Figure 9 depicts the location of operating and proposed wind and solar resources, county level capacity, and vintage of that capacity.

[17] Actual from the 2016 EIA-923 (through November) and ERCOT's January 2017 Generator Interconnection Status Report (2017).

Figure 9: Location of Existing and Proposed Wind and Solar Resources in ERCOT



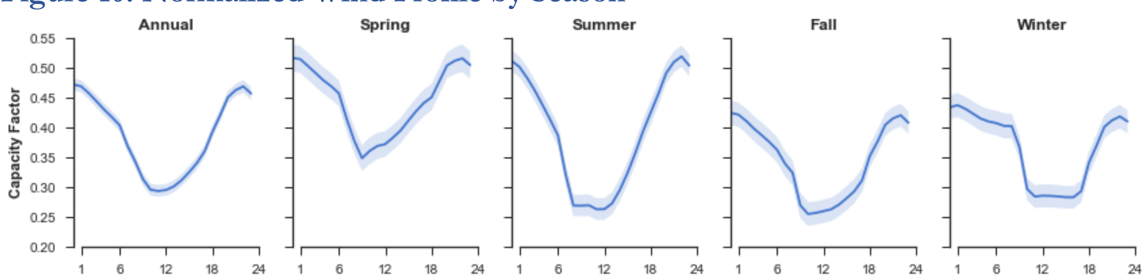
Weighting the profiles by existing and proposed resources, rather than just existing resources, is important because of trends in resource siting. Where once wind was historically centered in west-central Texas (Sweetwater, Midland, and Abeline), many proposed resources are further north in the Panhandle or south along the coast and Rio Grande valley. Coastal and inland resources have different profiles so the addition of resources in the south will change the composite wind profile. For solar, this difference is less important given the modest amount of capacity installed to date and the relative consistency of the resource profile. The profile is affected by geography, however, as the time of solar maximum moves later in the day as you move west (40 minutes between Houston and Marfa).

A1.1 Wind Profile

Wind generation profiles are generated using an hourly dataset produced by AWS Truepower for ERCOT as part of its 2015 Resource Adequacy assessment (ERCOT 2015b; AWS 2012). The data was generated using a proprietary numerical mesoscale weather model and composite power curves for different wind turbines. This dataset consists of hourly data for 84 existing and 144 hypothetical locations around the state for the period 1997 through 2014. Similar to Mann et al, county level wind profiles are generated using the capacity-weighted average of AWS's sites. For the counties that lacked data from AWS, composite counties were generated using a minimum of two different adjacent or near-by counties. There is significant variation in county output over the course of the day and the course of the year. Variation is particularly noticeable between the Panhandle, central Texas, and the Gulf coast.

An ERCOT system level profile was generated by weighting the county-level profiles by the amount of existing and proposed capacity in each county. This profile, depicted in Figure 10, was normalized between 0 and 1 and used as rating factors.

Figure 10: Normalized Wind Profile by Season



The composite profile has substantial variation within each day and across the seasons. On an annual basis, the composite wind profile has a mean capacity factor of 39%. All seasons have a "U" shape where generation is higher in the evening than during the middle of the day. Generation drops by half of more between maximum and minimum output. The spring season has the highest capacity factor in all hours. Table 11 summarizes key descriptive statistics about the profile by season.

Table 11: Composite Wind Profile Capacity Factor

Period	Annual	Spring	Summer	Fall	Winter
count	8760	2208	2208	2184	2160
mean	39%	44%	39%	34%	37%
std	21%	22%	20%	20%	20%
min	0%	0%	1%	1%	2%
10%	12%	14%	12%	10%	12%
50%	37%	44%	38%	31%	34%
90%	68%	74%	66%	64%	65%
max	86%	86%	82%	84%	81%

A1.2 Solar Profile

The solar profile used in this analysis was compiled in an analogous manner to that of the wind resources. Existing and proposed county level capacity was calculated using EIA Form 860 data and the ERCOT interconnection queue from February 2017. Projects are located in 18 counties around the state with a strong western bias. While not identical to the results found in the 2016 ERCOT Long Term System Adequacy analysis, solar distribution follows the same trends (ERCOT 2016, 45-47). Most solar is proposed for west Texas, a region known for its high insolation. The state is not expected to see high penetration rates of rooftop solar given the lack of advantageous residential incentive programs like net metering in most parts of the state. Austin and San Antonio, both served by municipal utilities, are expected to see material solar additions.

For each county, a unique generation curve was calculated for each location in the solar distribution using the PVWatts calculator published by the National Renewable Energy Laboratory (NREL 2017). PVWatt generates an annual output profile using insolation information for a typical meteorological year as well as parameters about the solar array itself. Following Mann et al, the modeled array is one-axis tracking arrays with 96% efficient inverters and a 1.1 DC-to-AC size ratio. These county level profiles were then aggregated into a system level profile by weighting each county profile by the amount of existing and proposed capacity in that county (See Figure 11). Descriptive statistics are provided in Table 12.

Figure 11: Normalized Solar Profile by Season

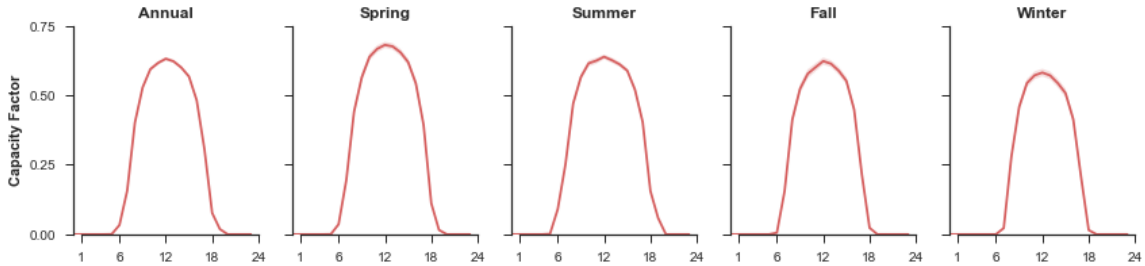


Table 12: Composite Solar Profile Capacity Factor

Period	Annual	Spring	Summer	Fall	Winter
count	8760	2208	2208	2184	2160
mean	23%	26%	26%	22%	20%
std	28%	30%	28%	28%	26%
min	0%	0%	0%	0%	0%
10%	0%	0%	0%	0%	0%
50%	3%	7%	13%	0%	0%
90%	67%	73%	66%	67%	62%
max	85%	85%	75%	77%	81%

The seasonal profile of solar exhibits far less variation than that of wind. In the winter, capacity factors are lower because of the lower angle of the sun and reduced daylight hours. Increased cloud cover further reduces winter capacity factors. Inverter losses and the 1-axis tracking reduces capacity factors, yielding a peak capacity factor of less than 1.0.

Appendix 2: Results Sensitivity Analysis

Sensitivities to key battery and model parameters are provided in this section. Sensitivity of results to battery duration and efficiency are modeled for the three economic dispatch modes. Additionally, the demand charge management modes include sensitivity by building type and peak-period duration. No sensitivities are presented for the carbon-minimizing dispatch mode – it is not a plausible operational configuration and is assessed previously only as a benchmark for the economic dispatch modes.

A2.1 Sensitivity to Efficiency

Battery efficiency is a major driver of induced carbon emissions. Batteries that are more efficient require fewer market purchases to offer the same benefits which, in turn, reduces induced emissions. In general, a more efficient battery will induced fewer carbon emissions.

Regardless of building type or scenario, DCM emissions decrease as storage efficiency increases. More efficient batteries require less market purchase (and the associated CO2) for the same amount of useful energy and, thus, reduce emissions.

For DCM with TOU rates, even 100% efficient batteries are unable to drive ESS emissions to zero, irrespective of building type. Emissions in the high solar scenarios are more variable by building type and are always higher than comparable wind scenarios. Emissions for the average building are always positive if more than 50GW of solar are on the system. DCM operation for the most advantageous building types may reduce carbon, but this is atypical.

More efficient batteries used for energy arbitrage tend to reduce the carbon emissions. Unlike DCM, however, this is not always the case. As batteries become more efficient, more buy/sell pairs become cost effective increasing energy storage utilization. That is, it becomes profitable to charge and discharge on previously uneconomic hours. These less profitable charge/discharge pairs have a smaller difference in price and a smaller difference in marginal carbon. These marginal pairs tend to have higher emissions rates compared to the pairs with large differences in price and therefore, increase emissions compared to runs without these pairs.

Figure 12: Sensitivity of Energy Arbitrage to Battery Efficiency (lbs/MWh)

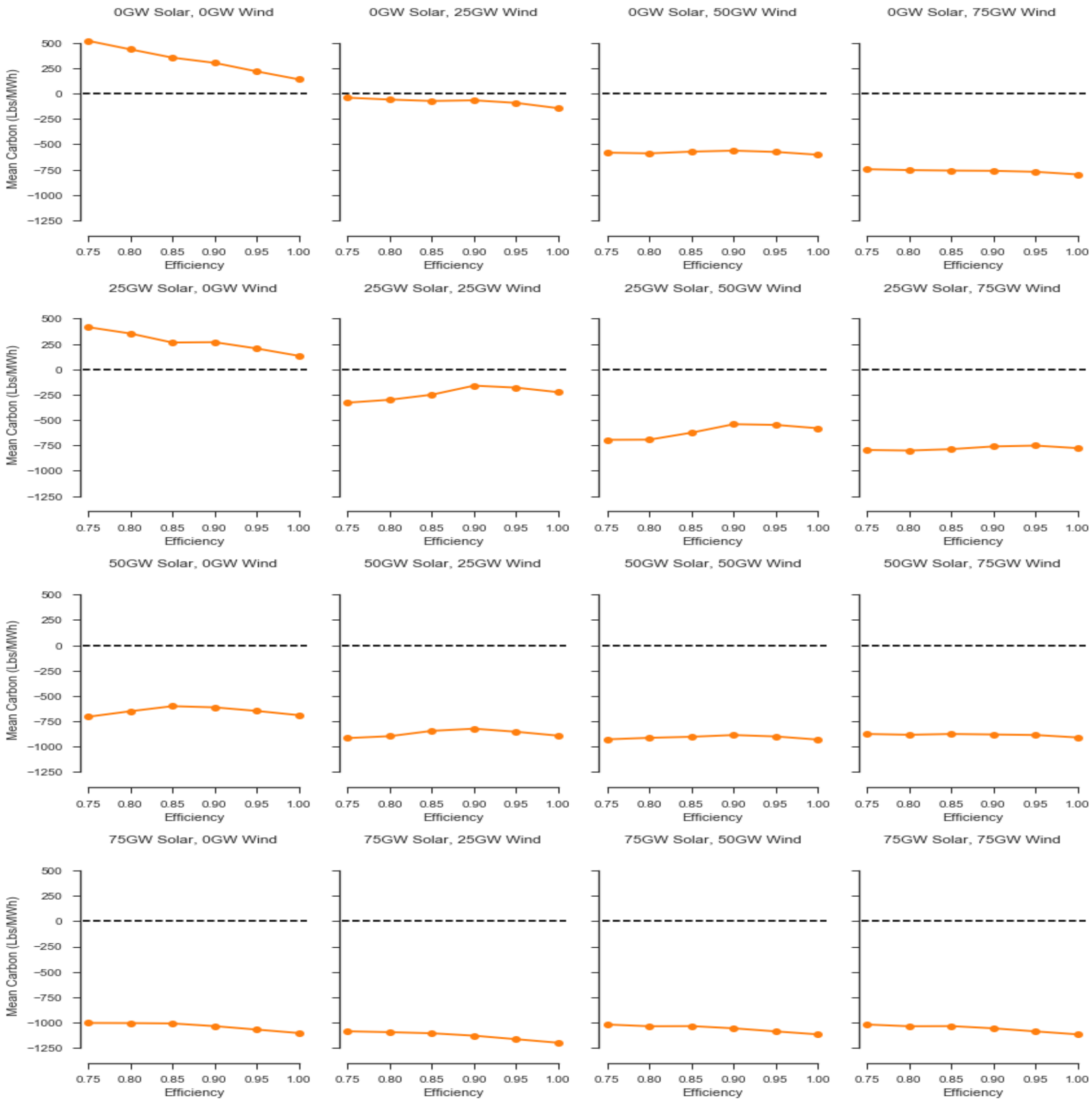
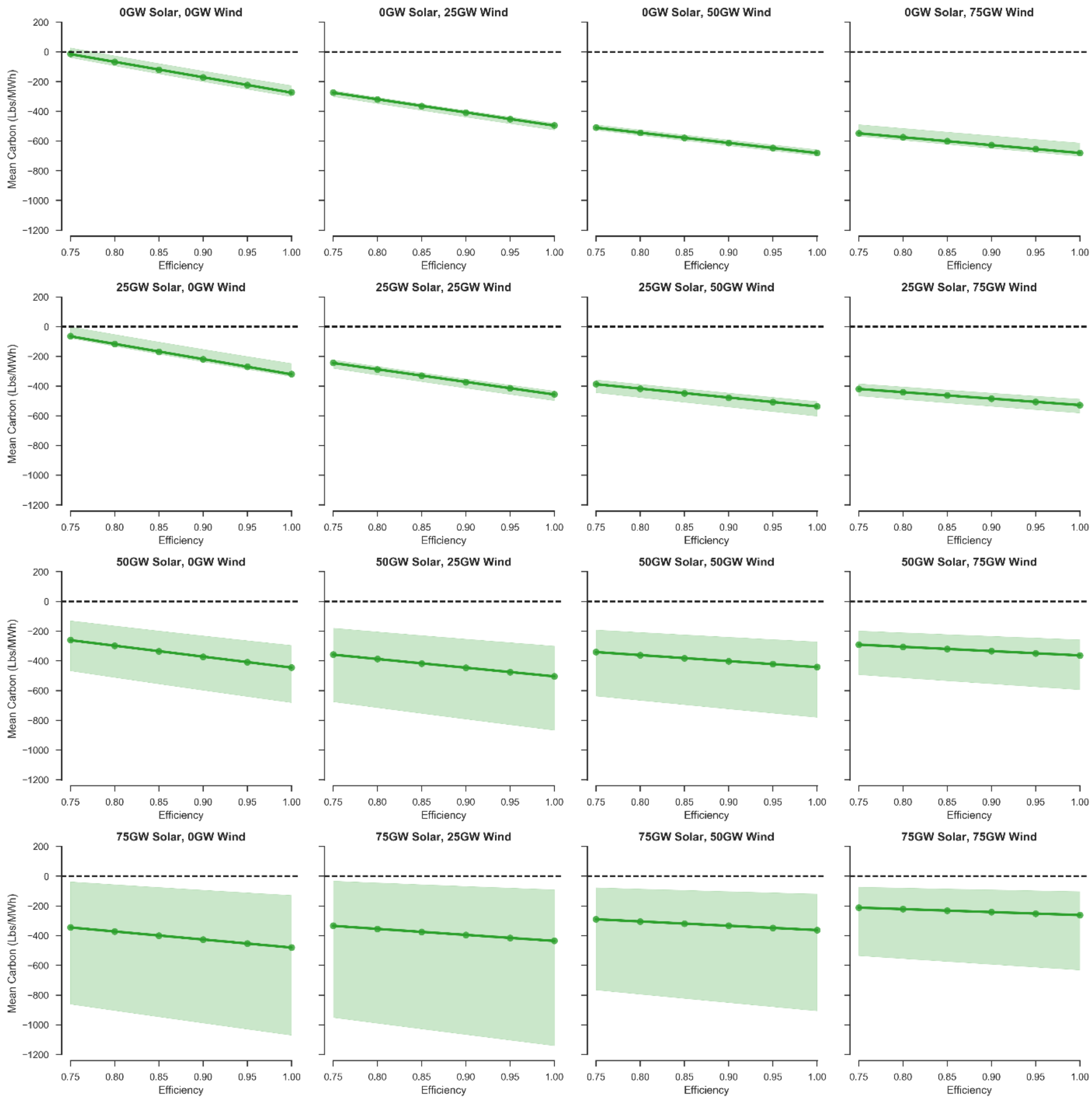
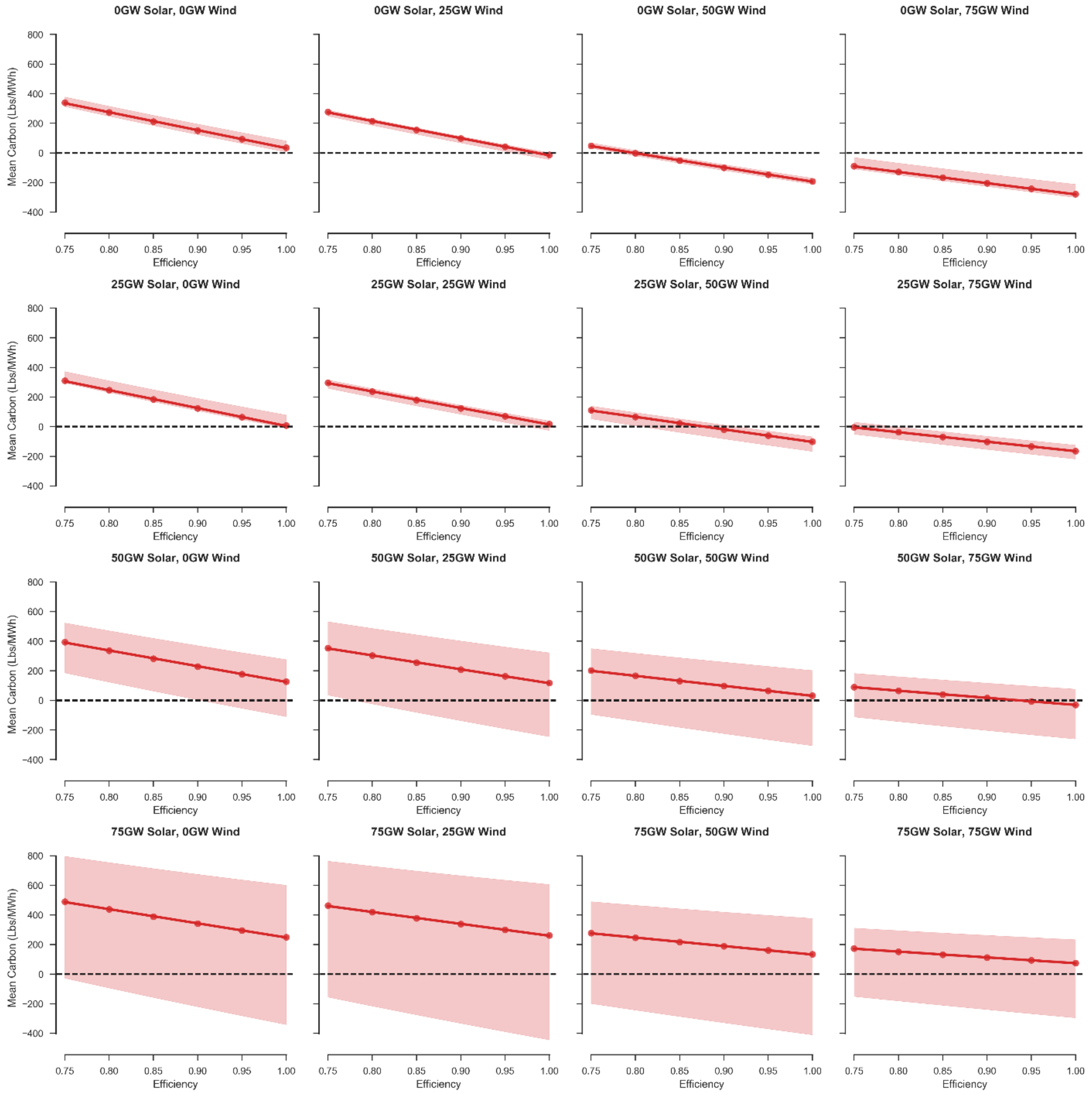


Figure 13: Sensitivity of DCM with Real-Time Energy Prices to Battery Efficiency (lbs/MWh)



Note: In this plot, the solid line represents the mean emissions for the average building (measured in lbs/MWh). The shaded area represents the range of results for all buildings from the least emitting to the most. Different building types may be the maximum or minimum plotted depending on the scenario.

Figure 14: Sensitivity of DCM with Time-of-Use Energy Prices to Battery Efficiency (lbs/MWh)



Note: In this plot, the solid line represents the mean emissions for the average building (measured in lbs/MWh). The shaded area represents the range of results for all buildings from the least emitting to the most. Different building types may be the maximum or minimum plotted depending on the scenario

A2.2 Sensitivity to Battery Duration

Battery duration changes how much total energy can be stored in a battery. For the same power output, a shorter duration battery can hold less total energy than a long duration battery. Batteries used in commercial applications generally have durations of two or four hours. I model batteries with durations of 2 to 12 hour durations.

Battery duration never changes the directional results for energy arbitrage although it does change mean emissions. As batteries increase in duration from 2-hours to 6-hours, there is a change in magnitude. Generally, emissions decrease as duration increases, but this is not always the case. Increasing duration from 6 hours to 12 hours does little for emissions. There are few days in which this added storage is actually utilized, so mean emissions remain relatively stable.

For demand charge management, a more consistent trend emerges. Longer durations relatively reduce emissions (compared to a 4hr battery) when wind is added to the system but increase induced emissions when solar is added to the system. As discussed in the results section, more wind makes storage more likely to charge from wind (reducing emissions) while more solar makes storage more likely to discharge into solar (increasing emissions). Longer duration batteries amplify this trend. In high wind scenarios, more wind generation can be purchased off-peak and used on-peak. In high solar scenarios more fossil fuel generation can be purchased in the evening and discharged during the day.

Figure 15: Sensitivity of Energy Arbitrage to Battery Duration (lbs/MWh)

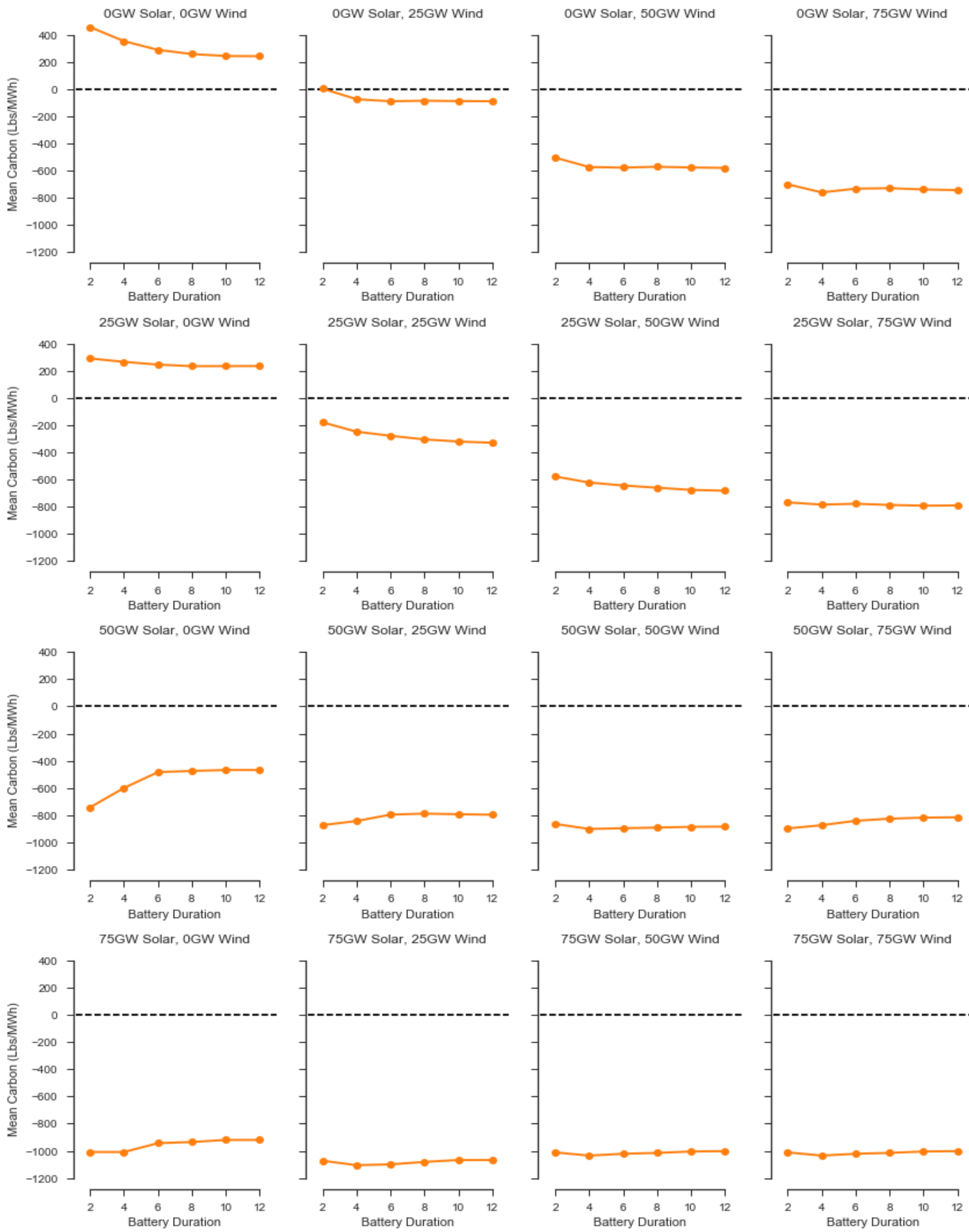


Figure 16: Sensitivity of DCM with Real-Time Energy Prices to Battery Duration (lbs/MWh)

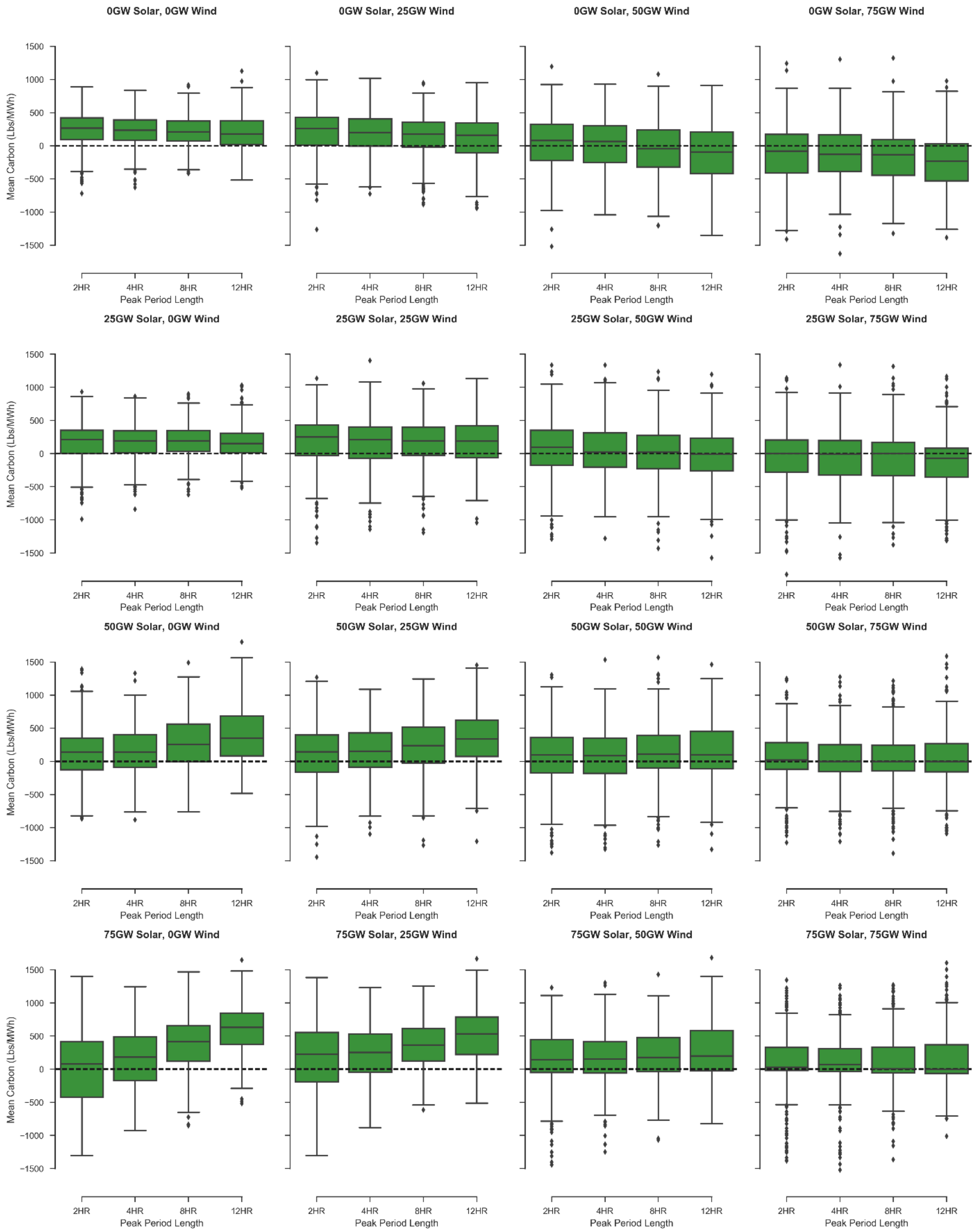
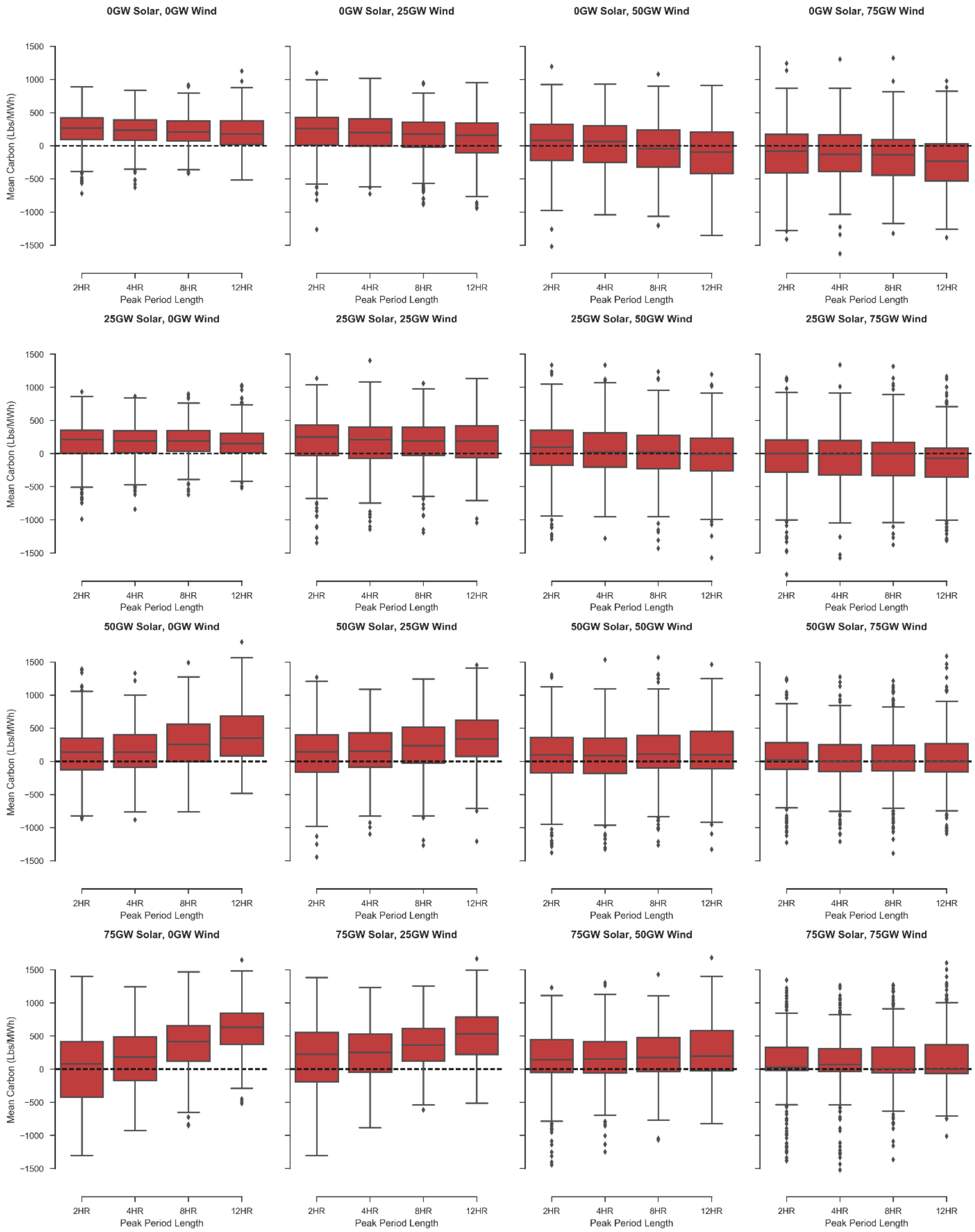


Figure 17: Sensitivity of DCM with Time-of-Use Energy Prices to Battery Duration (lbs/MWh)



A2.3 DCM Sensitivity to Peak Period Duration

Demand charge management exhibits the same sensitivity to peak period length as it does to battery duration. These effects have the same root cause. As the peak period is extended from its baseline 8-hours, solar heavy scenarios see relative increases in emissions. As peak period is shortened, solar heavy scenarios see a relative decrease in emissions. Short peak periods make it more likely that storage can charge from solar (and discharge either into solar or into fossil fuels) while long peak-periods diminish this possibility. With a 12-hour peak period, storage can charge from solar only in the very early morning – when solar is unlikely to be marginal. In a shorter, afternoon peak period, there are hours in which solar may be marginal and storage can charge itself.

Figure 18: Sensitivity of DCM with Real-Time Energy Prices to Peak-Period Duration (lbs/MWh)

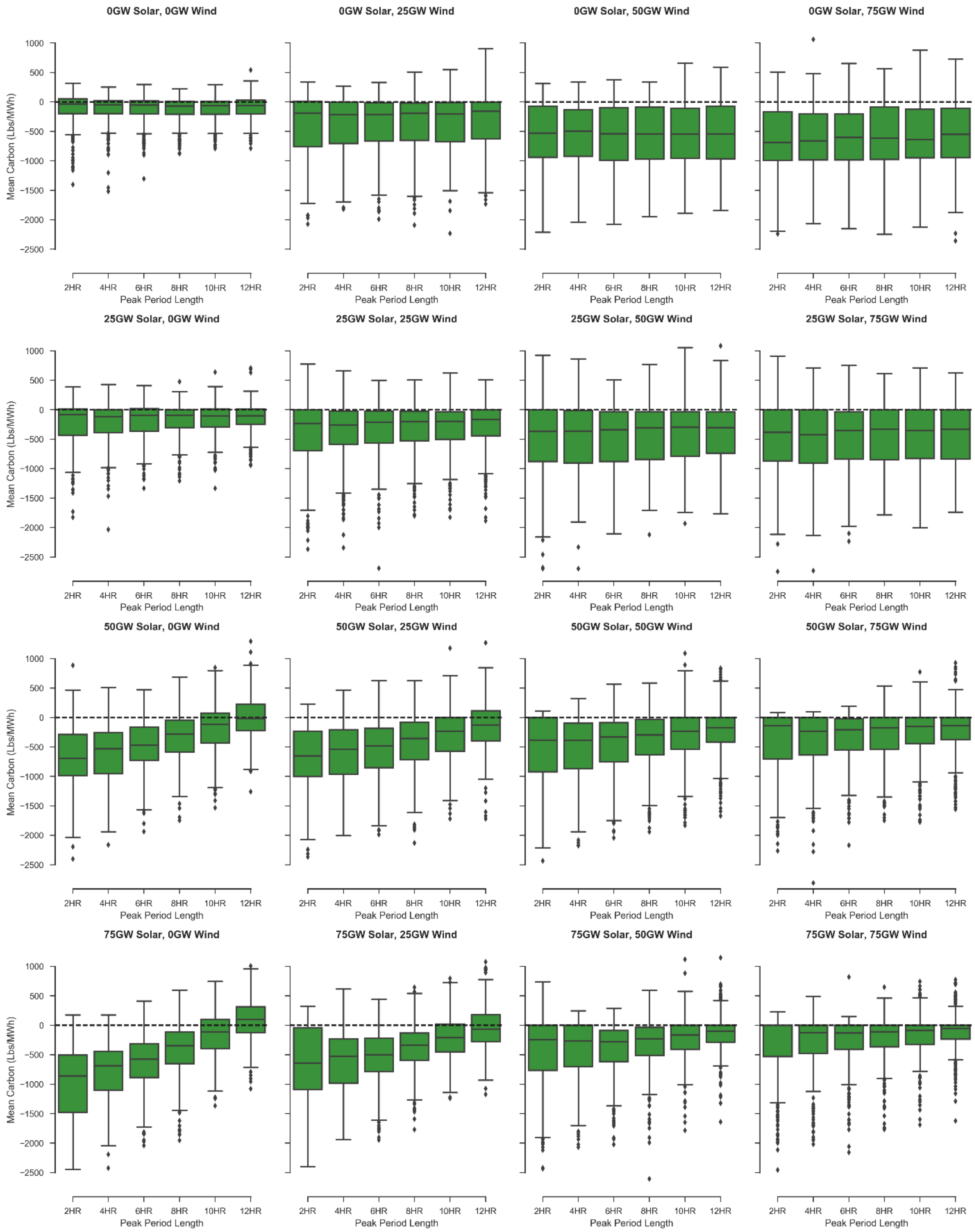
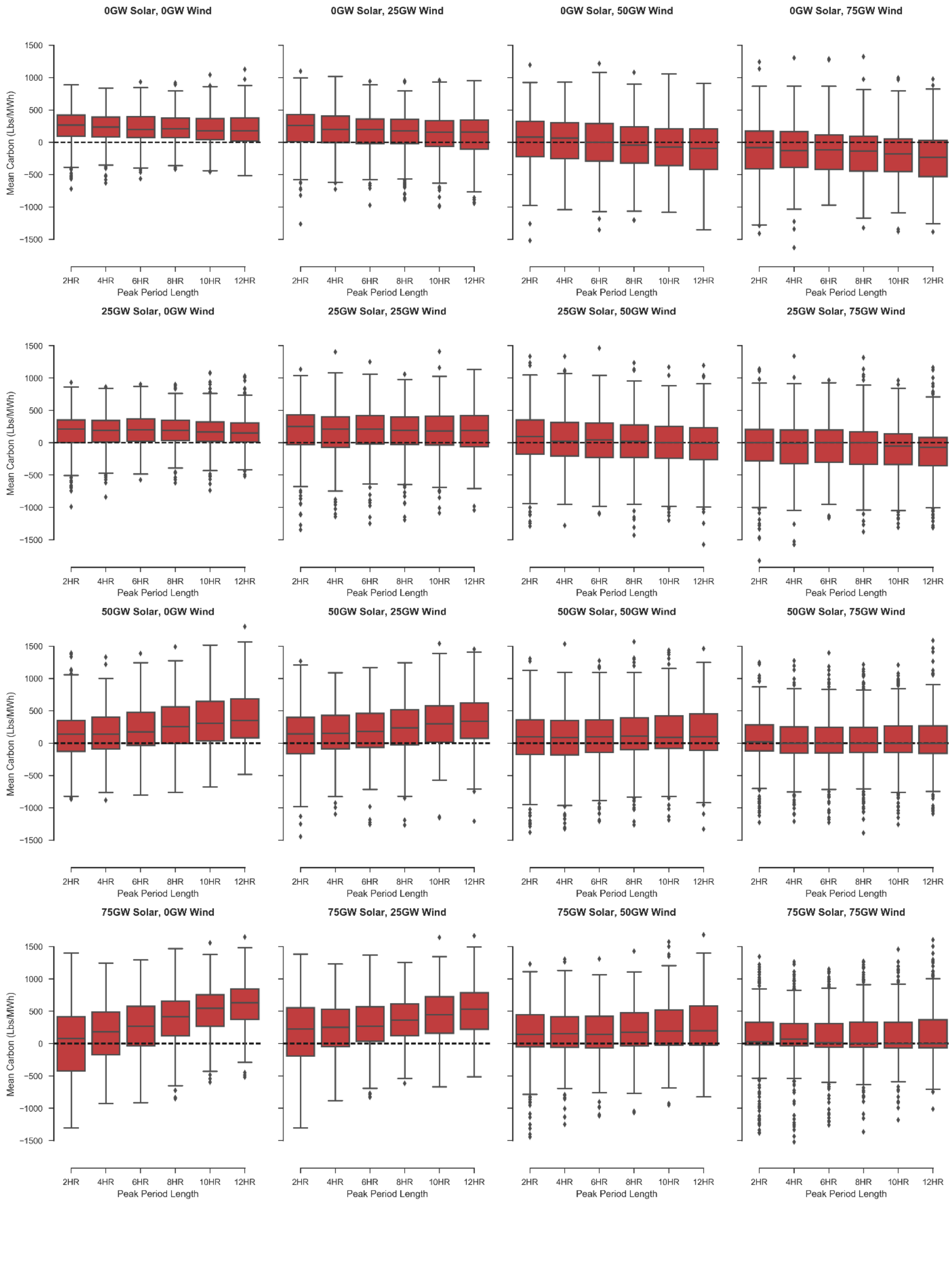


Figure 19: Sensitivity of DCM with Time-of-Use Energy Prices to Peak-Period Duration (lbs/MWh)



A2.4 DCM Sensitivity to Building Type

In the main results section, the "typical" building under DCM is presented. These average trends vary by building type because different load profiles require different storage dispatch which yields different emissions rates. In most scenarios, variation between buildings within a given scenario is modest compared to variation for a given building between scenarios. The subsequent figures depicts the distribution of daily emissions by building type for the four corner cases for DCM using real-time pricing and DCM using time-of-use pricing.

While many buildings have relatively uniform peak reductions across all discharge hours, certain types exhibit substantial variation. In the base case and high wind case, this asymmetric discharge does not materially alter carbon emissions but in the high solar scenarios, it will. The bottom left subplots in both Figure 20 and Figure 21 depict this behavior. Emissions from hotels and apartment buildings are sensitive to solar capacity additions because these buildings tend to peak on the tail end of the peak period, when solar output is beginning to wane. Discharge of storage for DCM, therefore, tends to displace more gas and coal than it does solar; hence the reduction in average emissions from other building classes.

Figure 20: Sensitivity of DCM with Real-Time Energy Prices to Building Type (lbs/MWh)

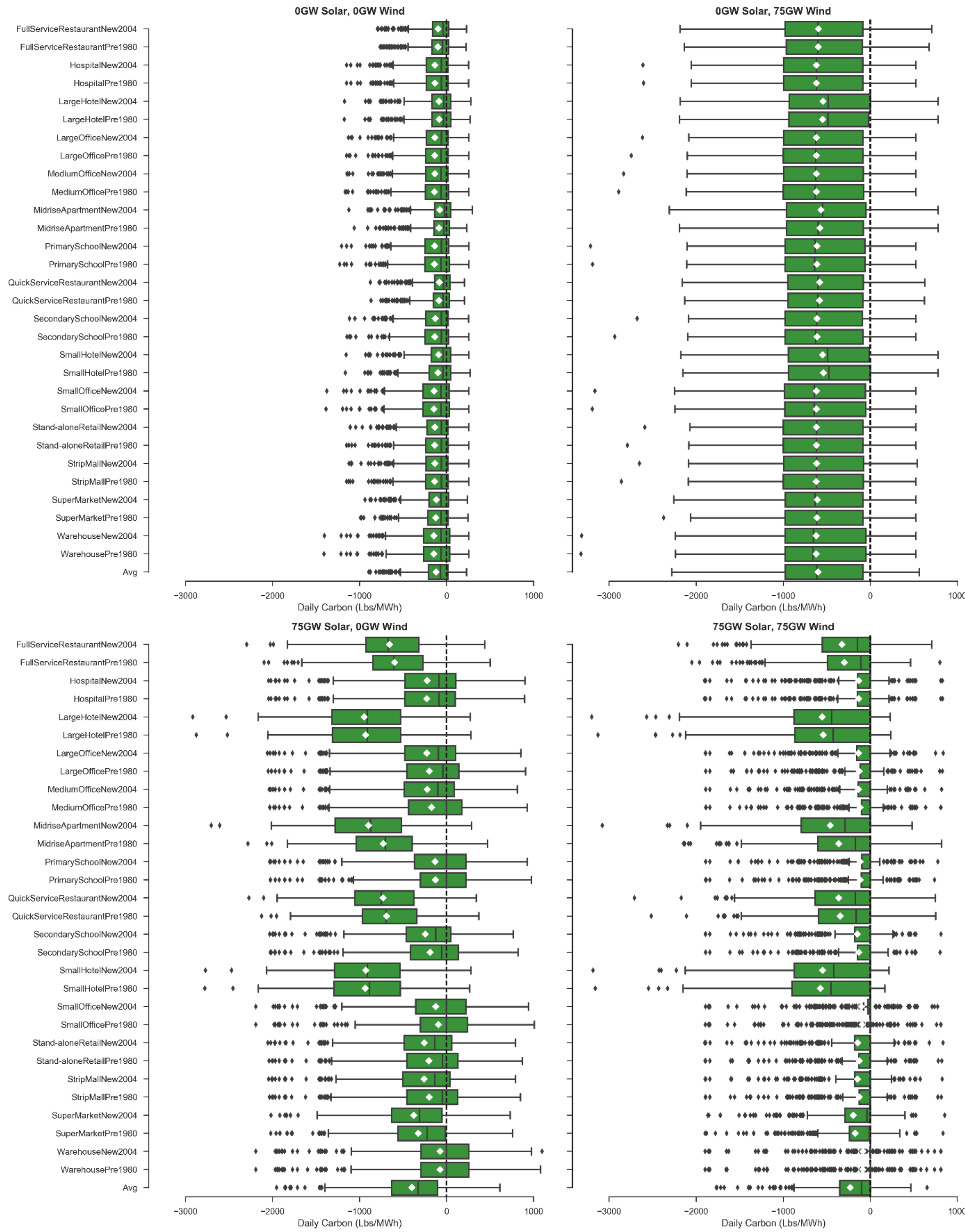
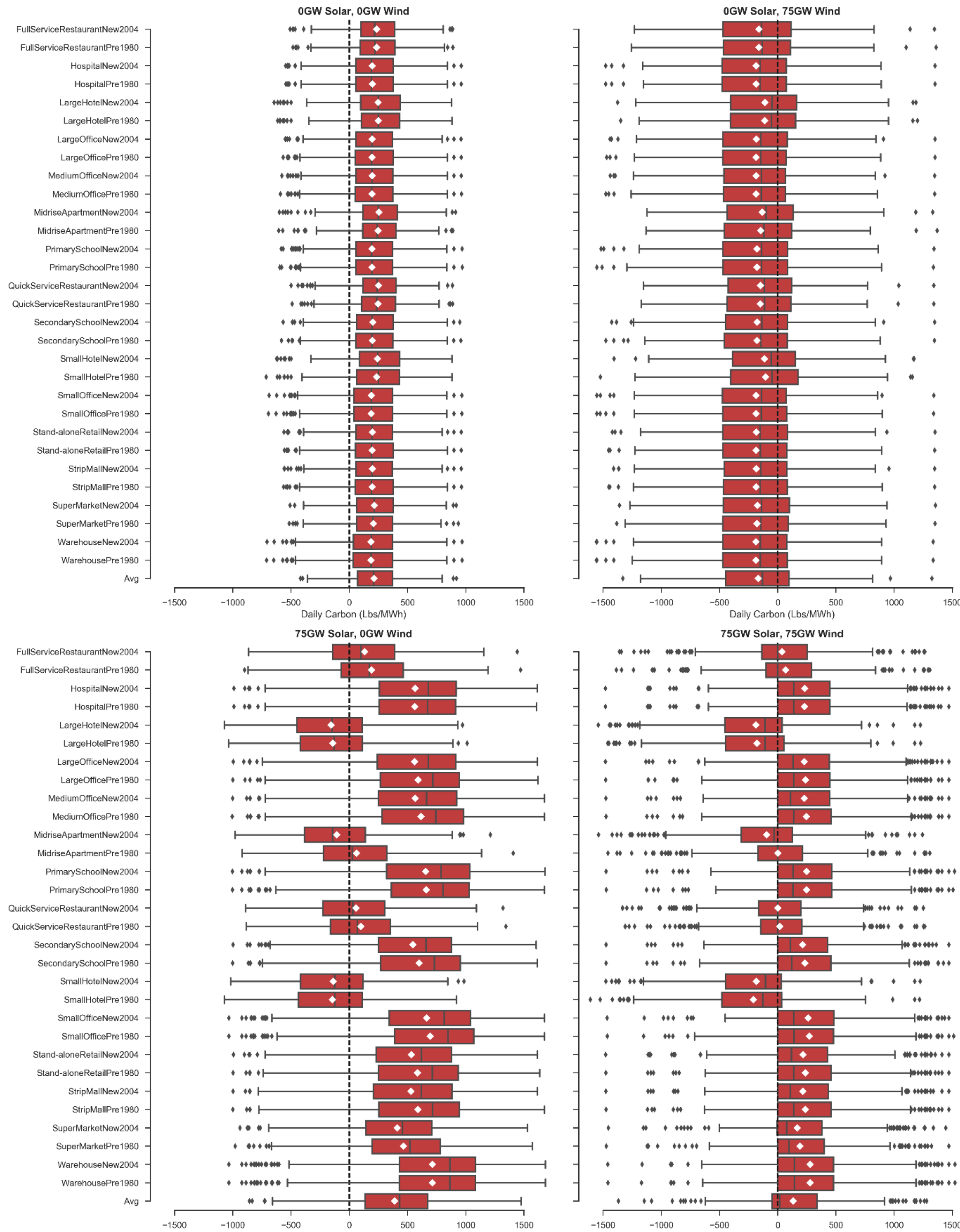


Figure 21: Sensitivity of DCM with Time-of-Use Energy Prices to Building Type (lbs/MWh)



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