

**Tradeoffs Between Revenue Enhancements and  
Emissions Reductions with Energy  
Storage-Coupled Photovoltaics**

by

Timothy David Heidel

S.B., Massachusetts Institute of Technology (2005)  
M.Eng., Massachusetts Institute of Technology (2006)

Submitted to the Engineering Systems Division  
in Partial Fulfillment of the Requirements for the Degree of

Master of Science in Technology and Policy

at the

Massachusetts Institute of Technology

June 2009

© 2009 Massachusetts Institute of Technology. All rights reserved.

Author .....  
Technology and Policy Program, Engineering Systems Division  
May 15, 2009

Certified by .....  
Stephen Connors  
Director, Analysis Group for Regional Energy Alternatives  
Thesis Supervisor

Accepted by .....  
Dava J. Newman  
Professor of Aeronautics and Astronautics and Engineering Systems  
Director, Technology and Policy Program



# Tradeoffs Between Revenue Enhancements and Emissions Reductions with Energy Storage-Coupled Photovoltaics

by

Timothy David Heidel

Submitted to the Engineering Systems Division  
on May 15, 2009, in Partial Fulfillment of the  
Requirements for the Degree of  
Master of Science in Technology and Policy

## Abstract

Energy storage has the potential to dramatically change the operation of photovoltaics by allowing for a delay between generation and use. This flexibility has the potential to impact both the revenue from generating electricity using photovoltaics and the associated emissions reductions. This thesis attempts to quantify the impacts of adding energy storage to photovoltaics.

The thesis formulates an optimization problem to solve for the optimal use of photovoltaics with energy storage from 2000 to 2005 in New England. The optimization is first solved using perfect information about historical solar generation, energy prices, and marginal emissions rates. Then, the model is solved using forecasted energy prices and emissions rates.

The analysis finds that adding energy storage to photovoltaics can increase annual revenues by over 30%. With energy storage capacity and power equal to solar capacity, annual revenues were found to increase between 19.3% and 31.1% with an energy storage efficiency of 100%. Unfortunately, the potential revenue increases were found to fall to between 9.1% and 21.3% with 80% efficient storage and between 3% and 14.5% with 60% efficient storage.

However, when owners utilize energy storage to maximize revenue, the changes in avoided emissions with energy storage are found to be negligible. Alternatively, it is possible to achieve significant increases in the emissions offset by photovoltaics with energy storage. However, when energy storage is utilized to maximize emissions reductions, revenue decreases. This tradeoff between the economic and environmental benefits that can be achieved when energy storage is added to photovoltaics means it is unlikely to be possible, without policy, to simultaneously achieve large increases in both revenue and avoided emissions. Policy mechanisms could be used to enable energy storage to enhance both the revenue from photovoltaics and avoided emissions.

Thesis Supervisor: Stephen Connors

Title: Director, Analysis Group for Regional Energy Alternatives



## Acknowledgments

This thesis has benefited immensely from the contributions of a large number of people. First, I would like to thank my research supervisor in the Technology and Policy Program (TPP), Steve Connors, for giving me the opportunity to work on an interesting problem. Steve's energy and enthusiasm are inspiring. This thesis has also benefited a great deal from discussions with other students in TPP.

I would also like to thank my PhD research supervisor, Marc Baldo, and the other members of the Soft Semiconductor Group at MIT. While they may not have contributed to the specific ideas, analysis, and results found in this thesis, they have played a large role in helping me keep my sanity throughout the process.

Finally, I would like to thank Nicole and my parents for their never-ending support and encouragement.



# Contents

<b>1</b>	<b>Introduction</b>	<b>13</b>
1.1	Central question . . . . .	17
1.2	Data and methodology . . . . .	18
1.3	Summary of results and conclusion . . . . .	20
1.4	Document roadmap . . . . .	21
<b>2</b>	<b>Data and Methodology</b>	<b>23</b>
2.1	Introduction to model methodology . . . . .	23
2.2	Key assumptions . . . . .	25
2.3	Limitations of method . . . . .	27
2.4	Optimization model formulation . . . . .	29
2.5	Data . . . . .	31
2.5.1	Solar generation . . . . .	31
2.5.2	Wholesale energy prices . . . . .	37
2.5.3	Marginal emissions rates . . . . .	41
2.6	Summary . . . . .	50
<b>3</b>	<b>Results with Perfect Information</b>	<b>51</b>
3.1	Photovoltaics with no storage: revenue and avoided emissions . . . . .	51
3.2	Maximizing revenue with energy storage . . . . .	54
3.2.1	Seasonal variations . . . . .	59
3.2.2	Energy storage efficiency . . . . .	60
3.2.3	Varied storage capacity and power ratings . . . . .	62

3.3	Maximizing avoided emissions with energy storage . . . . .	66
3.3.1	Seasonal variations . . . . .	69
3.3.2	Varied storage capacity and power ratings . . . . .	69
3.4	Summary . . . . .	73
<b>4</b>	<b>Results with Imperfect Information</b>	<b>75</b>
4.1	Information to inform optimizations . . . . .	76
4.2	Revenue optimization with day-ahead prices . . . . .	77
4.2.1	Day-ahead prices . . . . .	77
4.2.2	Results . . . . .	78
4.3	Emissions optimization with seasonal average emissions profiles . . . . .	81
4.3.1	Seasonally averaged emissions rate profiles . . . . .	81
4.3.2	Results . . . . .	83
4.4	Summary . . . . .	86
<b>5</b>	<b>Discussion and Policy Implications</b>	<b>87</b>
5.1	Policy implications . . . . .	87
5.2	Wholesale vs. retail electricity prices . . . . .	90
5.3	Most important characteristics of energy storage . . . . .	92
5.4	The cost of energy storage . . . . .	92
5.5	Short run vs. long run implications of results . . . . .	95
<b>6</b>	<b>Conclusion</b>	<b>97</b>
6.1	Summary . . . . .	97
6.2	Future work . . . . .	100
<b>A</b>	<b>Solar Generation Data Normalization</b>	<b>103</b>
<b>B</b>	<b>GAMS Optimization Model Formulation</b>	<b>107</b>



# List of Figures

1-1	Energy storage installed system ratings . . . . .	14
1-2	Applications for energy storage . . . . .	15
2-1	Average hourly solar radiation in New England. . . . .	33
2-2	Normalized hourly solar generation data . . . . .	34
2-3	Weekly and daily maximum solar generation . . . . .	35
2-4	Hourly solar generation in selected weeks . . . . .	36
2-5	Hourly real-time energy prices in New England. . . . .	39
2-6	Maximum daily real-time energy prices . . . . .	40
2-7	Hourly real-time energy prices in selected weeks . . . . .	42
2-8	CO <sub>2</sub> marginal emissions rates . . . . .	45
2-9	SO <sub>2</sub> marginal emissions rates . . . . .	47
2-10	NO <sub>X</sub> marginal emissions rates . . . . .	48
2-11	Marginal emissions rates in selected weeks . . . . .	49
3-1	Hourly revenue for photovoltaics only . . . . .	52
3-2	Hourly CO <sub>2</sub> emissions for photovoltaics only . . . . .	54
3-3	Hourly revenue for photovoltaics with energy storage, optimizing for revenue . . . . .	55
3-4	Optimal use of energy storage and photovoltaics in selected weeks . .	56
3-5	Seasonal impacts of adding energy storage to photovoltaics, optimizing for revenue . . . . .	59
3-6	Impact of energy storage efficiency . . . . .	60

3-7	Revenue increases for photovoltaics with varying energy storage capacities and powers . . . . .	63
3-8	Hourly revenue for photovoltaics with energy storage, optimizing for avoided emissions . . . . .	67
3-9	Seasonal impacts of energy storage, optimizing for avoided emissions .	70
3-10	CO <sub>2</sub> avoided emissions increases for photovoltaics with varying energy storage capacities and powers . . . . .	71
4-1	Real-time and day-ahead wholesale energy prices in selected weeks . .	79
4-2	Revenue increases for photovoltaics with varying energy storage capacities and powers using day-ahead prices in revenue optimization. . . .	82
6-1	Revenue increases for photovoltaics with varying energy storage capacities and powers . . . . .	98
A-1	Normalized hourly solar generation . . . . .	104
A-2	Comparison of normalized NSRD solar radiation data to normalized measured solar generation data in selected weeks . . . . .	106

# List of Tables

3.1	Revenue and avoided emissions for photovoltaics with no storage. . .	53
3.2	Revenue and avoided emissions for photovoltaics with energy storage.	58
3.3	Revenue with varied energy storage efficiencies. . . . .	61
3.4	Maximum revenue with unlimited energy storage. . . . .	65
3.5	Revenue and avoided emissions for photovoltaics with energy storage, optimizing for avoided emissions. . . . .	68
3.6	Maximum CO <sub>2</sub> avoided emissions with unlimited energy storage. . .	72
4.1	Revenue and avoided emissions with energy storage, optimizing for revenue using day-ahead energy prices. . . . .	80
4.2	Revenue and avoided emissions with energy storage, optimizing for avoided emissions using seasonally averaged emissions rate profiles. .	84
4.2	Revenue and avoided emissions with energy storage, optimizing for avoided emissions using seasonally averaged emissions rate profiles (continued). . . . .	85
5.1	Value of CO <sub>2</sub> avoided emissions necessary to incentivize emissions op- timization. . . . .	89
5.2	Present value of adding 1 MW/1 MWh storage to 1 MW photovoltaics.	94



# Chapter 1

## Introduction

Photovoltaics are currently experiencing a period of rapid growth. Annual global production increased from 1,744 MW in 2006 to 5,950 MW in 2008, a growth of 241% in only two years [1]. The growth in photovoltaics has largely been due to aggressive policy mechanisms such as rebates, feed-in tariffs, tax credits, and renewable portfolio standards [2][3]. These policy mechanisms have driven growth in manufacturing capacity and impressive cost reductions [4]. However, despite rapid growth, photovoltaics continue to provide only a small fraction of worldwide electricity generation [5].

Solar resource variability and intermittency are important limiting factors in the deployment and growth of photovoltaics at large scale [6]. The uncertainty associated with intermittency increases the risks and the costs of deploying photovoltaics relative to other generation technologies such as coal or natural gas [7]. Owners of photovoltaic generating plants are typically unable to bid into day-ahead energy wholesale markets in restructured power markets and can be subject to additional fees or penalties levied by the grid operator to ensure high grid reliability. These challenges will only become more important as photovoltaic installations continue to grow.

Energy storage technologies are also experiencing a period of rapid growth and have attracted significant investment in the past several years [10]. There are currently a range of technologies that have potential to provide utility-scale energy storage [8]. Figure 1-1 illustrates power and energy ratings for installed systems as of November

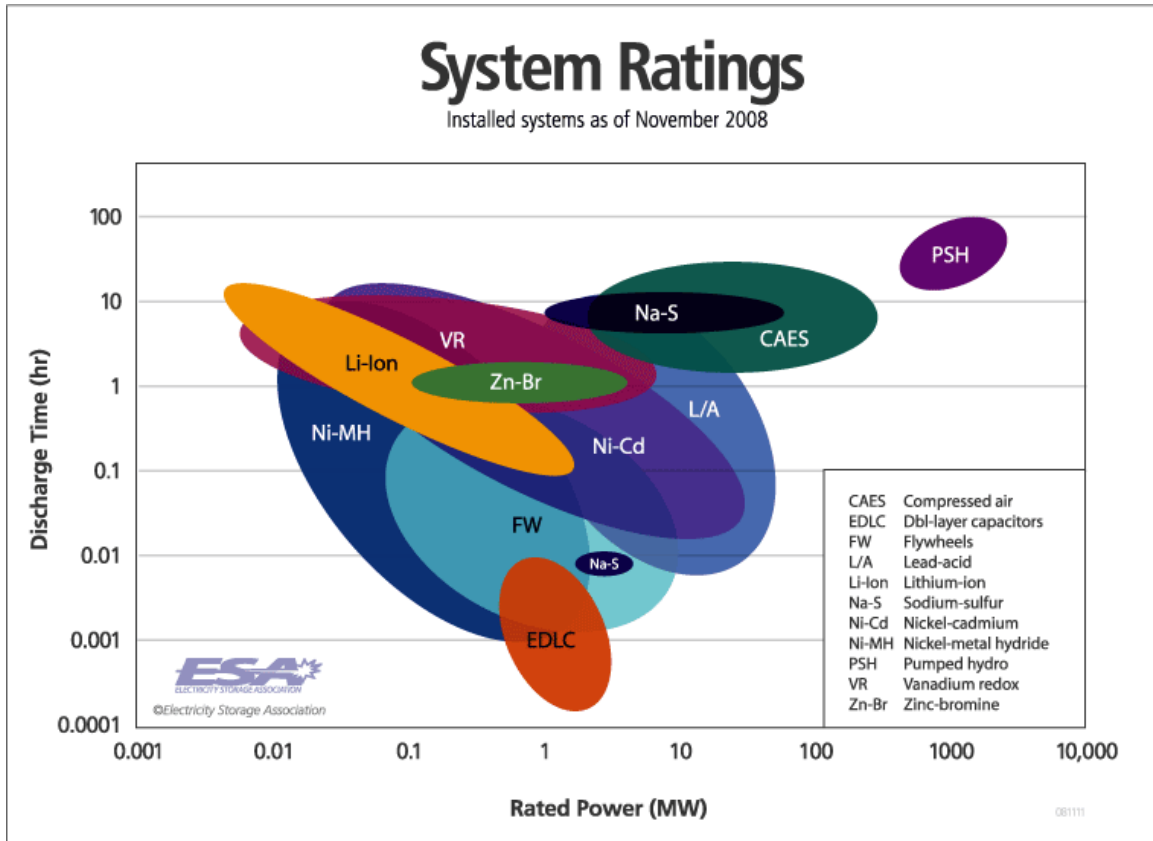
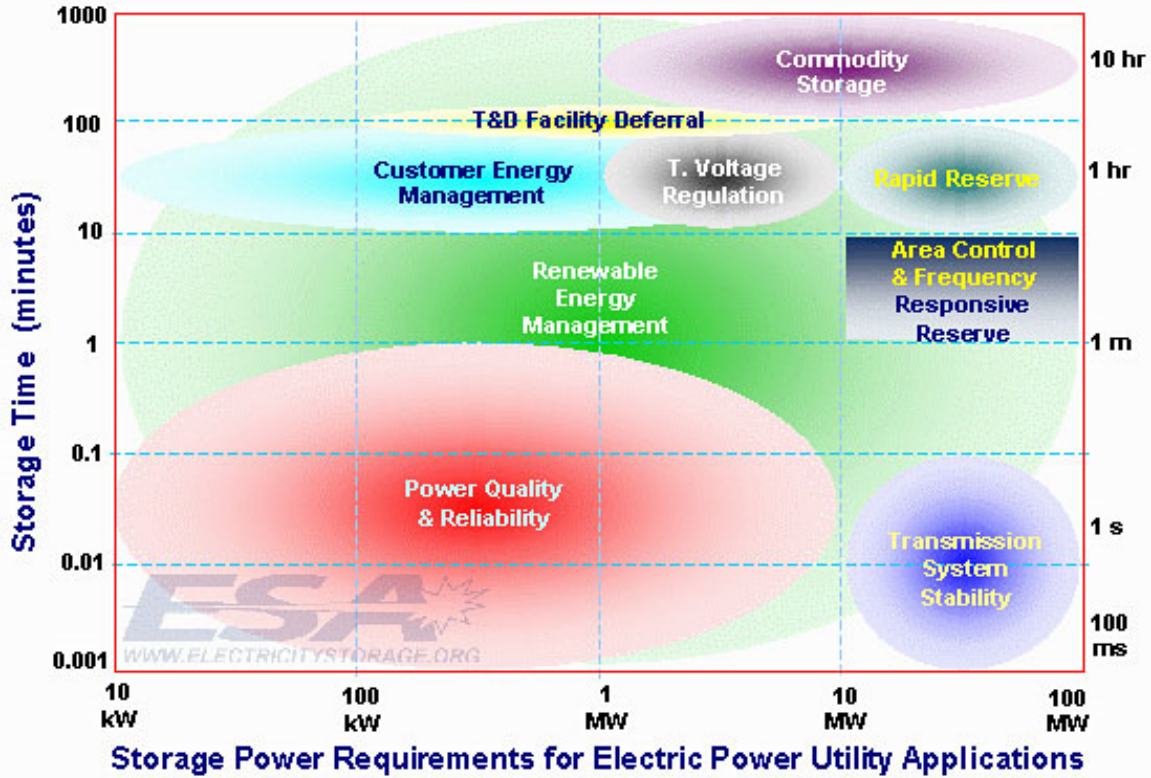


Figure 1-1: Energy storage installed system ratings. A variety of technologies are currently being pursued for the storage of electricity. Pumped hydro storage (PSH) and compressed air energy storage (CAES) have already been demonstrated at large scale while other technologies such as Lithium-Ion batteries (Li-Ion) and flywheels (FW) have only been demonstrated at smaller scales. Some technologies are ideally suited for high power applications while others are best matched for applications requiring large energy capacity [8][9]. Source: Electricity Storage Association[8].

2008 by storage technology. First, there are a number of competing battery storage chemistries in development including lithium ion, sodium sulphur, nickel cadmium, and zinc bromine. Lithium ion batteries, the mainstay technology for small electronics and laptop computers, is currently being pursued aggressively for the electric vehicle market. Sodium sulphur batteries have been deployed at utility-scale in a small number of pilot projects [11]. Next, vanadium redox and polysulfide bromide flow batteries, which utilize liquid electrolytes to store energy, have also started to attract attention. Flow batteries promise flexibility in both system power and system capacity. Vanadium redox flow batteries have been coupled to wind generation



Data from Sandia Report 2002-1314

Figure 1-2: Applications for energy storage. Electricity storage can serve many purposes on the modern power grid. Each application and the technology best matched to it depends on storage capacity (i.e., storage time) and storage power (i.e., charging/discharging rates). For example, systems designed to maintain transmission system reliability require high power but do not need long duration storage. Source: Electricity Storage Association[8].

in several locations worldwide [12]. Finally, there are a number of additional non-battery storage technologies that have significant potential. Compressed air energy storage, supercapacitors, and kinetic energy storage using flywheels are all showing great commercial promise. Detailed descriptions of each of these technologies is beyond the scope of this thesis and have been reported elsewhere [13][14][15].

Utility-scale energy storage installations can serve a range of purposes as illustrated in Figure 1-2 [16][17]. Energy storage systems can be used for commodity arbitrage in wholesale power markets to shift electricity generated during low-price periods to high-price periods [18]. In areas with high volatility in energy prices the systems can help reduce price fluctuations. Electricity storage systems can also be

used to provide ancillary services including voltage and frequency regulation or short term reserve capabilities [19][20]. Strategically located energy storage systems can also be installed to postpone necessary transmission and/or distribution upgrades [21]. The systems can eliminate transmission capacity constraints or bottlenecks [22]. System reliability can also be improved by utilizing energy storage systems to provide standby power during transmission or distribution system failures. Finally, energy storage technologies have the potential to alleviate some the problems associated with the variability and intermittency of renewable generation resources, thus enabling large scale deployment of renewables [23][24].

Energy storage systems can be used to provide two primary benefits when coupled with renewable generators. Variations on the power grid introduced by intermittent renewable generators can increase the costs of operating the grid through reduced reliability or a greater need for ancillary services [25]. Storage can absorb intermittency or minute-to-minute variations in generation reducing the additional costs imposed by renewable generation sources.

Electricity storage can also be used to time shift the delivery of electricity generated with renewables [26]. The impacts of time shifting the delivery of solar generated electricity is the primary focus of this thesis. Time shifting the delivery of solar generated electricity to periods with higher energy prices can improve the economics of employing photovoltaic systems. However, the added flexibility afforded by energy storage has the potential to impact not only the revenue from generating electricity using photovoltaics but also the emissions reductions associated with the installation of the photovoltaics. While revenue increases could make photovoltaics and energy storage more cost-competitive with conventional generation technologies, adding energy storage could actually *reduce* the emissions benefit associated with installing the photovoltaics alone. Shifting solar generation to higher priced periods could also shift generation to hours that have lower marginal emissions rates. Alternatively, at the cost of increased revenue, energy storage can be used to significantly increase the emissions offset by photovoltaics. The tradeoffs between these two scenarios are the focus of this thesis.



While storage can be used for all of the above applications individually, using storage to provide multiple services may be necessary to make storage economical in the short term. Many previous studies have tried to quantify the various economic benefits associated with the range of services storage can provide. Walawalkar et al. found that energy storage is best suited for energy arbitrage and providing regulation services in the New York power markets as they are currently structured [18]. Butler et al. studied a number of business cases for deploying energy storage including applications in reducing volatility, adding storage to boost the effective capacity of transmission lines, and adding storage to combined heat and power facilities to smooth output [27]. Shioshansi et al. estimated the arbitrage value of electricity storage in the PJM interconnection, considering the impacts of fuel price changes, transmission constraints, efficiency, storage capacity, and fuel mix [26].

Several general mathematical approaches have also been proposed to estimate the value of electricity storage. Mokrian and Stephen developed a “Stochastic Programming Framework” for valuing electricity storage focusing on optimizing intra-day arbitrage [28]. Haesen and Driesen developed a “Multi-objective Valuation of Electricity Storage Services” that attempts to perform a global optimization to find the optimal energy storage deployment from the perspective of the grid as a whole [29]. Both of these frameworks use multi-stage stochastic programming and dynamic programming to optimize energy storage use. The models are solved using idealized, modelled input data.

## 1.1 Central question

This thesis attempts to answer the following central question: **Does coupling energy storage to photovoltaics enhance or reduce the economic and emissions benefits associated with small to mid-scale photovoltaic installations?**

This question could be of great interest to policymakers designing renewable energy policies with environmental motivations. A detailed understanding of the potential tradeoff between the economic and environmental benefits of using photovoltaics cou-

pled with energy storage could help guide the design of new policies. The results of the analysis discussed here may also be of interest to energy storage researchers. The results indicate which technical attributes of energy storage systems — storage charging and discharging rates or storage capacity — are the most important parameters in the design of energy storage coupled photovoltaic systems.

Several previous studies have also attempted to quantify the impacts of coupling energy storage with renewable generation sources. Benitez et al. studied the economics of coupling wind power and hydroelectric energy storage in Alberta, Canada [30]. They developed a nonlinear mathematical optimization program to investigate the economic and environmental implications of high wind penetration. As in this thesis, they used historical data on the operation of the electric grid as inputs to their optimization model. They determined a cost for wind-generated electricity in Alberta and a cost for reducing CO<sub>2</sub> emissions. Finally, they found that new pumped hydropower storage facilities in Alberta could provide most of the peak load requirements eliminating the need for new peak-load generation facilities.

Bathurst and Strbac also studied the economic value of combining wind generation and energy storage [31]. They studied the optimal dispatch of energy storage given the short-term power exchange prices and potential wind farm imbalance penalties. They quantified the ability for storage to mitigate wind forecasting errors.

Finally, some studies have also focused on quantifying the impacts of coupling energy storage and photovoltaics. Su et al. examined the economics of actually coupling the two technologies and interfacing them with the grid [32]. Paatero and Lund investigated the network impacts such as voltage stability of adding energy storage to photovoltaics [33].

## 1.2 Data and methodology

In this thesis, I estimate what the benefits would have been of adding energy storage to photovoltaics for the years 2000 to 2005 in New England. I formulate and solve a Nonlinear Programming Problem (NLP) to optimize the use of photovoltaics with

energy storage using hourly historical time series electricity prices, solar generation, and power grid marginal emissions rates.

Throughout this thesis, I assume that owners/operators of photovoltaic installations are primarily motivated by the potential economic benefits offered by energy storage and will usually optimize the use of photovoltaics with energy storage to maximize revenue. However, environmentally motivated policy mechanisms could be designed to give owners incentive to also consider the avoided emissions from the operation of energy storage-coupled photovoltaics. Therefore, I also discuss the results of using the model to maximize emissions reductions. I discuss potential policy designs or scenarios where owners could place greater value on the emissions reductions associated with operating photovoltaics and energy storage.

Initially, the optimization problem is solved in the presence of perfect information about prices, emissions rates, and solar generation. Solving the model with perfect information gives an upper bound on the benefits that could be achieved with energy storage. The generator revenue and avoided emissions with energy storage are compared to the calculated revenue and emissions reductions for photovoltaics alone. The changes in the revenues and avoided emissions in these two cases represent the impacts of coupling energy storage to photovoltaic installations.

Solving the model with different energy storage charging rates, efficiencies, and capacities gives an indication of which technical attributes of energy storage systems are most important for photovoltaic applications. I also study how seasonal and weekly variations in the operation of the power system impact the potential benefits of adding energy storage to photovoltaics.

Finally, I solve the model while imposing limitations on the information used as inputs for the optimization to find more realistic estimates of the actual revenue and emissions enhancements that could be achieved with energy storage.

The results described in this thesis can be used to estimate the likely benefits of adding energy storage to existing or future photovoltaic installations in New England. While the scope of this study is restricted to the New England region, the same methodology can be applied to other regions.

### 1.3 Summary of results and conclusion

The results of the analysis reveal that there is a tradeoff between the economic and environmental benefits that can be achieved when energy storage is added to photovoltaics. The analysis finds that adding energy storage to photovoltaics can yield significant increases in revenue. With energy storage capacity and power equal to solar generation capacity, revenue increases were found to be between 19.3% and 30.5% with an energy storage efficiency of 100%. Unfortunately, the potential revenue increases were found to fall to between 9.1% and 21.3% with 80% efficient storage and between 3% and 14.5% with 60% efficient storage. However, when owners utilize energy storage to maximize revenue, the changes in avoided emissions with energy storage are found to be negligible. Adding energy storage to photovoltaics does not yield additional environmental benefits beyond those achieved by the installation of photovoltaics alone.

Alternatively, it is possible to achieve significant increases in the emissions offset by photovoltaics by adding energy storage. Adding energy storage with equivalent capacity and power to the capacity of the solar generation was found to yield avoided CO<sub>2</sub> emissions increases of up to 56.2% with 100% efficient storage. With large storage installations, it was found that avoided CO<sub>2</sub> emissions could increase as much as 116%. If policies were promulgated to give owners the incentive to maximize avoided emissions, energy storage could yield large emissions reductions. However, absent policy, when energy storage is utilized to maximize emissions reductions, revenue decreases.

Policy mechanisms could be used to enable energy storage to enhance both the revenue from photovoltaics and avoided emissions. A detailed understanding of the tradeoff between the economic and environmental benefits of using photovoltaics with energy storage could help guide the appropriate design of these policies. Ultimately, the value owners derive from CO<sub>2</sub> emissions reductions would have to be large enough to ensure the photovoltaics yield the same or greater revenue than if energy storage was used to maximize revenues without considering emissions reductions. The value of

CO<sub>2</sub> emissions reductions that would be necessary to achieve the maximum possible CO<sub>2</sub> emissions reductions was found to be in the range of \$40 to \$60 per metric ton.

Finally, the results of the analysis in this thesis may also be of interest to energy storage researchers. The results indicate that for the application of adding energy storage to photovoltaics for energy arbitrage, storage capacity is a more important parameter than storage power. If the cost of capacity (MWh) and power (MW) for a given technology are similar, the ideal ratio of storage power to storage capacity is roughly 0.3 or 0.4.

## 1.4 Document roadmap

In Chapter 2, I first detail the modeling methodology used in this thesis. I then suggest some of the key assumptions used throughout. Next, I discuss the formulation of the non-linear optimization problem. Finally, I characterize the energy price, solar generation, and emissions rates used as inputs to the model.

Chapter 3 and Chapter 4 discuss the results of the analysis. Chapter 3 discusses the optimal revenue and emissions benefits made possible by the addition of energy storage to photovoltaics in the presence of perfect information. The results represent an upper bound of what would be possible when coupling energy storage to photovoltaics. Chapter 4 details the revenue and emissions benefits that are likely to be achieved under more realistic circumstances with imperfect information. The chapter discusses the information that is likely to be most helpful in maximizing the benefits derived from energy storage.

Chapter 5 discusses the broader policy implications of these results. The chapter also discusses the most important characteristics of energy storage including cost, capacity, and power. Finally, the short and long term implications are discussed. Chapter 6 concludes and suggests future work.



# Chapter 2

## Data and Methodology

This chapter discusses the data and methodology utilized in this thesis to assess the impacts of coupling energy storage and photovoltaics. The analysis generates a counterfactual prediction of the benefits that would have been achieved by adding energy storage to photovoltaics for the years 2000 to 2005 in New England. I formulate and solve a Nonlinear Programming Problem (NLP) using the General Algebraic Modelling System (GAMS) to optimize the use of energy storage-coupled photovoltaics. The model uses hourly historical electricity prices, hourly estimates of solar generation, and hourly power grid marginal emissions rates.

### 2.1 Introduction to model methodology

In the absence of energy storage, electricity generated with photovoltaics must be used immediately. Photovoltaic generators are price takers and must sell energy to the grid at the prevailing real-time price of electricity.<sup>1</sup> Using hourly historical data for prices, solar generation, and marginal emissions rates it is straightforward to

---

<sup>1</sup>This thesis assumes the owner of the photovoltaics actually sells the energy generated using photovoltaics and, therefore, refers to the economic benefits of energy storage coupled photovoltaics as revenue. However, in the case of small photovoltaics installations, the owner may simply use the generated electricity locally in lieu of purchasing electricity from the grid. In these cases the economic benefits of coupling energy storage to photovoltaics would actually be in the form of savings instead of revenue. Furthermore, the benefits of adding energy storage to photovoltaics in these cases might differ from those studied in this thesis as the owner would also save any transmission, distribution, and delivery costs associated with grid purchased electricity.

determine both the revenues generated by photovoltaics and the avoided emissions due to the addition of photovoltaics to the power grid. However, with the addition of energy storage, owners of photovoltaic generation can choose to sell solar-generated electricity immediately or store the energy and sell it during higher priced periods. The time shift between solar generation and peak power grid prices has been well characterized previously [34].

The model formulated and solved in this thesis optimizes the operation of energy storage to either maximize generator revenues or maximize avoided emissions. The model compares the generator revenue and avoided emissions with energy storage to the calculated revenue and emissions reductions for photovoltaics alone. The change in the revenues and avoided emissions in these two cases represents the impact of coupling energy storage to photovoltaic installations.

Initially, the model is solved with perfect information about prices, emissions rates, and solar generation to find the upper bound of the benefits that could be achieved with energy storage. Optimization with perfect information is equivalent to an owner/operator having perfect predictions about future solar generation, energy prices, and emissions rates. In a practical application, it would be impossible for owners to have all this information. However, advanced forecasting tools can likely be developed to give good estimates for optimization. In this thesis, I explore some of the data inputs that could be used as simple forecasting tools such as day-ahead electricity prices or seasonally adjusted average daily price curves. Solving the optimization model using imperfect price and emissions inputs and calculating the resulting revenues using the actual values for prices and emissions gives an indication of how good simple algorithms could be.

Finally, solving the model with different energy storage charging rates, efficiencies, and capacities gives an indication of which technical attributes of energy storage systems are most important for photovoltaic applications. I also study how seasonal and weekly variations in the operation of the power system impact the potential benefits of adding energy storage to photovoltaics.



## 2.2 Key assumptions

In order to assess the impact of coupling energy storage to photovoltaics, I have developed a simplified model of the interactions between photovoltaics and the power grid. The model formulated in the next section relies on a number of important assumptions, each of which is described here.

First, the analysis depends on the primary assumption that the amount of electricity produced by the photovoltaic installation in question does not change the dispatch order of the electric power grid. The analysis assumes that the operation of energy storage-coupled photovoltaic installations causes fossil generating units operating at the margin to ramp up or down in any given hour but not be turned on or off. The historical energy prices and marginal emissions rates characterized below are only valid for the specific group of units generating power in each hour. If a photovoltaic installation were to cause a generator to be shut down in any given hour, the market clearing price for generation and the marginal emissions rates would change for that hour. Determining the dispatch order for fossil generating units requires complex optimal power flow models that take into account individual bids from each generator and a detailed knowledge of transmission constraints and load forecasts. This is beyond the scope of this thesis.

The assumption that the proposed photovoltaic installations with and without storage do not change the power grid dispatch order limits the analysis to small to mid-size photovoltaic facilities that are significantly smaller than most of the conventional generating units on the grid. This is true for the vast majority of photovoltaics installations currently being considered today but could change if installations grow significantly in size. It is difficult to quantify exactly what size generating facility would violate this assumption. However, it is expected that the analysis in this thesis would be relevant for the vast majority of photovoltaic installations that are likely to be installed in New England. As long as photovoltaics generation remains small relative to the total load, this assumption should hold.

A second related assumption required by this analysis is that time shifting pho-

photovoltaic generation does not require additional short term reserve capacity such as spinning reserves. The addition or elimination of the need for additional reserve capacity and the associated emissions changes are not taken into account in this analysis. This assumption also limits the maximum size of the photovoltaic installation for which this analysis is relevant.

A third assumption also relating to the operation of the power grid needed for this analysis is the assumption that photovoltaic generators are able to sell electricity to the grid at any time at the real time energy price determined in the wholesale markets. This assumption relies heavily on market regulations and policy mechanisms for small to medium size generators. Net metering and market participant rules continue to evolve. This assumption will likely always be satisfied for smaller photovoltaic installations in commercial and residential settings where the load and the photovoltaic system are on the customer side of the meter. In these cases, the analysis in this thesis will actually yield conservative revenue/savings impacts as the appropriate price to compare photovoltaic generation to would be the retail price of electricity which includes the transmission and distribution costs in addition to the cost of wholesale energy.

Finally, the analysis requires the assumption that owners and/or operators of photovoltaic installations are primarily motivated by the potential economic benefits offered by energy storage and will seek to optimize the use of photovoltaics with energy storage to maximize revenue. This behavior is typical for investments of any kind and the assumption should be satisfied in the vast majority of cases. Environmentally motivated policy mechanisms that give a value to avoided emissions could be designed to give owners incentive to also consider avoided emissions from the operation of energy storage-coupled photovoltaic generating facilities. I will discuss some of these potential policy designs or scenarios in Chapter 5.

## 2.3 Limitations of method

The approach to calculating the revenue impacts and the avoided emissions due to intermittent generation sources used in this thesis has a number of important limitations.

First, the analysis in this study is a strictly historical analysis. Care should be used in extrapolating the results of this thesis to predict future revenue and/or emissions impacts. The results of this thesis are the result of the specific solar radiation, energy prices, and emissions rates that occurred in the past. The results are derived from a large number of days over 6 years. Therefore, the results are expected to give the correct order of magnitude, or, at the very least, the direction of change when adding energy storage to photovoltaics. However, the analysis is not meant to be used to predict the exact revenue or emissions benefits that a specific system might realize.

Predicting future revenues is particularly difficult as the restructured electricity markets in New England continue to evolve. As existing markets become more established and new markets, such as the forward capacity market, are added, electricity prices and electricity price daily profiles could change significantly. Furthermore, the development of the retail market and price responsive demand could also change the relative price changes throughout the day. Changes such as these could have a large impact on the expected revenues associated with energy storage and photovoltaics.

Predicting future marginal emissions rates is also an area with significant uncertainty. Changes in the relative costs of fuel prices for conventional generation technologies would change the bidding strategies of different generators and, therefore, could have an impact on the carbon intensity of marginal electricity generation. High oil and natural gas prices could drive greater electricity production by coal generation facilities while policy frameworks that put a price on CO<sub>2</sub> emissions could shift greater generation to cleaner burning natural gas facilities.

Second, the analysis does not account for any geographical variations in the results. New England is treated as a homogeneous region. In reality, geographic locations in New England will actually experience different magnitudes of solar radiation (this

would be especially true in areas with significant shadowing, for example in valleys surrounded by hills or mountains). Furthermore, the prices for electricity in any given location could differ from the New England-wide energy price due to locational marginal prices. Finally, the specific plants that are ramped down due to energy sold by energy storage coupled photovoltaics could depend on local transmission or distribution constraints. In these cases the calculated marginal emissions rates are unlikely to have high accuracy.

Finally, even without significant changes in the future fuel mix on the New England grid, the calculation of marginal emissions rates described later in this chapter also has a number of limitations. Most importantly, the calculation does not account for electricity generation from non-fossil units. Non-fossil generation facilities, such as nuclear or hydropower plants, are not required to report emissions data to the EPA under the Clean Air Act. The method for calculating marginal emissions rates may not be entirely accurate if non-fossil plants are used to respond to changes in load. This is because the marginal emissions rates are calculated by taking a weighted average of the emissions of all of the plants following the load in any given hour. Nuclear plants typically run at full output and do not respond to short term changes in load. Therefore, the operation of nuclear plants should not typically impact the marginal emissions rates. Hydroelectric plants also do not have to report their operations to the EPA. Hydropower plants can and do respond to load. Therefore, their omission from the calculation of marginal emissions rates does adversely impact the accuracy of the calculations. However, hydropower makes up a relatively small proportion of the generation capacity in New England, limiting the magnitude of the potential inaccuracies. The method of calculating marginal emissions rates also has no way of accounting for changes in imports and exports of power from the New England region to other regions or vice versa. ISO-NE does not have detailed information on which units actually generate the power that is imported into New England. Therefore, it is impossible to calculate emissions rates for the imported power. The relatively small number of external connections on the New England power grid likely limits the potential magnitude of the adverse impacts of this limitation.

The limitations discussed above must be kept in mind when evaluating the results of this thesis and using the results to predict future values. The results discussions in the next two chapters should not be interpreted as precise calculations of exactly what revenues and avoided emissions photovoltaics with energy storage would have achieved in 2000 to 2005 or will achieve in the future. However, the results do indicate the direction and approximate magnitude of the impacts of adding energy storage to photovoltaics.

## 2.4 Optimization model formulation

An optimization model is used to quantify the impact of adding energy storage to photovoltaics. The model is run for each day in the study period. The objective for this model is to maximize revenue within a 24 hour period. The total revenue is calculated by taking the sum of the product of the energy price in each hour by the sum of the generation from the photovoltaics and the energy used from energy storage in each hour. The total revenue is maximized subject to the constraints on the energy storage efficiency, power, and capacity. The solar generation, energy prices, and marginal emissions rates in each hour are assumed to be known. Mathematically, the objective function is formulated as follows:

$$Revenue = \sum_{i=1}^{24} (PVUsed_i + STUsed_i) \times Price_i \quad (2.1)$$

where *Revenue* is the total revenue during the entire day, *PVUsed<sub>i</sub>* and *STUsed<sub>i</sub>* represent the power used in hour *i* from the photovoltaics and energy storage respectively, and *Price<sub>i</sub>* represents the wholesale energy price in hour *i*. *Price<sub>i</sub>* is an input to the model.

Similarly, the avoided emissions resulting from the use of an energy storage coupled photovoltaic installation is calculated by taking the sum of the product of the marginal emissions rate in each hour by the sum of the generation from the photovoltaics and the energy used from energy storage in each hour. This is formulated mathematically as follows:

$$AvoidedEmissions = \sum_{i=1}^{24} (PVUsed_i + STUsed_i) \times ER_i \quad (2.2)$$

where *AvoidedEmissions* is the total emissions reduction during the entire day, *PVUsed<sub>i</sub>* and *STUsed<sub>i</sub>* represent the power used in hour *i* from the photovoltaics and energy storage respectively, and *ER<sub>i</sub>* represents the marginal emissions rate for the emissions type in question in hour *i*. *ER<sub>i</sub>* is an input to the model. Avoided emissions values have been calculated for *CO<sub>2</sub>*, *SO<sub>2</sub>*, and *NO<sub>x</sub>* in this thesis.

All power generated in each hour must either be used immediately or added to energy storage:

$$PV_i = PVUsed_i + PVStored_i \quad (2.3)$$

where *PV<sub>i</sub>* is the energy generated by the photovoltaics in hour *i*, an input to the model, and *PVUsed<sub>i</sub>* and *PVStored<sub>i</sub>* represent the power used directly and the power stored, respectively, in hour *i*.

The amount of energy in storage at the end of each hour is given by the sum of the energy in storage at the end of the previous hour and the energy added to storage by generation multiplied by the storage efficiency less the energy in storage used in each hour. This is given as follows:

$$ST_i = ST_{i-1} + PVStored_i \times StorageLoss - STUsed_i \quad (2.4)$$

where *ST<sub>i</sub>* represents the energy in storage at the end of hour *i*, *PVStored<sub>i</sub>* represents the solar energy added to storage during hour *i*, *STUsed<sub>i</sub>* represents the amount of energy in storage used during hour *i*, and *StorageLoss* represents the efficiency of the energy storage, the fraction of energy retained in the process of storing and retrieving energy from the storage system. For the purposes of this analysis *StorageLoss* is assumed to be a constant value irrespective of the amount of time energy is stored.

The characteristics of the energy storage are described by the the following constraints:

$$0 \leq ST_i \leq StorageCapacity \quad (2.5)$$

$$0 \leq STUsed_i \leq StoragePower \quad (2.6)$$

$$0 \leq PVStored_i \leq StoragePower \quad (2.7)$$

where  $ST_i$ ,  $STUsed_i$ , and  $STStored_i$  represent the energy in storage after hour  $i$ , the energy in storage used during hour  $i$ , and the energy added to the storage during hour  $i$ , respectively.  $StorageCapacity$  and  $StoragePower$  represent the physical constraints on energy storage that are used as an input to the model.

The model above is formulated as a Nonlinear Programming Problem (NLP) and solved using the COINOPT solver in the GAMS environment.

## 2.5 Data

The model formulated above requires three sets of hourly time series data:

- Solar resource data
- Wholesale electricity prices
- Marginal emissions rates

I discuss each of these data sets in the following sections.

### 2.5.1 Solar generation

Solar radiation data from the National Solar Radiation Database (NSRD), a product of the Renewable Resource Data Center at the National Renewable Energy Laboratory, is used as input to the model [35]. The National Solar Radiation Database was originally released in 1992. At that time the database contained hourly solar radiation information for 239 weather stations throughout the United States for the years 1961-1990. Subsequently, in 2007, the database was updated to include the years 1991 to 2005 and expanded to 1454 stations. The database contains measured solar radiation data for some locations. However, the vast majority of the data is

generated using models based on meteorological and geographical inputs. The user manual contains the following disclaimer about the data in the database [35]:

Nearly all of the solar data in the original and updated versions of the NSRDB are modeled. The intent of the modeled data is to present hourly solar radiation values that, in the aggregate, possess statistical properties (e.g., means, standard deviations, and cumulative frequency distributions) that are as close as possible to the statistical properties of measured solar data over the period of a month or year. These data do not represent each specific hourly value of solar radiation to the same or equivalent accuracy as the long-term statistics.

The uncertainty in the solar input data should be kept in mind when interpreting the results of this thesis. The analysis in this thesis is intended to estimate the direction of change (positive or negative) and the order of magnitude of the benefits that could be achieved by coupling energy storage and solar installations. The thesis does not explicitly quantify or predict exactly what the benefits would have been at any specific location or in any specific hour. Instead, the analysis described below focuses on aggregate results over many hours and days; the results do not rely entirely on any specific hour's result. Therefore, the data found in the NSRD is sufficient.

The NSRD includes data for 66 sites located within the six states of New England. Specific details of each of the sites can be found elsewhere [35]. I average the hourly solar radiation from all of these sites in order to generate hourly time series data to use as an input to the model formulated below. Figure 2-1 displays the solar radiation, averaged across these 66 sites, for every hour from 2000 to 2005. Each subplot displays one year's worth of data with hours within each day displayed across the horizontal axis and days displayed on the vertical axis. These plots clearly indicate both the increase in the duration and the intensity of solar radiation during the summer months in New England. The plots also clearly show the variability that makes photovoltaics problematic; dark horizontal lines on these plots represent cloudy days with little direct solar radiation.



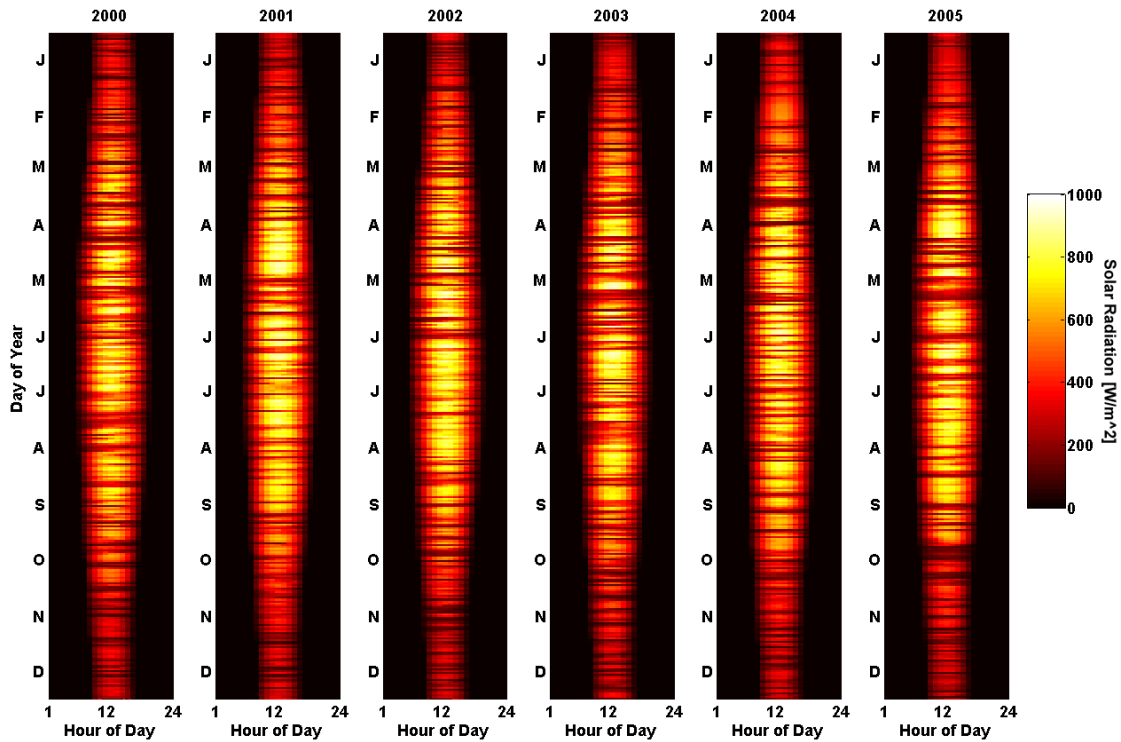


Figure 2-1: Average hourly solar radiation in New England. Average solar radiation at all of the New England sites in the NSRD for every hour from 2000 to 2005. Each subplot displays one year of data. The 24 hours in each day are displayed on the horizontal axis while the vertical axis represents all 365 days in each year. Longer days during the summer are clearly discernible in the middle of these plots. Horizontal black stripes throughout the data represent cloudy days with little solar generation.

While the shape of the generation from a photovoltaic generating facility is likely to match the shape of the solar radiation, one needs to assume a specific efficiency or capacity factor of the solar array to determine values for hourly generation.<sup>2</sup> In order to achieve as realistic an efficiency as possible I performed the normalization of the NSRD data using actual solar generation data from sites throughout the New England for the years 1998 to 2002.<sup>3</sup> The solar radiation data in the NSRD was scaled to represent a 1 MW photovoltaic installation. This size installation is used

<sup>2</sup>There is an assumption here that the power generated from a photovoltaic array will vary linearly with illumination intensity. The linearity of this relationship varies with different photovoltaic technologies.

<sup>3</sup>Generation data for actual solar installations in New England was supplied by Schott Applied Power for an earlier study. Unfortunately, data after 2002 was unavailable, necessitating the use of the modeled NSRD data in this study.

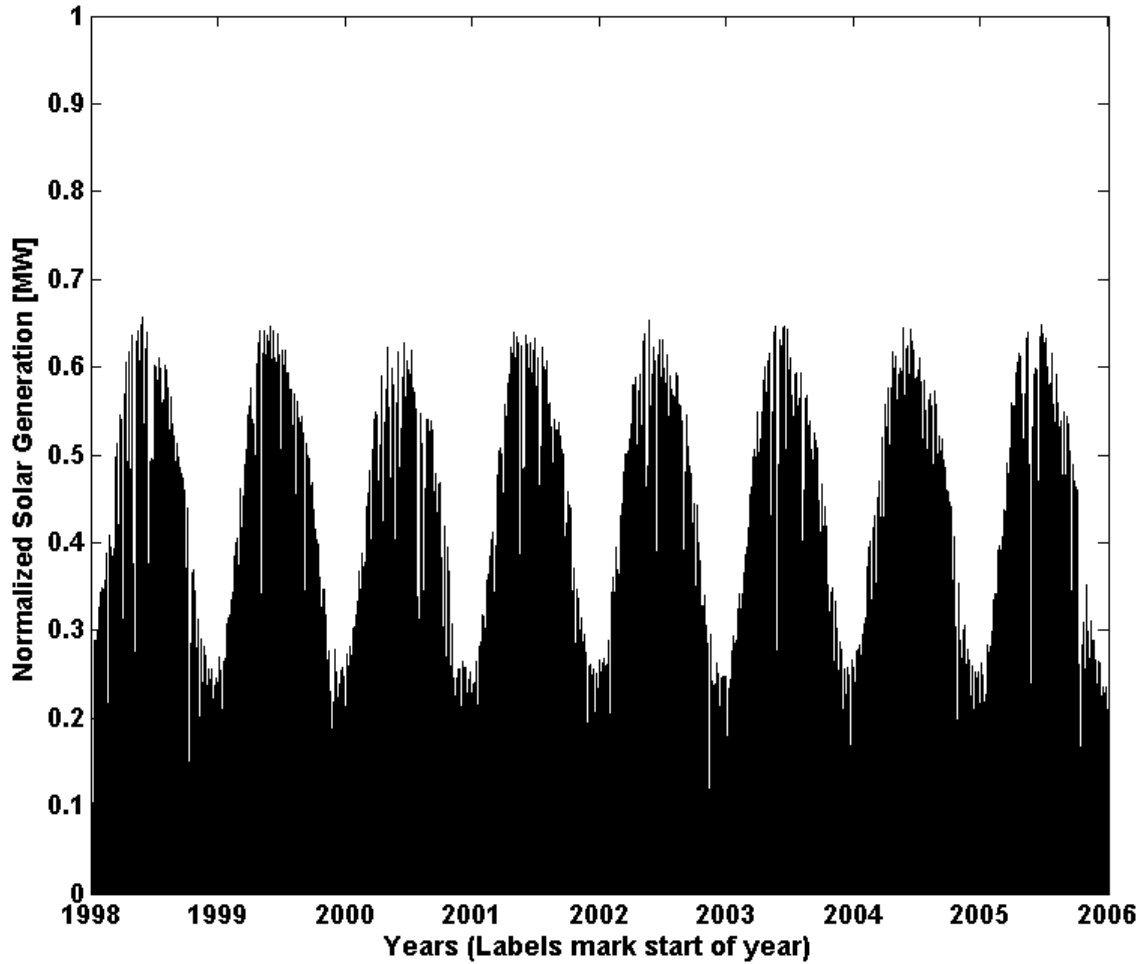


Figure 2-2: Normalized hourly solar generation data. The data is normalized to represent generation from a 1 MW capacity installation. While the specific generation in any given day varies from year to year, the overall shape of the solar generation curve is similar for each year.

throughout the analysis in this thesis. Energy storage capacities and powers are always quoted relative to this installation size. Appendix A gives additional detail on the process used to normalize the NSRD solar radiation data to represent the hourly power output of a 1 MW photovoltaic installation. Figure 2-2 displays the hourly solar generation after normalization. This plot clearly indicates that while the generation on any given day may vary from year to year, the overall shape of the generation curve is similar in each year.

Figure 2-3(a) displays the weekly maximum solar radiation for the years 2000 to 2005. This plot also confirms that while the solar radiation may vary significantly on

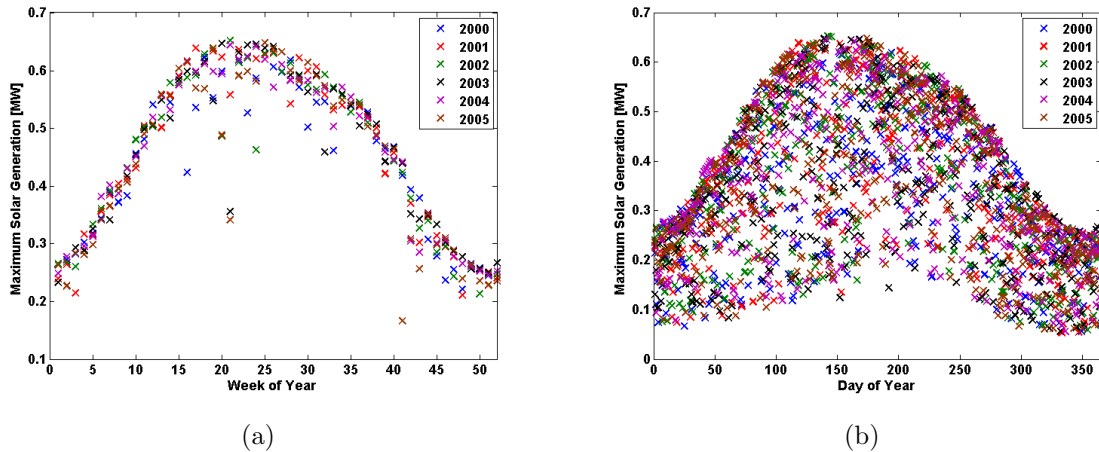


Figure 2-3: Weekly and daily maximum solar generation. (a) Weekly maximum average solar generation from 2000 to 2005. While there are minor differences from year to year, the weekly maximum solar radiation levels are similar each year. As expected, higher radiation values occur in the summer relative to the winter. The seasonal variation in solar radiation will likely cause significant seasonal variations in the impacts of coupling energy storage and photovoltaics. (b) Daily maximum solar generation from 2000 to 2005. The maximum solar generation from day to day is highly variable.

an hour by hour or day by day basis, the weekly and monthly features are consistent from year to year. The use of energy storage is expected to smooth the hour-by-hour and day-by-day variations in the solar resource. Therefore, the aggregate impact of adding energy storage to photovoltaics should be consistent from year to year.

Hourly and daily variations in solar generation are the most important ones for the application of energy storage. Day to day solar generation variability is illustrated in Figure 2-3(b) for the years 2000 to 2005. Figure 2-3(b) displays the maximum solar generation for each day throughout the year. While this figure shows the same increase in maximum generation during the summer months illustrated earlier in Figure 2-3(a), it also shows the significant variation from day to day within each week of the year. This figure illustrates the variable nature of solar generation based on weather changes and indicates that the variability is greatest during summer months.

Finally, Figure 2-4 illustrates the hourly solar generation for four representative weeks throughout 2005. As expected, the height and width of each day's solar generation curve is highest during the summer and the solar generation is centered around

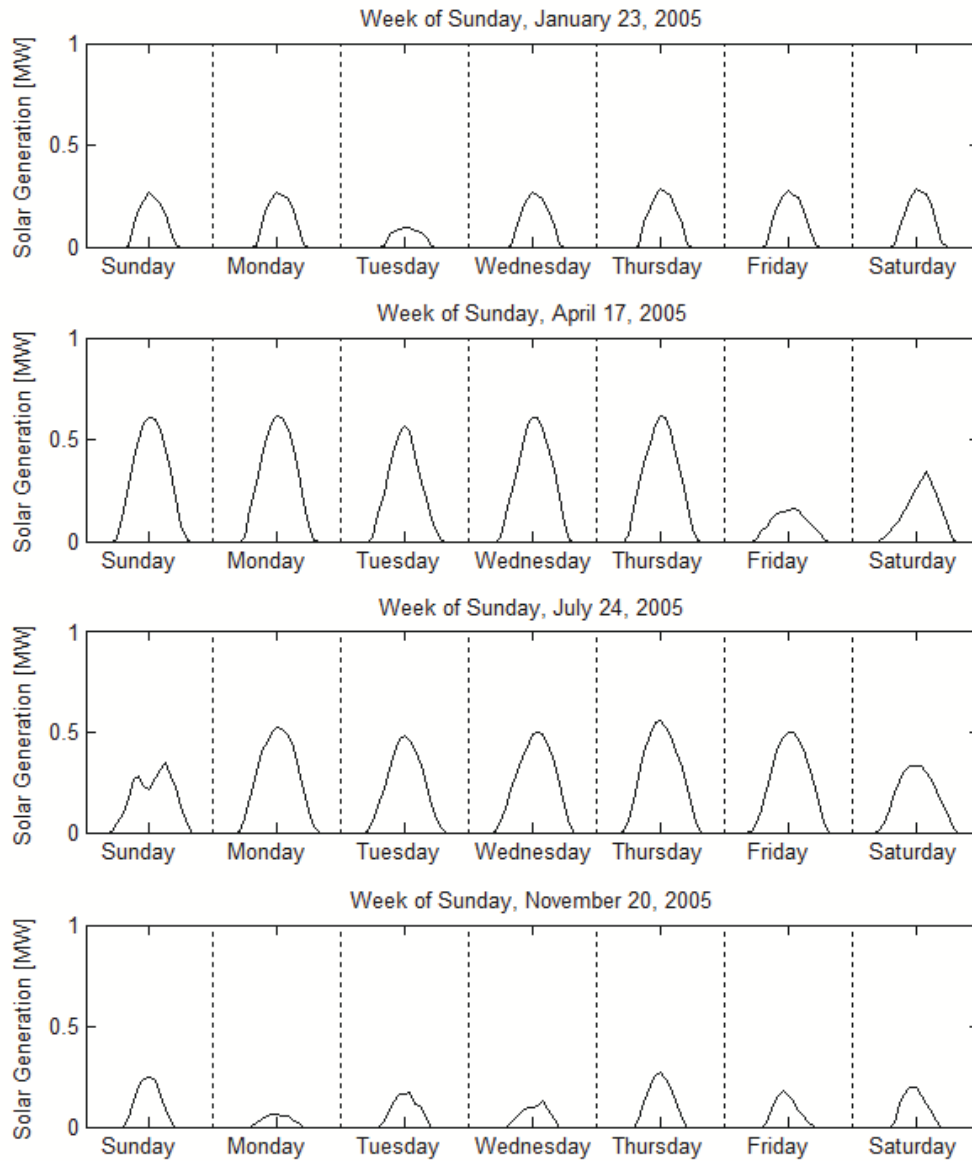


Figure 2-4: Hourly solar generation in selected weeks. The shape of solar generation in each day is relatively constant while the magnitude can change significantly based on weather. As expected, the peak generation during summer months is greater than the peak generation during the winter. Solar generation is also spread across a wider range of hour during the summer months relative to winter generation.

midday throughout the year. Occasional cloudy days with lower solar generation are also clearly illustrated. The difference in shape between the curves illustrated here and the shape of hourly energy prices to be discussed below creates the opportunity for energy storage to add economic value to photovoltaic installations.

## **2.5.2 Wholesale energy prices**

Historical energy prices are also required by the model formulated above. Hourly energy prices from the New England power market are used as input to the model. The New England power market is comprised of several regulated and semi-regulated submarkets governing the sale of a variety of products and services related to the delivery of reliable electricity to end users. These submarkets can be grouped roughly into three primary categories: (1) markets that deal in the actual sale of electricity, (2) markets for the transmission and distribution of electricity, and (3) markets to maintain reliability in the operation of the grid. This last set of markets includes the sale of ancillary services such as voltage and frequency stability, the operation of short term reserves, and capacity markets to ensure sufficient future capacity.

Utility-scale energy storage can participate in most of the markets listed above. Energy storage's relative value in each of the markets depends on the specific technical attributes of the energy storage and the location where it is deployed. For example, energy storage would have greater value in transmission markets in locations with significant transmission system congestion. In realistic installations, energy storage is likely to be operated in a manner that allows it to participate in multiple markets. For example, an energy storage system could simultaneously be used for commodity arbitrage and for the provision of ancillary services. Energy storage technologies such as solid-state batteries that are not designed to be discharged deeply are ideally suited for this type of use.

This thesis focuses on the participation of solar generation with energy storage in markets for the actual sale of electricity. In New England, there are two primary markets for the sale of electricity: a day-ahead market and a real-time market. The day-ahead market is the primary market where wholesale electricity is bought and

sold. Each day, generators submit quantity and price bids to the grid operator, the New England Independent System Operator (ISO-NE), for their operation in each hour of the following day. ISO-NE then performs a least-cost security-constrained unit commitment and dispatch analysis on all of the submitted bids in order to determine the generation units that should operate in each hour to meet the predicted load at the lowest cost. In order to bid into the day-ahead market, generators must have some level of certainty regarding their operations on the following day. In addition to other penalties that may be assessed, generators that are unable to actually supply the energy that they were dispatched for in the day-ahead market must buy the difference in the real-time market.

The real-time market is a balancing market that makes up for differences in the actual load and the predicted load and differences between dispatched generation and real generation in each hour. Photovoltaics typically sell their generation in the real-time market. The analysis in this thesis assumes photovoltaic generators are able to sell electricity in the real-time market.

Historical real-time energy price data from ISO-NE is used as an input to the model [36]. Hourly real-time energy price data is available for free download from ISO-NE's website for every hour from May 1, 1999, the date New England restructured wholesale markets began preliminary operation. The ISO-NE data includes the energy price in each hour as well as congestion and marginal loss components at 940 different nodes throughout New England. The "energy price", congestion component, and marginal loss component together define the locational marginal prices at each of these locations in each hour. In this analysis I have only used the "energy price" component in calculating the changes in revenue due to energy storage. Using only the "energy price" values gives a conservative estimate of changes in revenue that would have resulted from the addition of energy storage to photovoltaics in most locations throughout New England. The increases in revenue could be significantly higher in specific locations with high congestion or high losses where locational marginal prices can spike during high load periods.

Figure 2-5 displays the hourly real-time energy prices in New England for the years

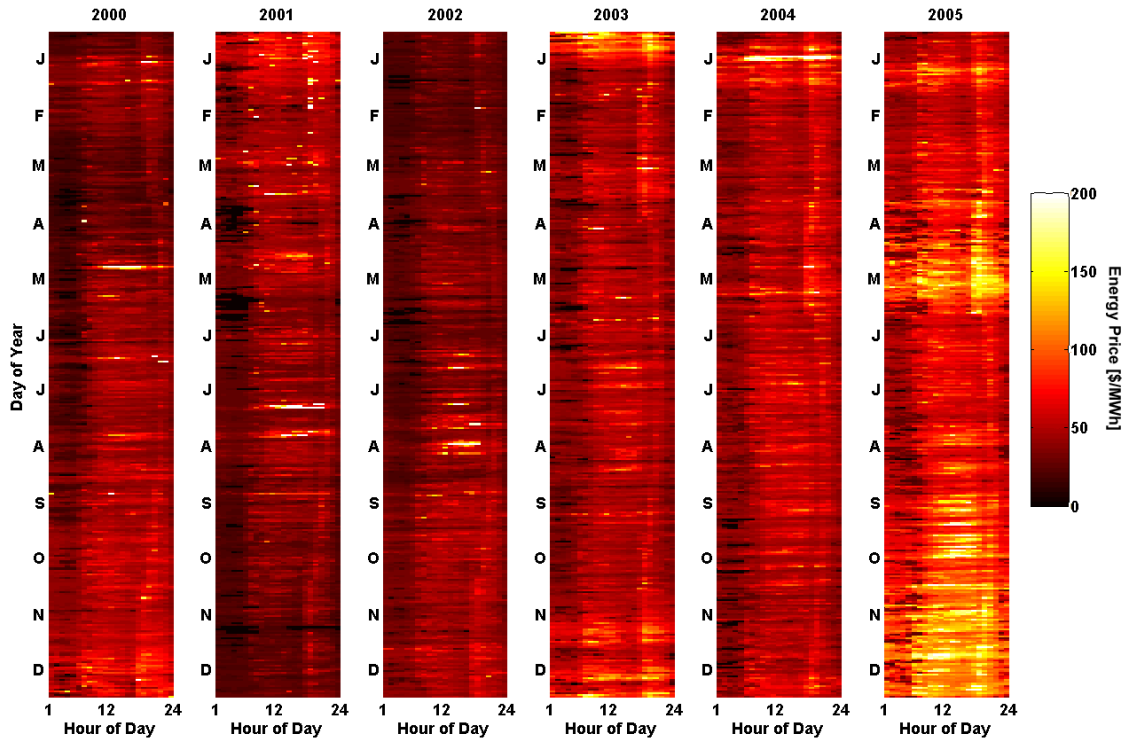


Figure 2-5: Hourly real-time energy prices in New England. Each plot displays the final real-time hourly energy prices for one year. The 24 hours in each day are represented on the horizontal axis while the 365 days of the year are on the vertical axis. As illustrated by the color bar at right, Brighter colors indicate higher prices while dark areas represent lower prices. It is difficult to isolate reliable seasonal changes in energy prices. However, peak prices in white appear more commonly in the winter and summer periods. In New England, energy prices are typically set by natural gas generating facilities. Therefore, the differences in prices from year to year likely reflect the changes in natural gas prices. (This is the most likely explanation for the high prices in 2005.)

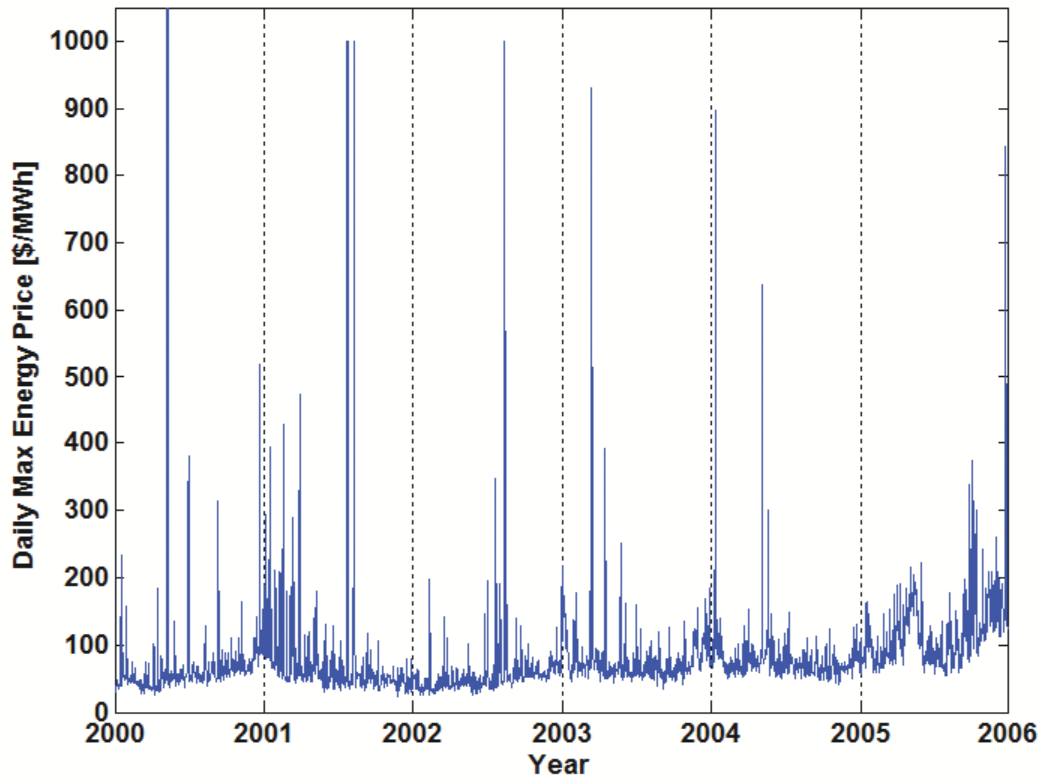


Figure 2-6: Maximum real-time daily energy prices. The maximum real-time price of electricity can vary dramatically from day to day. Since 2001 New England has had a price cap on generator bids of \$1000/MWh. This price cap was reached in both 2001 and 2002 but then was not reached from 2003 to 2005. The data indicates that very high price hours are relatively rare and can occur in any season.

2000 to 2005. Brighter colors in these plots indicate higher prices while dark areas represent lower prices. A number of notable features are visible in these plots. First, two vertical stripes are apparent in each of the plots corresponding to price peaks both in the morning period and the evening period throughout the year. These peaks are more pronounced in the winter. The second of these peaks occurs later in the evening during the summer months. Comparing these plots to the solar generation plots in Figure 2-1 illustrates the time shift between peak solar generation and peak energy prices in New England. Energy storage is expected to be able to eliminate the shift between peak prices and peak solar generation illustrated in these two figures.

While there is significant variation in prices from one day to the next, there do



not appear to be any consistent seasonal variations from year to year. For the most part, the highest price peaks occur in summer and winter. However, price spikes can also occur during other periods. Figure 2-6 plots the daily maximum energy prices for the years 2000 to 2005. This plot clearly shows the infrequency of peak energy prices. The plot also illustrates that peak prices can occur at any time of the year.

Given the infrequency of peak energy prices, the primary value of adding energy storage to photovoltaics is unlikely to result from shifting solar generation to very high priced periods. Instead, the value from adding energy storage to photovoltaics is more likely to arise primarily from intra-day shifts in generation. Figure 2-7 displays the hourly energy prices for four selected weeks in 2005. It is difficult to identify a typical daily cost curve shape during any of these weeks. The shape of the energy price curve in any given day can vary significantly from the previous day. Evening price peaks are observed in both the winter and spring weeks. Consistent with the data displayed earlier in this section, this plot confirms that the overall level of prices does not appear to be correlated with season. Natural gas sets the marginal prices in New England during most peak hours. Therefore, the overall level of the energy prices in any given week appears to be a reflection of the underlying cost of natural gas. The level of prices is not the most important feature that determines the economic value added by energy storage. Instead, the relative changes in prices within each day will determine the magnitude of the impact on revenues that energy storage can yield.

### **2.5.3 Marginal emissions rates**

An estimate of the marginal emissions rates during each hour is required to estimate the impact on emissions resulting from the addition of energy storage to photovoltaics. Marginal emissions rates describe the emissions that are offset by adding a small amount of renewable generation to the power grid. When a small quantity of solar generation is added to the grid, the fossil generators are required to serve a smaller load. Reductions in the output of the fossil generators lead to reductions in emissions. The use of marginal emissions rates is an attractive way to estimate the benefits of

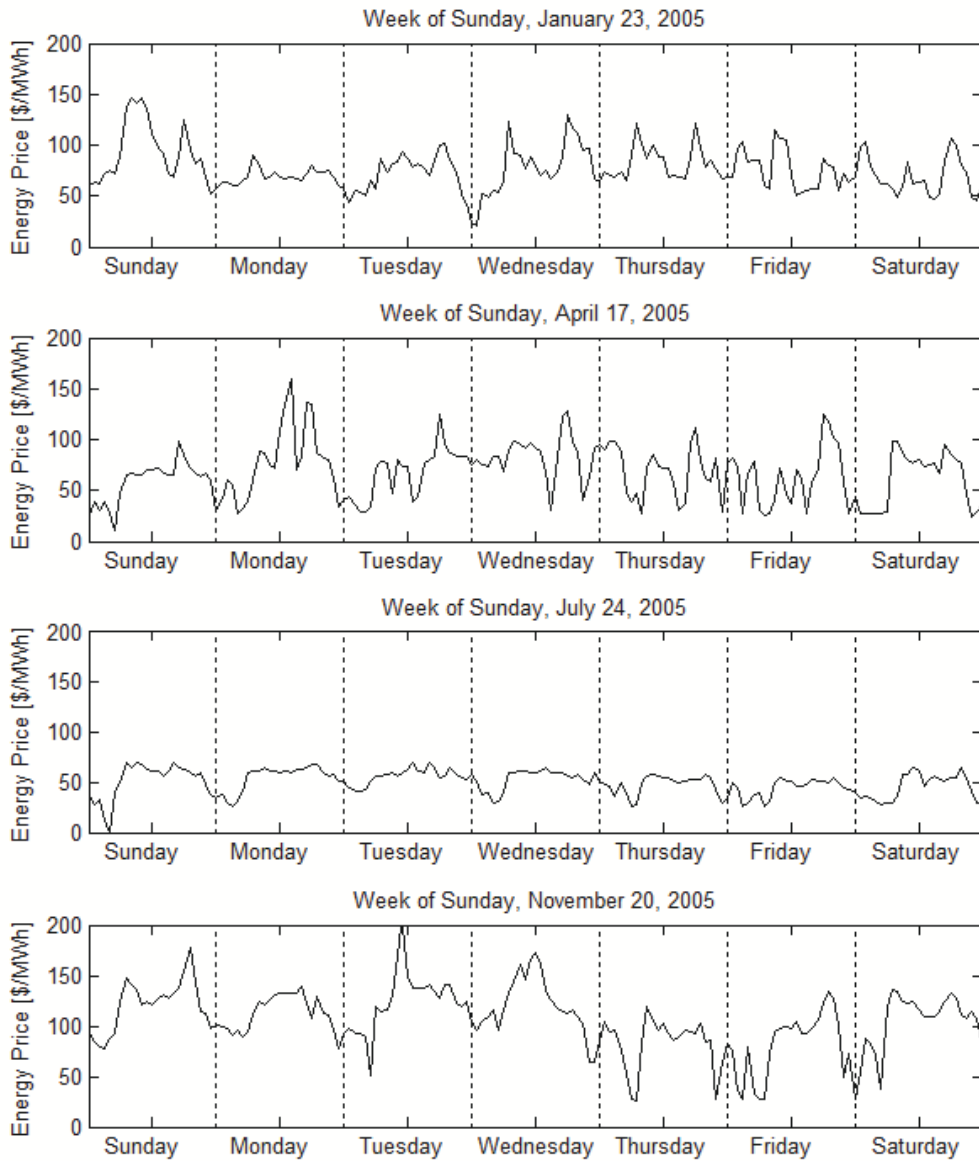


Figure 2-7: Hourly real-time energy prices in selected weeks. It is difficult to identify a typical daily cost curve shape. The shape of the energy price curve in any given day can vary significantly in shape from the previous day. Evening price peaks are observed in both the winter and spring week illustrated above. This plot confirms that the overall level of prices does not appear to be correlated with season.

small to mid-scale renewable installations that do not change the operation of the grid as a whole.

The Analysis Group for Regional Energy Alternatives (AGREA) at MIT, has developed a framework for calculating historical marginal emissions rates. Previously, the framework has been used to assess the emissions impacts of wind and solar generation as well as the impact of exposing consumers to real-time prices [37][38][39][40]. This thesis is the first attempt to apply the avoided emissions framework to estimate the impact of utility-scale energy storage.

The AGREA avoided emissions methodology uses data from the US Environmental Protection Agency’s Continuous Emissions Monitoring (CEM) dataset and Emissions & Generation Resource Integrated Database (eGRID) [41][42]. The CEM dataset includes hourly measurements of emissions data and operating parameters for every fossil generating unit throughout the United States. The CEM dataset was originally designed as part of the Acid Rain Program initiated by the 1990 Clean Air Act. Every electricity generating unit using high sulfur fuel or with a capacity greater than 25 MW must measure and report hourly emissions of CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>X</sub>. In addition to the emissions data, units must also report other operating parameters such as heat rate and generation output in each hour. The data in the CEM dataset is available for free download from the EPA website [43]. The eGRID database is used to identify the geographic location of the units with operational data in CEM. The geographic location of the units is then used to separate units into different regions. For the purposes of this thesis, the eGRID data was used to identify all of the generation units in New England.

The calculation of marginal emissions rates has been discussed in some depth elsewhere [40]. The method to calculate marginal emissions rates is briefly summarized here.

First, we identify generating units that are following the load shape in each hour. These units are identified by first calculating the current output of each unit as a fraction of total capacity. Units that are not operating, operating at full load, or operating at very low output (i.e., turning on or off) are not counted as “Load

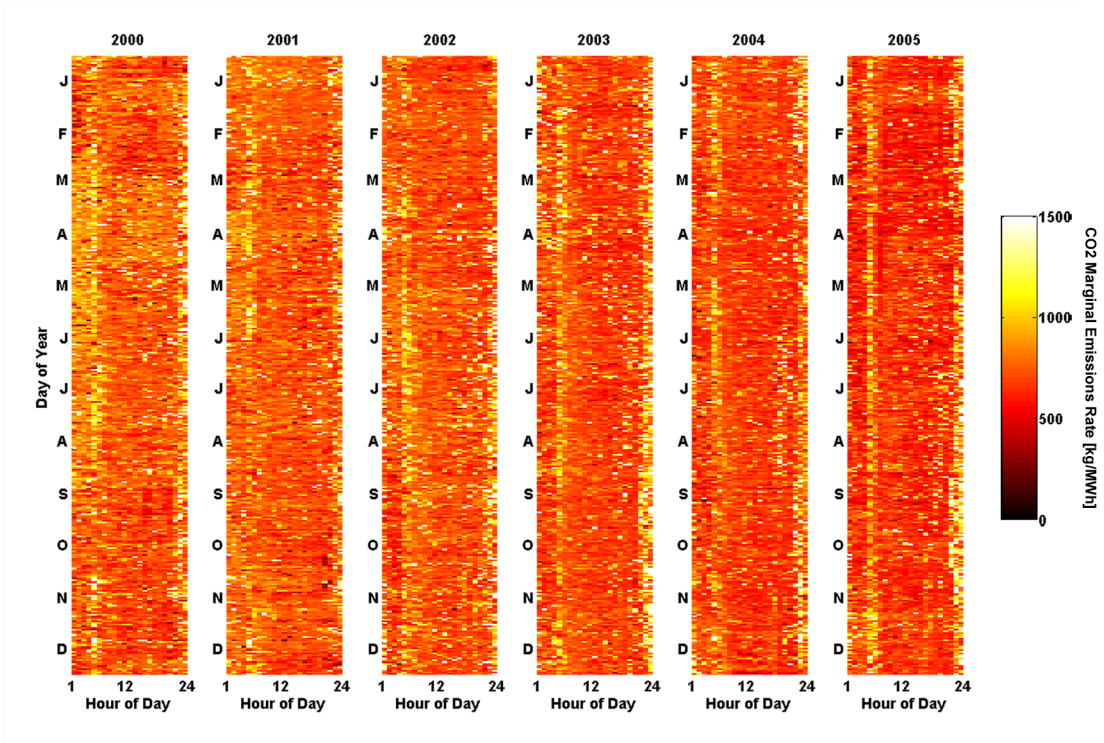
Shape Following.” The change in output from one hour to the next for each of the remaining generation units is compared to the change in total system load. If a generation unit’s output and the system load change in the same direction then that unit is designated as “Load Shape Following.” Further, if a unit was identified as “Load Shape Following” in a previous hour and that unit’s output and the system load did not change, that unit is still considered to be “Load Shape Following” in the subsequent hour.

Finally, to calculate the marginal emissions rates in each hour, we take a weighted average of the emissions from units following the system load in each hour. We perform the weighted average for each hour by taking the rate of emissions for each “Load Shape Following” generation unit (i.e., emissions divided by electricity output in that hour) and weight it by the change in load for that unit with respect to the total change in load of all units that are following the load in that hour. This is expressed mathematically as follows:

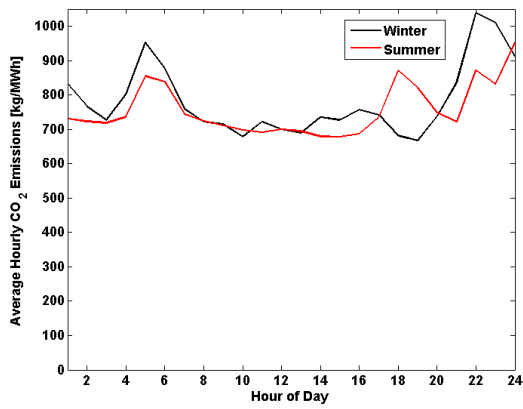
$$\text{hourly marginal emissions rate} = \sum_{LSF} \frac{CO_2 \text{ emissions}}{\text{unitload}} \times \frac{\Delta \text{unitload}}{\sum_{LSF} \Delta \text{unitload}} \quad (2.8)$$

Once the marginal emissions rates have been calculated, the emissions avoided as a result of renewable generation are determined by multiplying the hourly solar generation in each hour [MWh] by the marginal emissions rate in each hour [kg/MWh]. This calculation is repeated for each of the different emissions types under consideration (CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>X</sub>).

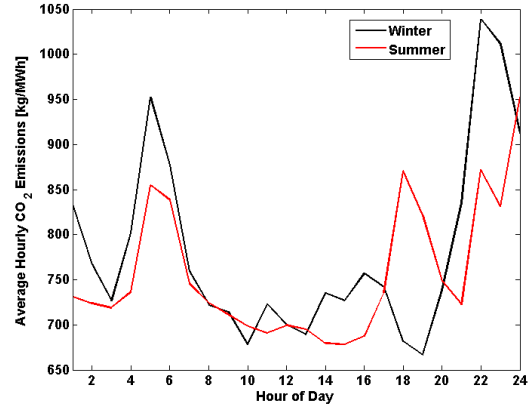
Figure 2-8(a) displays the calculated CO<sub>2</sub> marginal emissions rates in each hour for the years 2000 to 2005. As in the previous plots, each subplot in this figure contains data for all the hours in one year. The figure shows significant variation in the hourly rate of CO<sub>2</sub> emissions each day. There are two features to this plot that are interesting. First, marginal CO<sub>2</sub> emissions exhibit two distinct peaks each day in the early morning hours and late evening hours. These peaks are observed as vertical lines in Figure 2-8(a). Second, in contrast to the solar generation and energy prices



(a)



(b)



(c)

Figure 2-8: CO<sub>2</sub> marginal emissions rates. (a) Hourly CO<sub>2</sub> marginal emissions rates 2000 to 2005. (b) and (c) Daily average CO<sub>2</sub> marginal emissions rates by season in 2005.

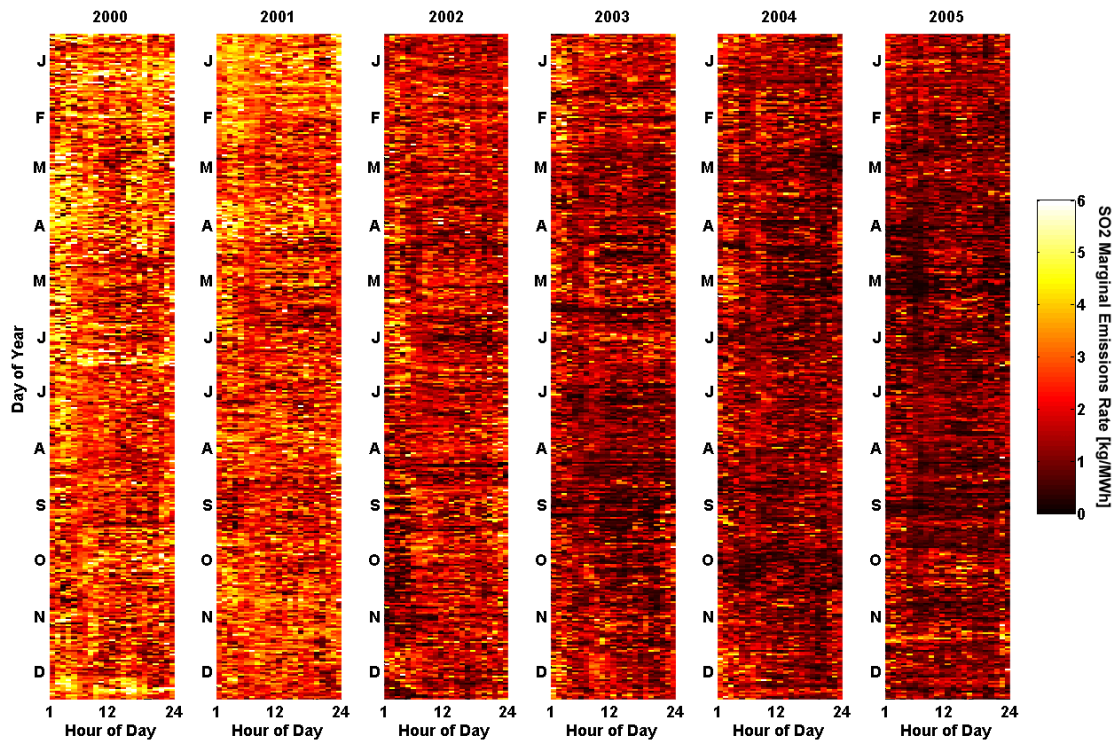
discussed earlier, the marginal CO<sub>2</sub> rates show little seasonal variation throughout the year. The magnitude of CO<sub>2</sub> emissions in each day is similar in the winter and summer.

Figure 2-8(b) displays the average hourly CO<sub>2</sub> emissions rates for the summer and winter in 2005 (a typical year). The emissions rate is observed to peak during the 5th hour of each day (4:00 am to 5:00 am) in both the winter and summer seasons. The evening peak appears to shift later during the summer relative to the winter. The evening peak in the winter occurs in the 22nd hour of the day (9:00 pm to 10:00 pm). The summer evening peak occurs in the last hour of the day (11:00 pm to 12:00 am). This figure also illustrates the magnitude of the changes throughout the day. The peak average hourly emissions rate in the winter is 1038 kg/MWh while the minimum is 667 kg/MWh.

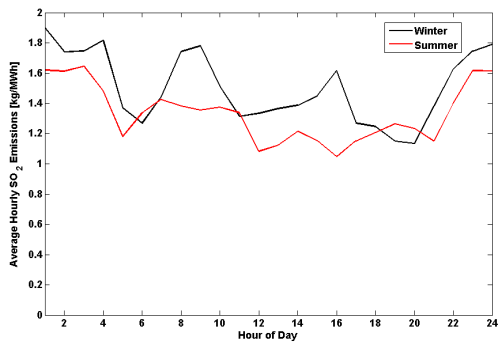
Figure 2-9(a) and Figure 2-10(a) display the calculated SO<sub>2</sub> and NO<sub>X</sub> marginal emissions rates in each hour for the years 2000 to 2005, respectively. The most striking feature in these plots is the observed reduction in SO<sub>2</sub> and NO<sub>X</sub> emissions during these years. The emissions rates for both quantities are far higher in 2000 and 2001 than in 2004 and 2005. The drop in emissions of these two quantities can be attributed to emissions trading programs implemented as a result of the Clean Air Act. Second, in contrast to the CO<sub>2</sub> rates, the SO<sub>2</sub> and NO<sub>X</sub> emissions rates show clear seasonal trends. The emissions of both quantities are highest during the winter months and lowest during summer months. This pattern is particularly clear in 2005.

Figure 2-9(b) and Figure 2-10(b) display the daily average SO<sub>2</sub> and daily average NO<sub>X</sub> emissions rates, respectively, for the summer and winter seasons in 2005 (a typical year). The SO<sub>2</sub> emissions rate is observed to peak less predictably than the CO<sub>2</sub> rates described above. The average SO<sub>2</sub> rate appears to be slightly higher in the winter in most hours compared to the summer. The average NO<sub>X</sub> emissions rate is fairly constant throughout the day. Therefore, it is unlikely that energy storage will change the avoided emissions of NO<sub>X</sub> dramatically. The average daily NO<sub>X</sub> emissions rate is significantly higher in the winter compared to the summer.

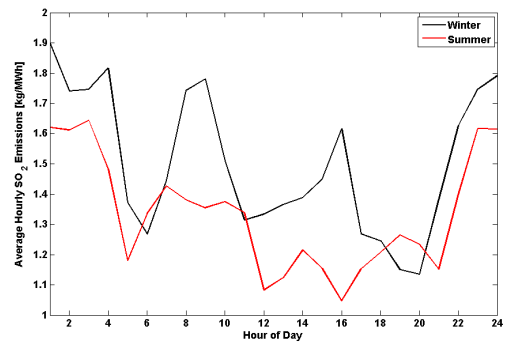
Figure 2-11 displays hourly marginal emissions rates for four selected, representa-



(a)

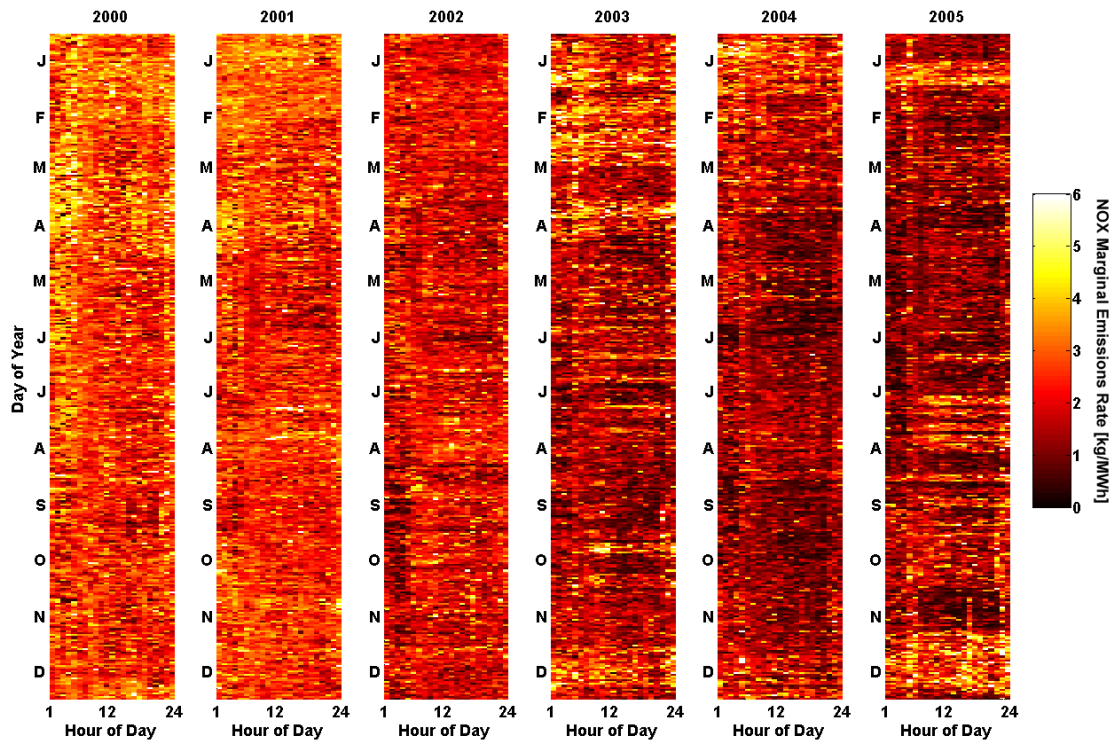


(b)

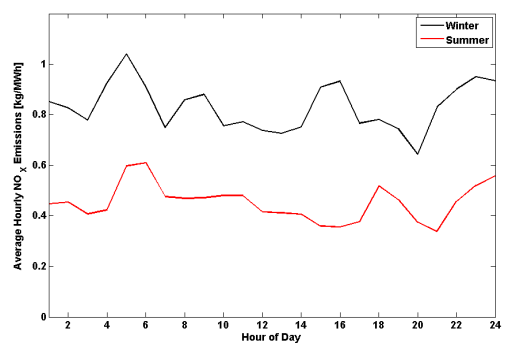


(c)

Figure 2-9: SO<sub>2</sub> marginal emissions rates. (a) Hourly SO<sub>2</sub> marginal emissions rates 2000 to 2005. (b) and (c) Daily average SO<sub>2</sub> marginal emissions rates by season in 2005.



(a)



(b)

Figure 2-10: NO<sub>x</sub> marginal emissions rates. (a) Hourly NO<sub>x</sub> marginal emissions rates 2000 to 2005. (b) Daily average NO<sub>x</sub> marginal emissions rates by season in 2005.



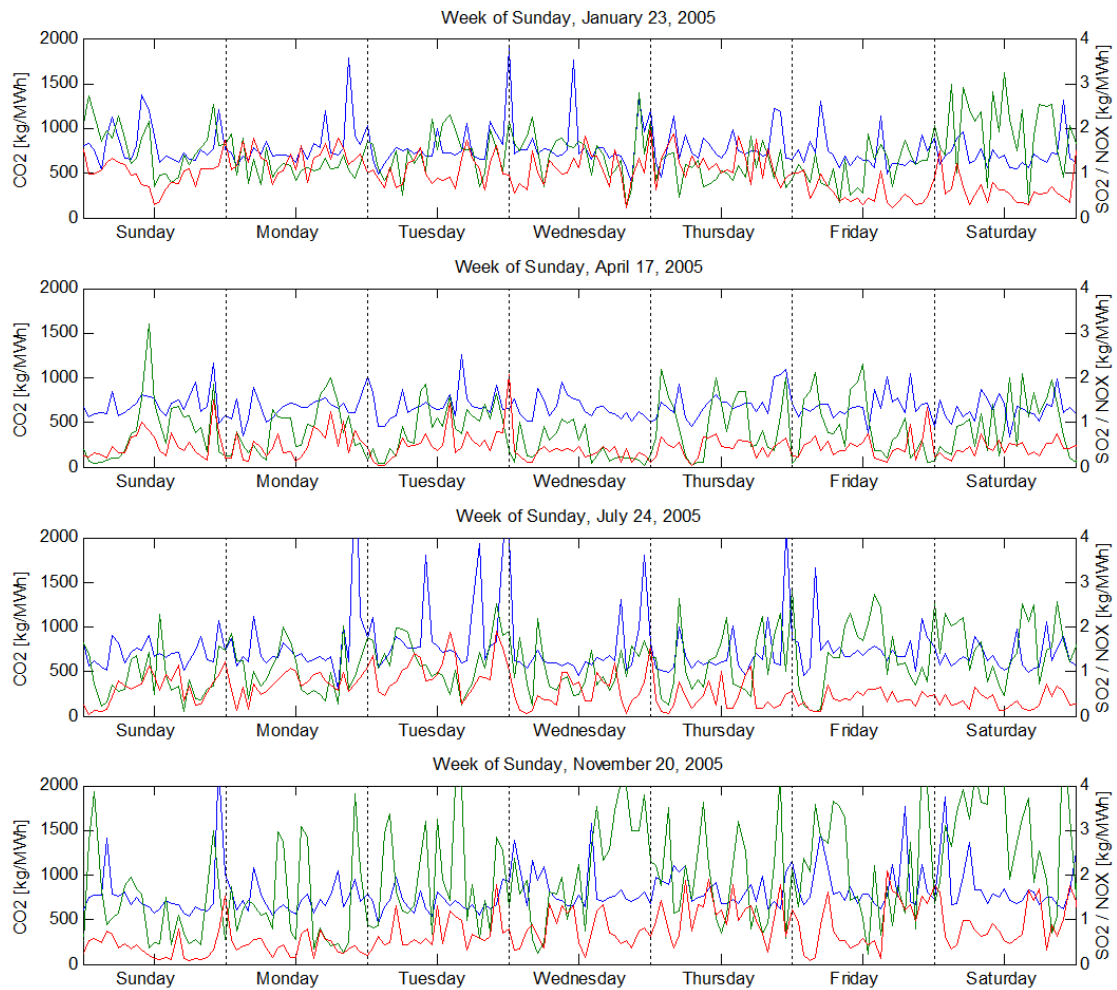


Figure 2-11: Marginal emissions rates in selected weeks.

tive weeks. These plots indicate the uncertainty in the emissions rates in each hour of each day. The marginal emissions rates' hourly fluctuations and the lack of a clear daily shape in each season indicate the importance of studying the interaction of photovoltaics, storage, and emissions rates on an hourly basis. It would be quite difficult to estimate the avoided emissions due to photovoltaics and/or storage using seasonal averages or statistical descriptions of emissions rates alone.

The CO<sub>2</sub> marginal emissions rate is fairly consistent across most hours of the day with specific spikes during some periods. The hours with significantly higher emissions can occur at any time of day. These shifts are determined by the specific generator dispatch in each hour. Therefore, without knowing the specifics of the dispatch procedure (including a detailed system model) it is difficult to isolate exactly what causes sharp increases in the CO<sub>2</sub> marginal emissions rate. The SO<sub>2</sub> and NO<sub>x</sub> emissions rates experience larger fluctuations each day relative to the CO<sub>2</sub> emissions rate. As in the case of the CO<sub>2</sub> emissions rate, there is no consistent daily shape to the emissions rates.

## 2.6 Summary

This chapter has discussed the data and methodology utilized in this thesis to assess the impacts of coupling energy storage and photovoltaics. The chapter started by detailing the methodology employed and its key assumptions and limitations were discussed. Next, the specific optimization model employed by the analysis was formulated. Finally, the solar generation, electricity prices, and marginal emissions rates to be used as inputs to the model were characterized.

# Chapter 3

## Results with Perfect Information

This chapter discusses the results of solving the model formulated in Chapter 2 with perfect information about hourly energy prices, hourly solar generation, and hourly marginal emissions rates. First, revenue and avoided emissions for photovoltaic installations with no storage are calculated. These results serve as a base case to compare to results with energy storage. As discussed in Chapter 2, a photovoltaic installation size of 1 MW is assumed throughout this thesis. This size installation makes it easy to scale the results to other system sizes. Energy storage capacity and power are also defined relative to the solar installation size.

### **3.1 Photovoltaics with no storage: revenue and avoided emissions**

Without storage, energy generated by photovoltaics must be used or sold immediately; there is no ability to shift generation to higher priced hours. Therefore, the revenue and avoided emissions achieved with photovoltaics alone are straightforward to calculate. The solar generation in each hour is multiplied by the energy prices and marginal emissions rates in each hour. Figure 3-1 displays the calculated hourly revenue for a 1 MW photovoltaic installation with no energy storage. Brighter colors indicate higher revenue. As expected, the overall shape of the hours with positive

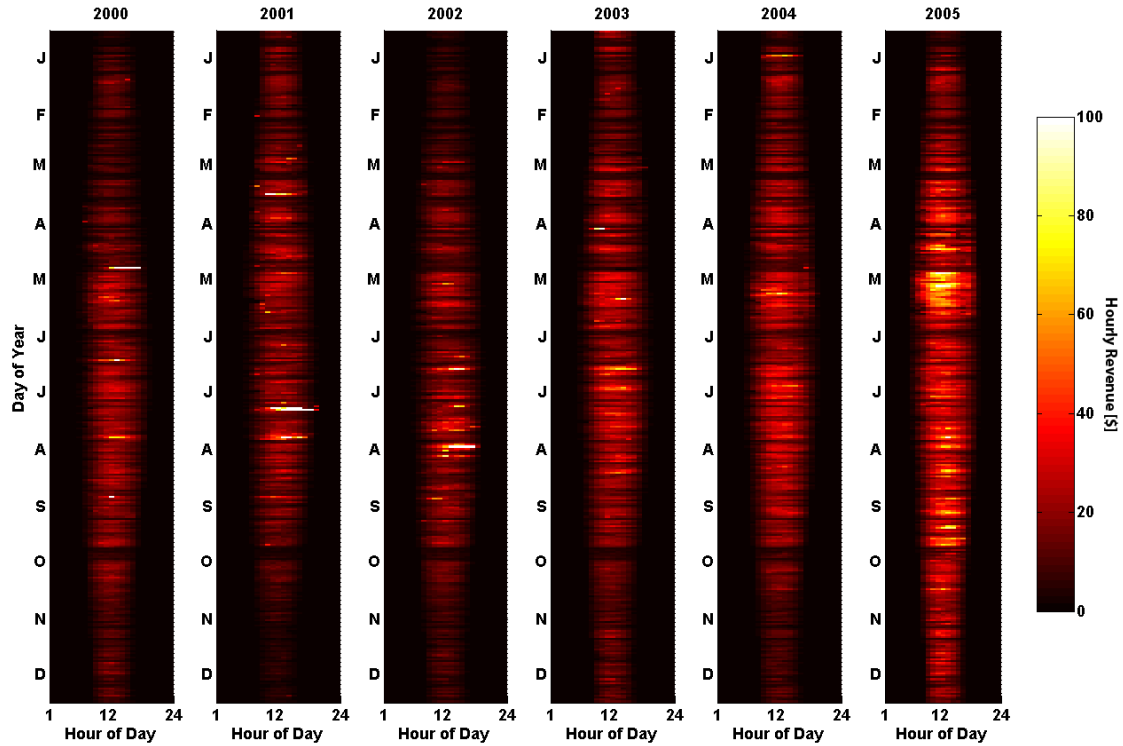


Figure 3-1: Hourly wholesale revenue for photovoltaics only.

revenue in this plot matches the shape of solar generation hours. Figure 3-2 displays the calculated CO<sub>2</sub> avoided emissions for photovoltaics with no energy storage.

Table 3.1 includes the calculated total and average revenue and avoided emissions for 2000 to 2005. Unfortunately, these values, the baseline for the analysis in this thesis, are not consistent from year to year. In the case of the revenue results, the changes are likely a result of changes in natural gas prices driving changes in the wholesale energy prices in New England. Higher energy prices overall is certainly the reason for the high revenue increase found for 2005. The reduction in the CO<sub>2</sub> emissions is most likely a reflection of the increasing quantity of cleaner, natural gas fired generation plants in the early part of this decade. The reduction in CO<sub>2</sub> emissions rates could also be due to changes in the operation and dispatch of nuclear and/or hydroelectric generating plants as the the New England power market evolved. Finally, as mentioned earlier, the dramatic reductions in the SO<sub>2</sub> and NO<sub>X</sub> emissions rates are likely the result of the implementation of the Clean Air Act.

Table 3.1: Revenue and avoided emissions for photovoltaics with no storage.

Quantity	Units	Year									
		2000	2001	2002	2003	2004	2005				
Total Revenue	\$	42731	44812	38147	49983	52013	75784				
Average Revenue	\$/MWh	46.35	48.67	41.43	54.28	56.41	82.30				
Total CO <sub>2</sub> Avoided Emissions	kg	703139	688130	698637	659389	644116	624089				
Average CO <sub>2</sub> Avoided Emissions	kg/MWh	763	747	759	716	699	678				
Total SO <sub>2</sub> Avoided Emissions	kg	2315	2223	1656	1221	1109	1004				
Average SO <sub>2</sub> Avoided Emissions	kg/MWh	2.51	2.41	1.80	1.33	1.20	1.09				
Total NO <sub>X</sub> Avoided Emissions	kg	794	779	649	540	423	473				
Average NO <sub>X</sub> Avoided Emissions	kg/MWh	0.86	0.85	0.70	0.59	0.46	0.51				

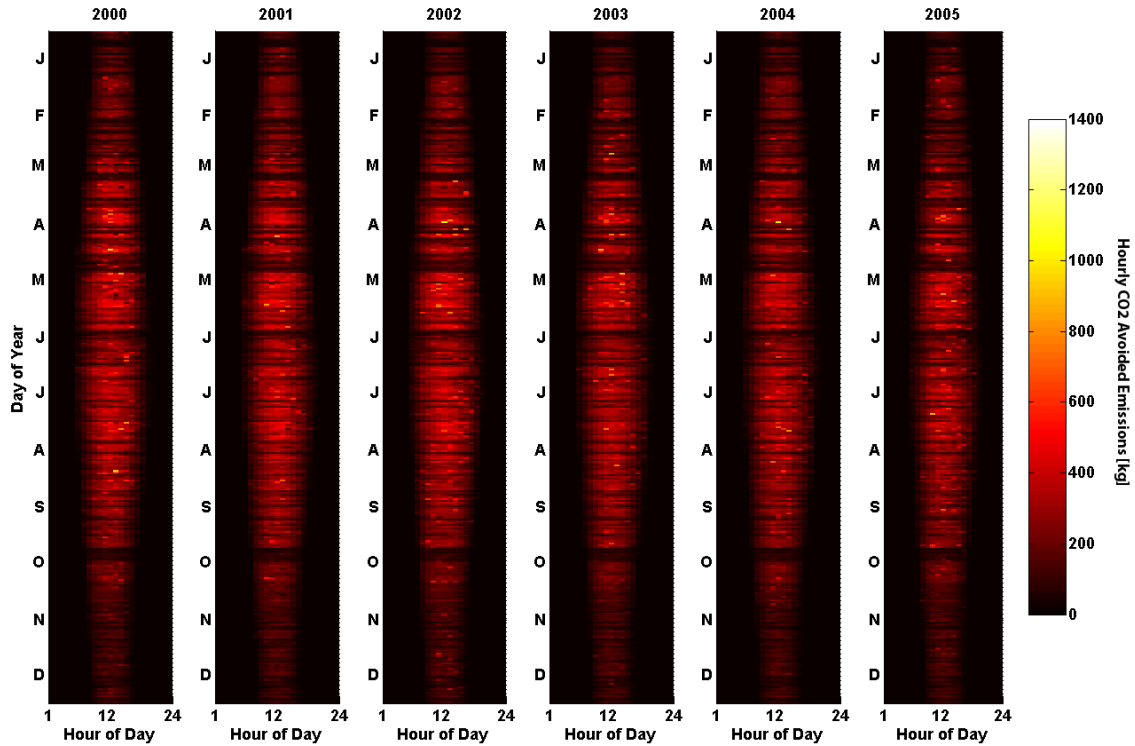


Figure 3-2: Hourly CO<sub>2</sub> emissions for photovoltaics only.

The shifts apparent in the baseline should remind the reader that this thesis does not intend to predict in any definitive way the exact revenues or avoided emissions that would be associated with any future photovoltaic and storage installation. Instead, the focus of this thesis is the relative impact of adding energy storage to photovoltaics. Therefore, most of the results to follow will focus primarily on the relative impacts of adding energy storage in any given year.

### 3.2 Maximizing revenue with energy storage

As expected, energy storage can increase revenues derived from generating electricity using photovoltaics. Initially, an energy storage capacity of 1 MWh and an energy storage power of 1 MW are selected and the optimization model is solved. These capacities, the same size as the photovoltaics generation capacity, were selected as a starting point for analysis. In order to give an upper bound on the possible impacts of

energy storage, in these initial results, the efficiency of storage is assumed to be 100%. The impact of energy storage efficiency is discussed later in this section. Results with different energy storage capacities, powers, and efficiencies are also discussed later in this chapter.

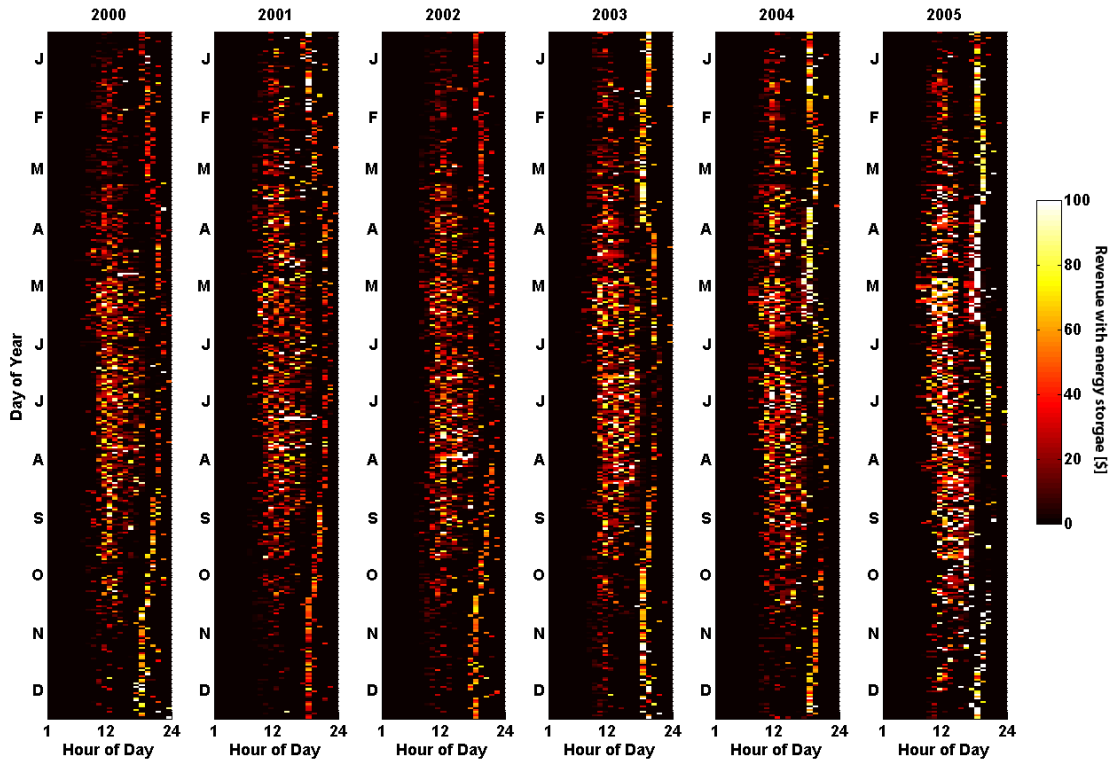


Figure 3-3: Hourly revenue for photovoltaics with energy storage, optimizing for revenue.

Figure 3-3 illustrates the calculated hourly revenue for a photovoltaic installation with energy storage. In contrast to Figure 3-1, the hourly revenue with energy storage is concentrated over fewer hours. The hours with revenue (i.e., the hours that solar generation is actually sold to the grid) are also, on average, shifted later in the day with storage. These results are consistent with the description of energy prices in Chapter 2. In particular, the evening peak in prices throughout the year, illustrated by a vertical stripe on the right side of each plot, is clearly visible. The optimal use of solar generation appears to be to store generation during the day and use it during the evening.

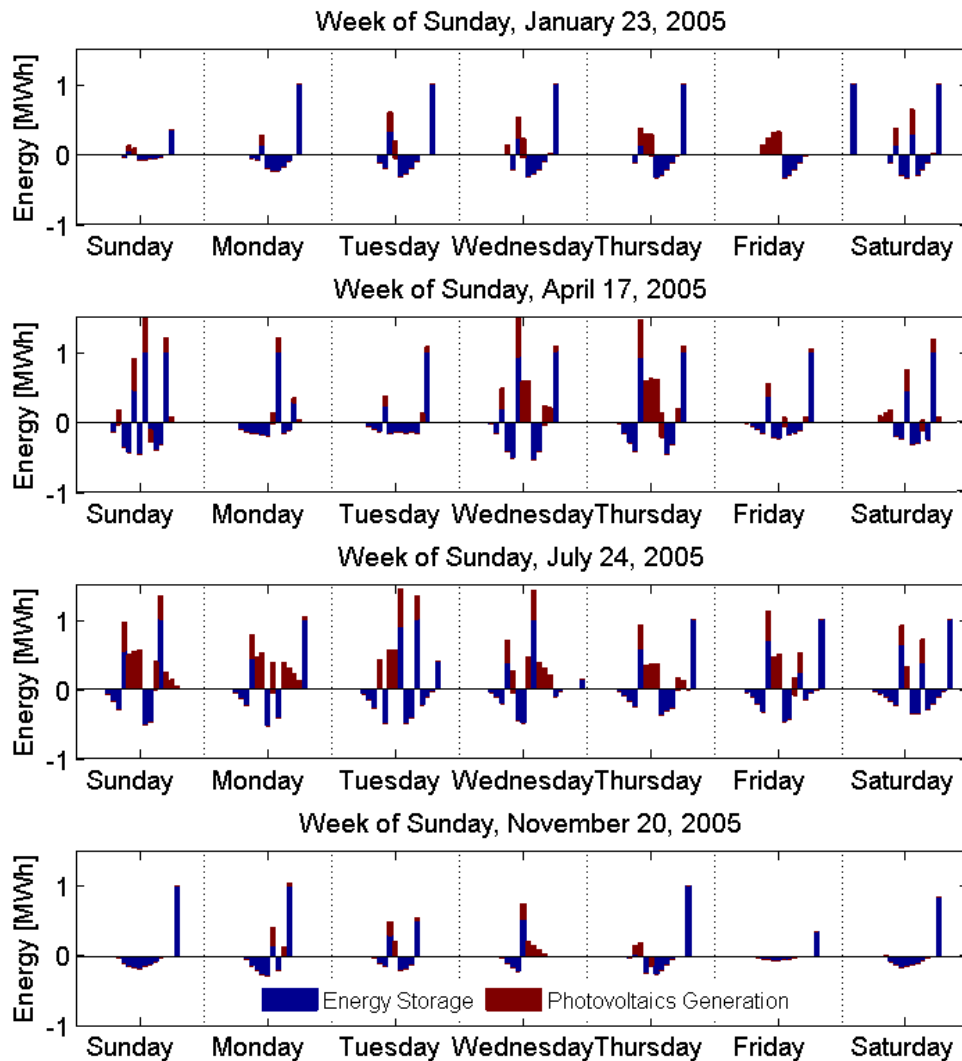


Figure 3-4: Optimal use of energy storage and photovoltaics in selected weeks. Photovoltaics generation used directly (without entering storage) in red, energy storage use is in blue. Negative values correspond to charging the energy storage system. Positive values correspond to selling power in the wholesale electricity market.



Figure 3-4 displays the optimal hourly use of energy storage for selected weeks. Negative values on this plot correspond to using solar generation to charge energy storage instead of selling it immediately. Positive values correspond to selling energy in the wholesale electricity market. This plot reveals that the storage nearly always discharges energy equal to the storage power during the highest priced hour in the early evening. The storage system is also used to shift some morning solar generation to just before mid-day on some days. In these cases, the storage system is charged twice each day, once in the morning and once in the afternoon.

With a 1 MW/1 MWh energy storage system, with optimal storage operation, 58% of the solar generated energy throughout the year entered the energy storage system instead of being sold immediately. The other 42% of the solar generated energy was sold immediately.

Table 3.2 summarizes the results of solving the model with 1 MW/1 MWh energy storage. The table displays both absolute values and the percentage change in each quantity relative to the base case with no energy storage. Positive avoided emissions changes in this table are desirable; a positive change denotes a larger emissions reduction. The objective of the model was to maximize revenue. The total revenue with energy storage increased in each year between 19.3% and 30.5%. Interestingly, the magnitude of the increase in revenue appears to decrease sharply after 2001 from approximately 30% to approximately 20%. This change is likely due to evolution in the operation of the New England wholesale power market. New England adopted the “Standard Market Design” in 2003 adding a day-ahead power market and other rule changes. The increases in revenue appear somewhat stable after 2002 at approximately 19.5%

The changes in avoided emissions with energy storage are small compared to the changes in revenue. The avoided emissions for CO<sub>2</sub> are unchanged or slightly positive on average. This means that adding energy storage to photovoltaics has a negligible effect on the emissions offset by the photovoltaics. The avoided emissions are actually reduced for SO<sub>2</sub> from -1.8% to -5.6% with the introduction of energy storage. This means that the addition of energy storage has a negative impact on SO<sub>2</sub> emissions

Table 3.2: Revenue and avoided emissions for photovoltaics with energy storage.

Quantity	Units	Year			
		2000	2001	2002	
Total Revenue	\$	55758	58777	46400	+21.6%
Average Revenue	\$/MWh	60.48	63.83	50.39	+21.6%
Total CO <sub>2</sub> Avoided Emissions	kg	706120	688628	694326	-0.6%
Average CO <sub>2</sub> Avoided Emissions	kg/MWh	766	748	754	-0.6%
Total SO <sub>2</sub> Avoided Emissions	kg	2263	2175	1623	-2.0%
Average SO <sub>2</sub> Avoided Emissions	kg/MWh	2.45	2.36	1.76	-2.0%
Total NO <sub>X</sub> Avoided Emissions	kg	798	775	641	-1.2%
Average NO <sub>X</sub> Avoided Emissions	kg/MWh	0.87	0.84	0.70	-1.2%

Quantity	Units	Year			
		2003	2004	2005	
Total Revenue	\$	59661	62137	90389	+19.3%
Average Revenue	\$/MWh	64.79	67.40	98.16	+19.3%
Total CO <sub>2</sub> Avoided Emissions	kg	664586	648483	631409	+1.2%
Average CO <sub>2</sub> Avoided Emissions	kg/MWh	722	703	686	+1.2%
Total SO <sub>2</sub> Avoided Emissions	kg	1161	1047	986	-1.8%
Average SO <sub>2</sub> Avoided Emissions	kg/MWh	1.26	1.14	1.07	-1.8%
Total NO <sub>X</sub> Avoided Emissions	kg	537	403	475	+0.2%
Average NO <sub>X</sub> Avoided Emissions	kg/MWh	0.58	0.44	0.52	+0.2%

<sup>1</sup> Energy storage efficiency = 100%.

<sup>2</sup> Revenue changes make no assumptions about energy storage capital and/or maintenance costs.

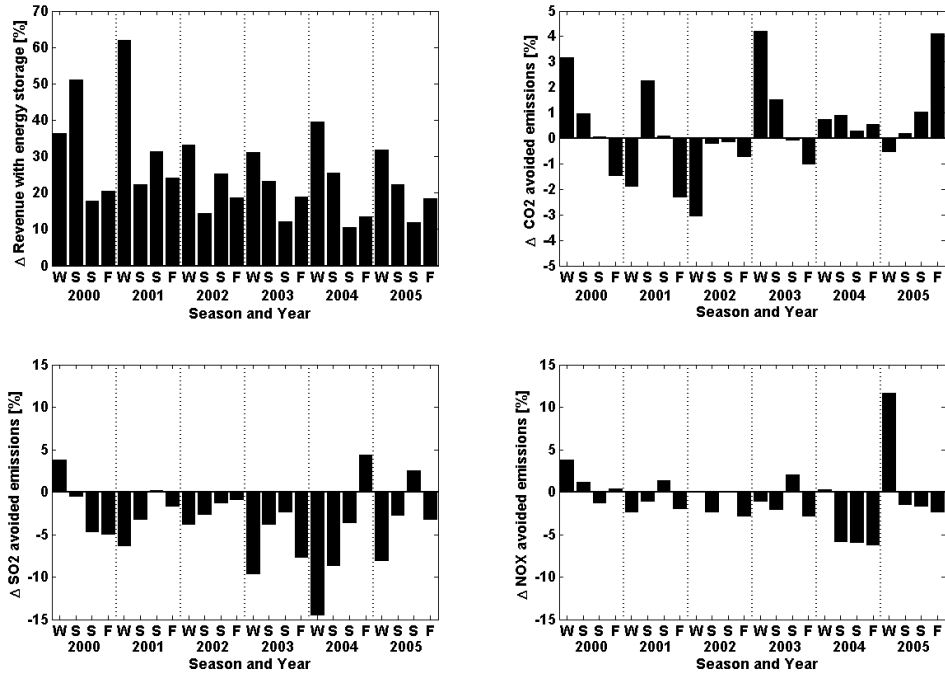


Figure 3-5: Seasonal impacts of adding energy storage to photovoltaics, optimizing for revenue.

compared to photovoltaics alone. Finally, the avoided emissions for  $\text{NO}_x$  appear unchanged or slightly negative.  $\text{NO}_x$  emissions were reduced 4.8% in 2004. However, this change is inconsistent with the other years in the study.

### 3.2.1 Seasonal variations

Figure 3-5 illustrates the contributions to the changes listed above in each season of each year. These plots illustrate that while revenue increases in every season, the avoided emissions for  $\text{CO}_2$ ,  $\text{SO}_2$ , and  $\text{NO}_x$  can increase or decrease. The avoided emissions values for  $\text{SO}_2$  and  $\text{NO}_x$  decrease more often than they increase. This is consistent with the annual decreases in these two quantities discussed above. Unfortunately, it is difficult to isolate consistent seasonal trends. The largest revenue increases occur in the winter for 5 of the 6 years. However, the relative difference in revenue increases between the winter and other seasons varies from year to year. The avoided emissions changes show no clear seasonal correlation.

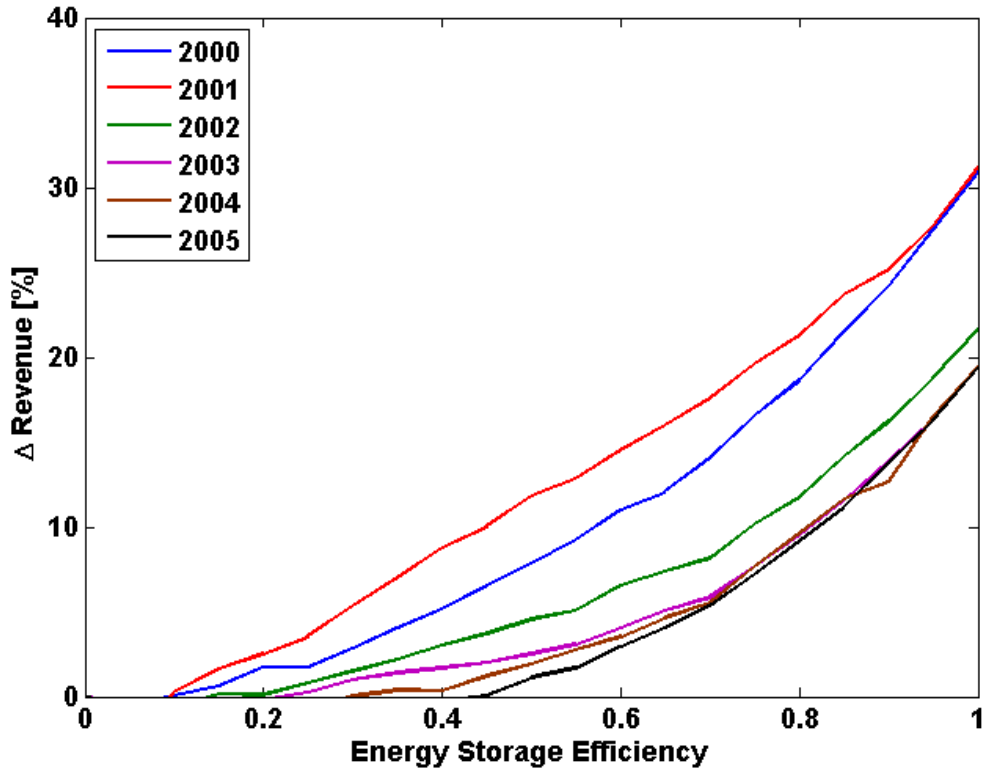


Figure 3-6: Impact of energy storage efficiency. Storage efficiency is a critical feature of energy storage systems coupled to photovoltaics. This is especially true during the later years in this study.

### 3.2.2 Energy storage efficiency

The results discussed above assume perfectly efficient energy storage. In reality the efficiency of energy storage technologies vary widely. For example, grid-scale energy storage using pumped hydro has a typically efficiency in the range of 70-85% while thermal energy storage technologies can achieve greater than 90% efficiency [10]. As might be expected, the round-trip energy storage efficiency has a dramatic impact on the possible increased revenues when coupling energy storage to photovoltaics. Figure 3-6 displays the increases in revenue achieved with the energy storage system discussed above (1 MW/1 MWh) with varying energy storage efficiencies. There are several interesting features in this figure. First, there is a clear efficiency threshold below which energy storage is unable to provide an increase in revenue. With very low efficiency, the difference in prices between hours is not great enough to overcome

Table 3.3: Revenue with varied energy storage efficiencies.

Quantity	Units	Year					
		2000		2001		2002	
Revenue (No Stor.)	\$	42731	N/A	44812	N/A	38147	N/A
Revenue (60% Eff.)	\$	47434	+11.0%	51328	+14.5%	40637	+6.5%
Revenue (80% Eff.)	\$	50694	+18.6%	54337	+21.3%	42620	+11.7%
Revenue (100% Eff.)	\$	55758	+30.5%	58777	+31.1%	46400	+21.6%

Quantity	Units	Year					
		2003		2004		2005	
Revenue (No Stor.)	\$	49983	N/A	52013	N/A	75784	N/A
Revenue (60% Eff.)	\$	52011	+4.1%	53848	+3.5%	78042	+3.0%
Revenue (80% Eff.)	\$	54765	+9.6%	57001	+9.6%	82703	+9.1%
Revenue (100% Eff.)	\$	59661	+19.4%	62137	+19.5%	90389	+19.3%

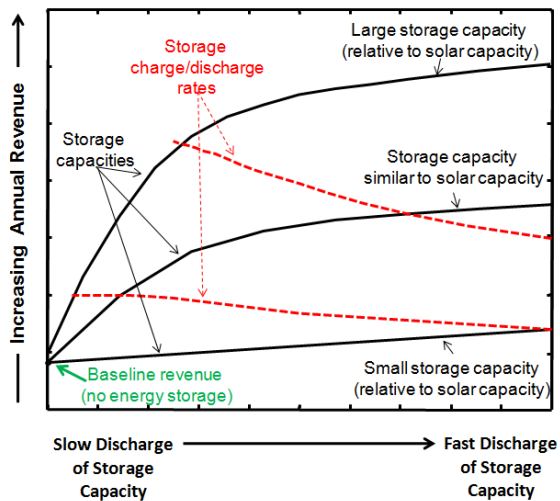
the storage losses. Next, storage efficiency appears to become even more important throughout the study period. The later years studied (2003 to 2005) are shifted to the bottom right of this plot with a higher threshold efficiency. This is likely due to reduced price volatility in these later years due to the maturation of the New England power markets. Finally, the concave shape of these curves indicates that increased energy storage efficiency exhibits increasing returns with greater efficiency. This gives strong incentives to pursue higher efficiency energy storage.

Table 3.3 displays the revenue increases that would have been achieved from 2000 to 2005 for a 1 MW photovoltaic installation with energy storage (1 MW / 1MWh) with varying energy storage efficiencies. As expected, given the previous figure, energy storage systems with lower energy efficiencies achieve significantly lower revenue increases. An energy storage system with an efficiency of 80% would have achieved less than half the revenue increase possible with an energy storage efficiency of 100% from 2003 to 2005. Very small revenue gains of approximately 3.5% are observed with an energy storage efficiency of 60% in these later years.

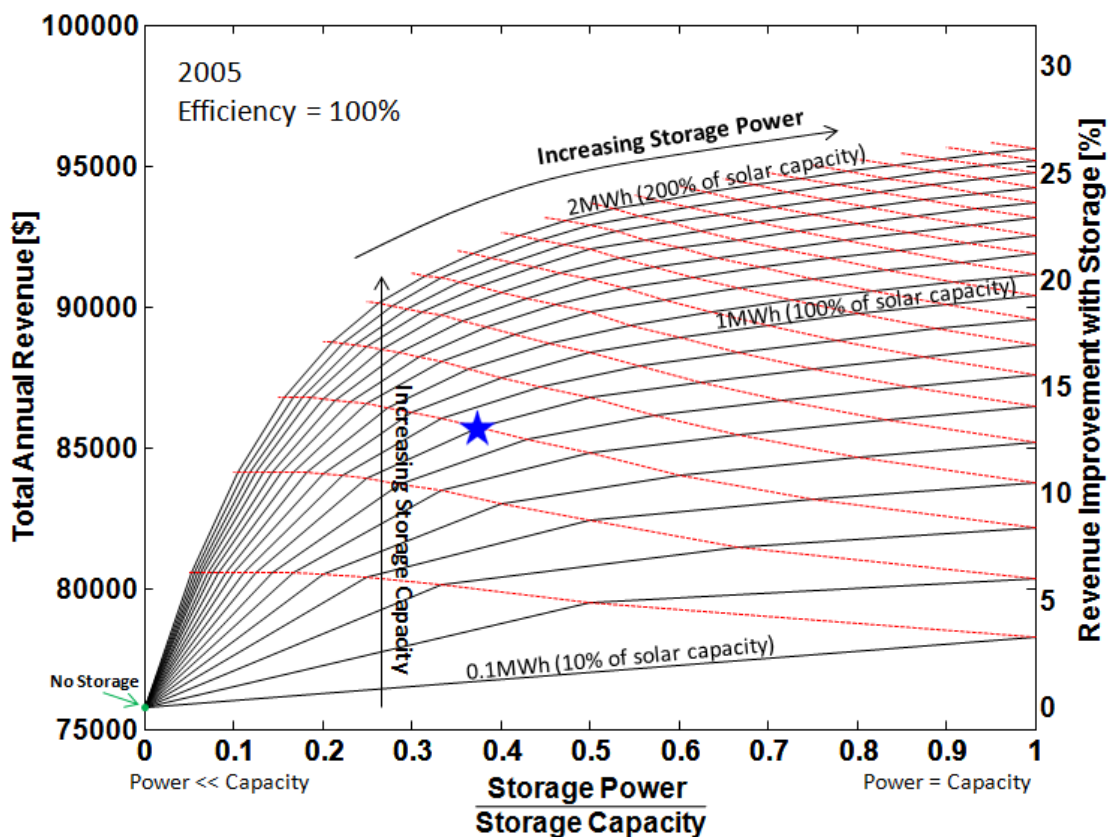
### 3.2.3 Varied storage capacity and power ratings

Figure 3-7 illustrates the results of solving the model for maximum revenue with varying energy storage capacity (MWh) and power (MW) ratings in 2005. Figure 3-7(a) gives a summary schematic to aid the reader in understanding the full results shown in Figure 3-7(b). The base case revenue for photovoltaics with no energy storage is denoted by a green dot at the lower left. The black lines represent different energy storage capacities. The energy storage capacity is varied from 0.1 MWh to 2 MWh or 1/10 of the assumed solar capacity to 2 times the solar capacity. Each black line represents an increase of 0.1 MWh in capacity. The horizontal axis corresponds to the ratio of storage power to storage capacity. This ratio is sometimes used to differentiate energy storage technologies. For the purpose of this study, systems with energy storage power less than or equal to energy storage capacity are considered. Therefore, values along the right edge of the plot correspond to energy storage systems with matching values for power and capacity (i.e., 0.5 MW and 0.5 MWh, 1 MW and 1 MWh, etc.) The dotted red lines correspond to different storage power ratings. Storage powers are varied between 0.1 MW to 2 MW. Systems with a storage power greater than capacity are only relevant to intra-hour interactions with the power grid and are outside the scope of this thesis. (The data used here is limited to hourly intervals.) The solar capacity is constant at 1 MW and the efficiency of storage is assumed to be 100%. The vertical axis corresponds to the absolute revenue with energy storage (indicated on the left) and the relative increase in revenue with energy storage (indicated on the right). The point marked by the blue star corresponds to a storage capacity of 0.8 MWh and a storage power of 0.3 MW. For this system, the storage power to storage capacity ratio is 0.375. The point corresponds to a total revenue of \$85,700.

The revenue optimization results with varying storage capacity and power ratings reveal several interesting characteristics. First, at a given storage capacity (i.e., a single black line), the majority of the potential revenue benefit is achieved with relatively low storage power. This is especially true for systems with higher capacities.



(a)



(b)

Figure 3-7: Revenue increases for photovoltaics with varying energy storage capacities and powers (a) Results plot schematic (to aid understanding of full results of plot below) (b) Revenue increases for photovoltaics with varying energy storage capacity and powers. See text for full explanation.

For example, studying the top black curve, corresponding to a storage capacity of 2 MWh, with a storage power rating of 0.6 MW (0.3 power to capacity ratio) a 20.3% revenue increase is achieved. Increasing the storage capacity to 2 MW (greater than a threefold increase in storage power) yields a 26% revenue increase. Adding additional energy storage power (at a constant capacity) suffers from diminishing returns. The plot indicates that storage capacity also experiences diminishing returns with increasing capacity.

These results indicate that if the costs of storage capacity and storage power were similar, the ideal system would have higher storage capacity and lower storage power. A power to capacity ratio of approximately 0.3 or 0.4 would likely be ideal. Of course, as the relative costs of storage power and storage capacity change, the ideal balance of the two is also likely to change. The results also indicate that energy storage systems with very low charging and discharging rates can yield significant revenue enhancements. The curves at the left of the figure rise rapidly at low storage power to storage capacity ratios. This plot, however complex, can be used to quickly map the potential benefits for any proposed energy storage system with a given power to capacity ratio and size.

The optimal strategy for using energy storage changes as the ratio of storage power to storage capacity increases. At low power to capacity ratios, the energy storage must be charged and discharged over several hours. Therefore, the energy storage system is in the process of charging for most of the day and the energy is discharged over multiple evening hours. With high ratios of storage power to capacity, the discharge becomes significantly more peaked. As discussed earlier in this chapter, when the storage power equals the storage capacity, the storage system is typically fully discharged during a single hour in the early evening.

With low storage power (i.e. slow charging and discharging rates) only a small portion of the energy storage capacity can be discharged during the highest priced hour. This limitation causes less solar generated energy to be stored. For example, as discussed above, with a 1 MW/1 MWh storage system, 58% of the solar generated energy was stored rather than used immediately, the other 42% of the generated



Table 3.4: Maximum revenue with unlimited energy storage.

Quantity	Units	Year					
		2000		2001		2002	
Total Revenue	\$	60943	+42.6%	69878	+56.0%	52512	+37.7%
Average Revenue	\$/MWh	66.10	+42.6%	75.89	+56.0%	57.03	+37.7%

Quantity	Units	Year					
		2003		2004		2005	
Total Revenue	\$	67282	+34.6%	69978	+34.5%	100608	+32.8%
Average Revenue	\$/MWh	73.07	+34.6%	75.90	+34.5%	109.26	+32.8%

<sup>1</sup> Energy storage efficiency = 100%.

energy was sold immediately. For a system with the same energy storage capacity but a power rating of only 0.1 MW, the fraction of energy stored drops to 23% of the total generation. With this system, 77% of the solar generated energy is sold immediately.

Finally, the model was solved to maximize revenue for a 1 MW photovoltaic installation with unlimited energy storage capacity and power. The results represent the maximum possible revenue increases that could be achieved with energy arbitrage using energy storage. The maximum attainable revenue is given in Table 3.4. Adding unlimited energy storage to photovoltaics yielded annual revenue increases as high as 56%. The maximum revenue increases stabilized at approximately 33% during the last several years studied. These increases are approximately 50% higher than the revenue increases discussed previously with energy storage ratings equal to the photovoltaics capacity. In order to achieve these results, the capacity and power for the energy storage system must be approximately five times greater than the capacity of the solar generation. Of course, given the high cost of energy storage it is unlikely one would actually want to install storage to achieve these maximums. Instead these results are offered to give a sense of the fundamental limit of the increases possible with energy storage.

### 3.3 Maximizing avoided emissions with energy storage

Absent policy mechanisms to incentivize emissions reductions, the impacts of adding energy storage to photovoltaics described in the previous section are the most likely results. In the vast majority of cases, owners of photovoltaics generation facilities are likely to try to maximize their revenue increase from adding energy storage in order to maximize the return on their investment. However, in recent years, a variety of policies have been proposed that promise to value emissions of greenhouse gases (GHG), including CO<sub>2</sub>. These policies, aimed at achieving emissions reductions in a wide variety of industries (including the electric power sector) could provide incentives for photovoltaics owners to optimize for emissions reductions instead of revenue maximization. Many of these schemes propose giving payments (or credits) to those who achieve emissions reductions. In these schemes, the value of the emissions reductions achieved with storage could be greater than the increased revenue possible. With these potential policy mechanisms in mind, this section discusses the results of solving the model with the objective of maximizing avoided emissions increases instead of revenue.

As in the previous section, the model is first solved with an assumed energy storage capacity of 1 MWh and power of 1 MW. The solar generation capacity is assumed to be 1 MW. The model and inputs are unchanged except that the objective for the model is now to maximize avoided emissions of CO<sub>2</sub>. In Chapter 2, it was observed that CO<sub>2</sub> emissions are at a maximum in the late night and early morning periods. Therefore, in order to achieve the highest avoided emissions value as possible, the model was modified to consider the time period from 5:00am to 5:00am instead of midnight to midnight. This change does not impact the revenue calculations above but does have a large impact on the optimized emissions reductions. The change has little impact on revenue because the highest priced periods are in the late afternoon or evening periods and there is typically no solar generation prior to 5:00 am each day. This thesis only considers the optimization of the use of energy storage for 24

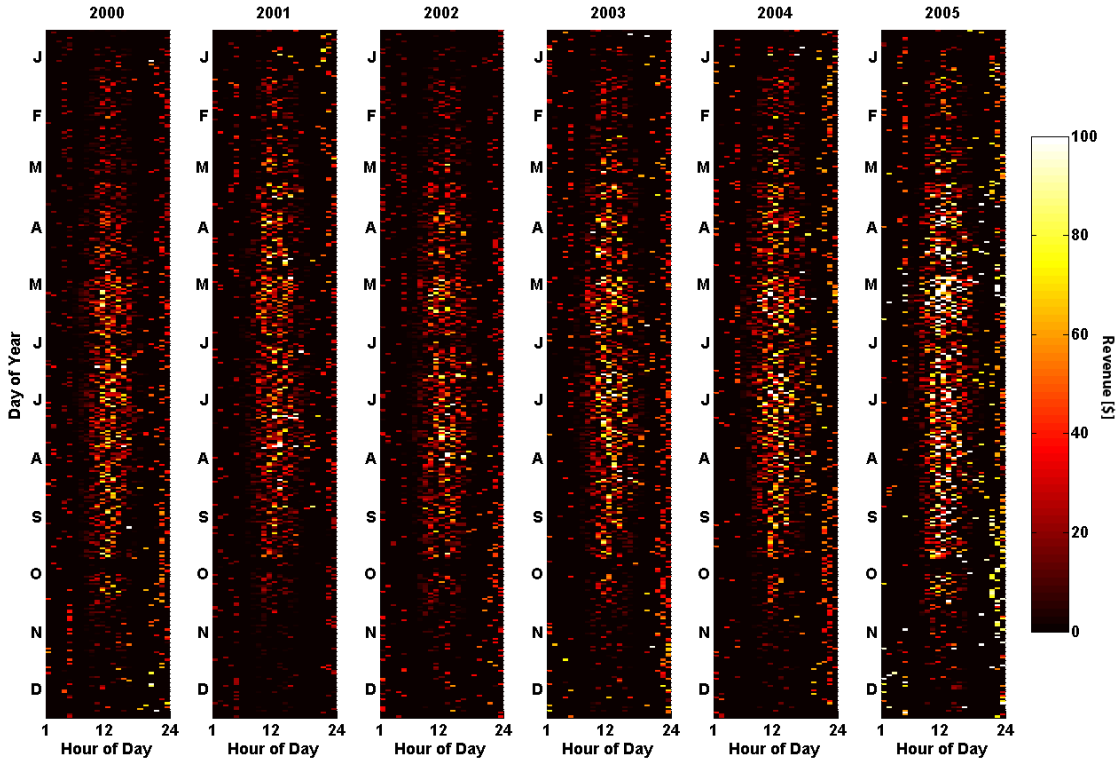


Figure 3-8: Hourly revenue for photovoltaics with energy storage, optimizing for avoided emissions.

hour periods. Multiple day energy storage is an important area for further study.

Figure 3-8 illustrates the results of optimizing the use of storage to maximize emissions reductions. The plot shows the hourly revenue from an energy storage-coupled photovoltaic system. In contrast to the results described earlier, the use of solar generated electricity is shifted to the early morning hours with energy storage. This is not surprising given the peak in the  $\text{CO}_2$  emissions rate described earlier. A significant portion of the solar generation is also shifted into the late evening hours corresponding to the other peak in the  $\text{CO}_2$  emissions rate. Consistent with greater solar generation during the summer, the number of hours with revenue are more plentiful during the summer months in these plots.

Table 3.5 gives the results of the avoided emissions maximization for a 1 MW/1 MWh energy storage system. The results differ dramatically from those found in the previous section. The total revenue derived with an energy storage coupled

Table 3.5: Revenue and avoided emissions for photovoltaics with energy storage, optimizing for avoided emissions.

Quantity	Units	Year					
		2000	2001	2002	2005		
Total Revenue	\$	37674	-11.8%	40393	-9.9%	34736	-8.9%
Average Revenue	\$/MWh	40.86	-11.8%	43.87	-9.9%	37.72	-8.9%
Total CO <sub>2</sub> Avoided Emissions	kg	1013692	+44.2%	984033	+43.0%	1021494	+46.2%
Average CO <sub>2</sub> Avoided Emissions	kg/MWh	1099	+44.2%	1069	+43.0%	1109	+46.2%
Total SO <sub>2</sub> Avoided Emissions	kg	2578	+11.4%	2562	+15.3%	1877	+13.4%
Average SO <sub>2</sub> Avoided Emissions	kg/MWh	2.80	+11.4%	2.78	+15.3%	2.04	+13.4%
Total NO <sub>X</sub> Avoided Emissions	kg	971	+22.3%	936	+20.1%	777	+19.7%
Average NO <sub>X</sub> Avoided Emissions	kg/MWh	1.05	+22.3%	1.02	+20.1%	0.84	+19.7%

---

Quantity	Units	Year					
		2003	2004	2005	2005		
Total Revenue	\$	46107	-7.8%	49296	-5.2%	70040	-7.6%
Average Revenue	\$/MWh	50.07	-7.8%	53.47	-5.2%	76.06	-7.6%
Total CO <sub>2</sub> Avoided Emissions	kg	1005088	+52.4%	948593	+47.3%	975073	+56.2%
Average CO <sub>2</sub> Avoided Emissions	kg/MWh	1092	+52.4%	1029	+47.3%	1059	+56.2%
Total SO <sub>2</sub> Avoided Emissions	kg	1423	+16.6%	1273	+14.8%	1174	+17.0%
Average SO <sub>2</sub> Avoided Emissions	kg/MWh	1.55	+16.6%	1.38	+14.8%	1.28	+17.0%
Total NO <sub>X</sub> Avoided Emissions	kg	693	+28.2%	554	+31.0%	637	+34.6%
Average NO <sub>X</sub> Avoided Emissions	kg/MWh	0.75	+28.2%	0.60	+31.0%	0.69	+34.6%

<sup>1</sup> Energy storage efficiency = 100%.

photovoltaic system consistently decreases when optimizing for emissions reductions. Adding energy storage and maximizing avoided emissions causes revenues to decrease. The decrease in revenue fell throughout the study period except for the final year. The largest decrease in revenue was an 11.8% drop in 2000. The smallest decrease was a 5.2% decrease observed in 2004. As expected, when energy storage is used to maximize CO<sub>2</sub> avoided emissions, the avoided emissions for CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>X</sub> all increase relative to the avoided emissions achieved with photovoltaics alone. The CO<sub>2</sub> avoided emissions were observed to increase by as much as 56.2% and increased by more 43% or more in every year. For example, in 2005, a 1 MW photovoltaic installation would have achieved a 624 metric ton reduction in CO<sub>2</sub>. The avoided emissions jumps to 975 metric tons with a 1 MW/1 MWh energy storage system. The magnitude of the increases in avoided emissions for SO<sub>2</sub> and NO<sub>X</sub> are smaller than those for CO<sub>2</sub> but are also consistently positive. The avoided emissions of SO<sub>2</sub> increase between 11.4% and 17% while the increases for NO<sub>X</sub> are between 19.7% and 34.6%. The magnitude of the increase in NO<sub>X</sub> avoided emissions appears to increase towards the end of the study period.

### **3.3.1 Seasonal variations**

The seasonal impacts of solving the model for maximum CO<sub>2</sub> avoided emissions are summarized in Figure 3-9. There does not appear to be any correlation between revenue reductions, SO<sub>2</sub> avoided emissions, or NO<sub>X</sub> avoided emissions and season. However, there is a clear correlation between increased CO<sub>2</sub> avoided emissions and season. Adding energy storage to photovoltaics has the greatest impact on CO<sub>2</sub> emissions during the winter and fall. The smallest impact occurs during the summer periods.

### **3.3.2 Varied storage capacity and power ratings**

Figure 3-10 displays the results of maximizing CO<sub>2</sub> avoided emissions with a variety of energy storage capacities and powers. The shape of the results is similar to the shape

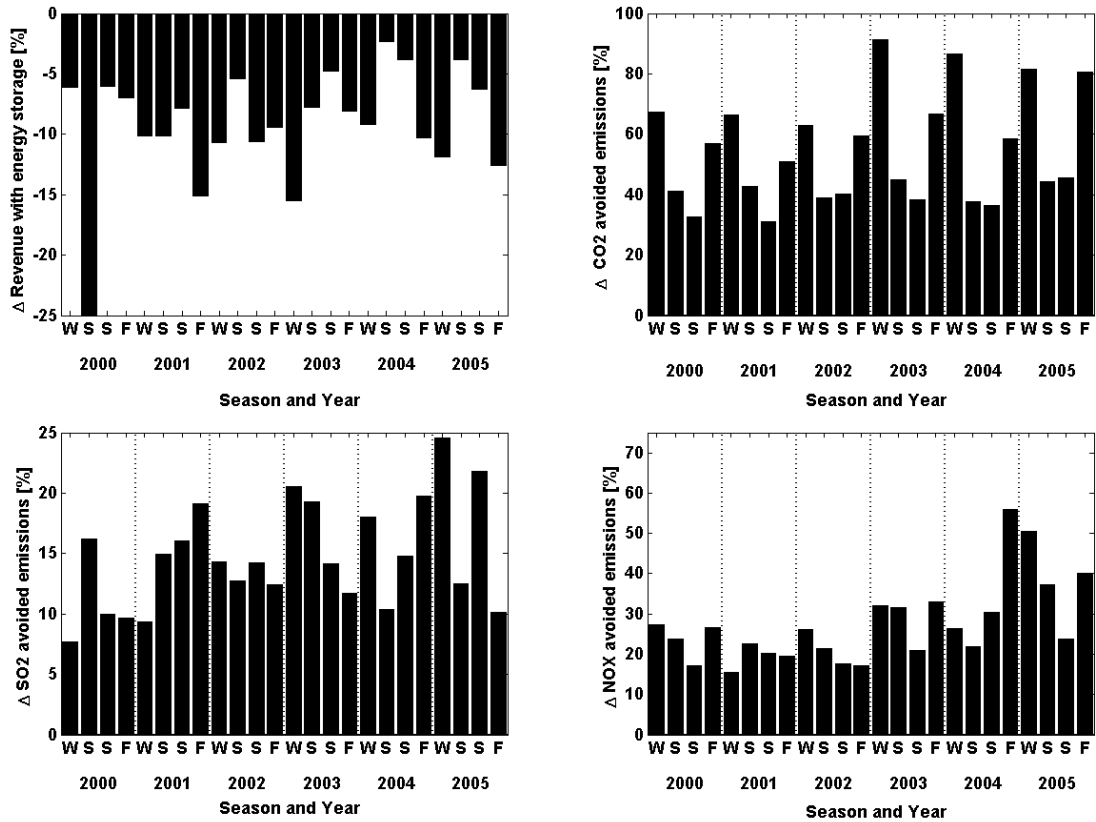


Figure 3-9: Seasonal impacts of energy storage, optimizing for avoided emissions.

found for revenue maximization. However, the relative magnitude of the changes are far larger. The largest emissions reduction observed here is for a 2 MW / 2MWh system which yields an increase in avoided emissions of CO<sub>2</sub> of 84%. Energy storage systems with capacity equal to power achieve the highest magnitude of additional CO<sub>2</sub> emissions reductions. However, the majority of the increase is also achieved using the same storage capacity and a much smaller storage power. In the case of maximizing emissions reductions, storage capacity also appears more important a parameter than storage power.

As in the previous section, the model was solved for photovoltaics with unlimited energy storage to find the fundamental limit on the impacts of adding energy storage to photovoltaics. The results represent the maximum possible increases in the quantity of avoided emissions for a photovoltaics system with energy storage compared to the same photovoltaics system with no storage. The results are given in Table 3.6.

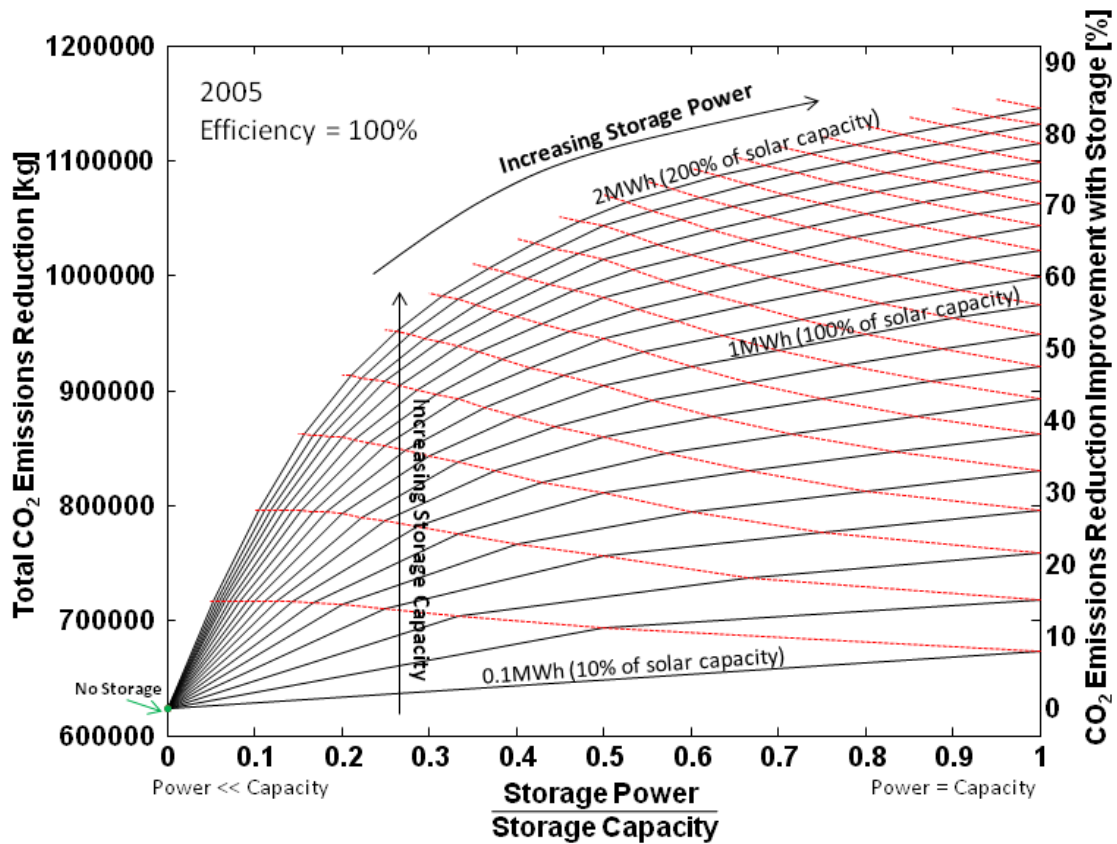


Figure 3-10: CO<sub>2</sub> avoided emissions increases for photovoltaics with varying energy storage capacities and powers. The base case avoided emissions for photovoltaics with no energy storage is denoted by a green dot at the lower left. The black lines represent different energy storage capacities. The energy storage capacities vary from 0.1 MWh to 2 MWh (10% of the solar capacity to 200% of the solar capacity) each black line represents an increase of 0.1 MWh in capacity. The horizontal axis corresponds to the ratio of the energy storage power to energy storage capacity. Therefore, values along the right edge of the plot correspond to energy storage systems with matching values for power and storage (i.e., 0.5 MW and 0.5 MWh, 1 MW and 1 MWh, etc.) The red dotted lines represent constant energy storage power curves. The solar capacity is constant at 1 MW and the efficiency of storage is assumed to be 100%.

Table 3.6: Maximum CO<sub>2</sub> avoided emissions with unlimited energy storage.

Quantity	Units	Year					
		2000		2001		2002	
Total	kg	1340600	+90.7%	1317289	+91.4%	1392901	+99.4%
Average	kg/MWh	1454	+90.7%	1431	+91.4%	1513	+99.4%
Quantity	Units	Year					
		2003		2004		2005	
Total	kg	1377037	+108.8%	1280660	+98.8%	1351457	+116.6%
Average	kg/MWh	1495	+108.8%	1389	+98.8%	1468	+116.6%

<sup>1</sup> Energy storage efficiency = 100%.

Adding unlimited energy storage to photovoltaics yielded annual increases in avoided emissions of CO<sub>2</sub> as high as 116.6%. This means adding energy storage to photovoltaics has the potential to double the emissions offset with the photovoltaics alone. As before, these results are offered simply to give a sense of the fundamental limit of the increases that are possible with energy storage. Achieving these results would require an energy storage system with capacity and power approximately four times greater than the photovoltaics capacity. They are not likely to be achieved given the current high cost of storage technologies.

At first glance, the large increases in avoided emissions with energy storage discussed here appear attractive. However, shifting large amounts of solar generation into the evening hours may not be desirable. Fossil generating units are often already operating at reduced output during the evening hours. The efficiency of these units typically falls as the output falls. Shifting large amounts of solar generation to the late evening or early morning would cause fossil units to reduce their output and, therefore, their efficiency even more. Furthermore, causing fossil plants to reduce output further and/or turn off during the overnight periods could have implications on costs and prices the following day. Coal generation facilities have slow turn-on rates and are not designed to turn on and off routinely. Thus, shifting solar generation to late night hours could have impacts on the stability of the energy price markets and the



efficiency of generation during the overnight periods.

### **3.4 Summary**

This chapter has discussed the optimal use of photovoltaics with energy storage. The model was first solved with the objective of maximizing the revenue increase from adding energy storage to photovoltaics. The results indicate that while large increases in revenue are possible, when maximizing for revenue there is negligible change in avoided CO<sub>2</sub> emissions. The model was then solved with the objective of maximizing avoided emissions. The results reveal that large increases in avoided emissions are possible with energy storage. However, revenues decrease when energy storage is used to maximize avoided emissions.



# Chapter 4

## Results with Imperfect Information

The results discussed in Chapter 3 use perfect information about solar generation, energy prices, and/or marginal emissions rates to optimize the use of energy storage-coupled photovoltaics. The results represent an upper bound on the potential economic and emissions benefits possible with energy storage. However, as described in Chapter 2, in reality energy prices and marginal emissions are both highly volatile. It would be impossible for an owner of an actual photovoltaic system to predict with certainty future prices and/or emissions rates. Therefore, it is unlikely that the results in Chapter 2 could actually be achieved.

Owners of energy storage-coupled photovoltaics installations will instead try to predict future prices and emissions rates and use the results of these forecasts to optimize the use of energy storage in any given day. Forecasting is a very broad, complex field of study that has been successfully used in a wide range of industries. Many researchers have devoted significant effort in forecasting renewable generation for both wind and solar [44]. Energy price forecasting is already done routinely by financial participants in electricity markets and a range of advanced price forecasting methods have been proposed [45][46]. As electricity wholesale markets continue to evolve and participants become more sophisticated, modelling methodologies are likely to continue to improve. Policies aimed at emissions reductions could also prompt efforts in forecasting grid emissions rates.

State-of-the-art forecasting algorithms for hourly solar generation, energy prices,

and marginal emissions rates are beyond the scope of this thesis. Such forecasting studies are an important area of future work as they hold great promise for unlocking some of the potential benefits of adding energy storage to photovoltaics. Instead, in this thesis I study two simple, relatively straight-forward prediction schemes. The results of solving the model with these simple forecasting schemes give a sense of the difficulty of achieving the impacts discussed in the previous chapter.

## 4.1 Information to inform optimizations

The analysis in the previous Chapter uses three sets of input data to inform the optimization: (1) solar generation, (2) energy prices, and (3) marginal emissions rates. The problem of solar generation is one that has been studied extensively before. The shape of generation each day is very consistent while the magnitude changes with the weather. However, short term (i.e, next day) forecasts relying on day-ahead weather forecasts are fairly straight forward. The optimization routine discussed in this thesis focuses on finding the optimal schedule for using solar generated electricity each day subject to the constraints imposed by the energy storage. Uncertainty in solar generation would be difficult for this modelling framework to handle and is best left for a study that relies on linear decision making in each hour. Such a treatment would require the ability to make hourly adjustments to the scheduling of storage based on a comparison between prediction and reality in each hour. Including these decisions in the current framework would be quite difficult and are therefore left as future work.

Instead, the forecasting schemes discussed here attempt to forecast the inputs directly impacting the actual objective function: the energy prices in case of maximizing revenue and marginal emissions rates in the case of maximizing avoided emissions. In the case where an owner of energy storage-coupled photovoltaics wants to maximize revenue, a careful prediction of energy prices in each hour would be desired. There are likely a wide range of variables that could be used to predict energy prices. One input in particular that could be a useful predictor of real-time prices is the price

of electricity in the day-ahead wholesale energy market. The next section optimizes the use of energy storage using day-ahead energy prices. However, the model still assumes the energy will actual be sold at real-time prices (the storage owner remains a price taker in the real-time energy market). Therefore, while the optimization uses day-ahead energy prices to schedule the use of energy storage, the actual revenue is calculated using real-time energy prices.

In the case where the owner attempts to maximize avoided emissions, estimates of marginal emissions rates would be needed. Once again, there are many sources of information that could be used to inform these estimates. One source of information is the seasonally averaged shape of daily emissions discussed in Chapter 2. The second set of results in this chapter adopts these seasonal average emissions rate profiles in the optimization to maximize avoided emissions. However, the ultimate magnitude of avoided emissions will rely on the actual marginal emissions rates. Therefore, the results are calculated based on the actual emissions rates.

## **4.2 Revenue optimization with day-ahead prices**

As discussed in Chapter 2, the market for energy in New England is split into two separate markets: a day-ahead market and a real-time balancing market. Photovoltaics, due to their variability, typically participate as price takers in the real-time market. The analysis in this thesis is restricted to photovoltaics and energy storage also participating in the real-time market. The energy prices discussed in the previous chapter were real-time energy prices. This section explores the use of day-ahead prices as a forecasting tool in the optimization of the use of energy storage.

### **4.2.1 Day-ahead prices**

Day-ahead energy prices are established by clearing the market for energy in each hour based on bids submitted by generators each day for the next operational day. Generator bids in New England are submitted in the morning and day-ahead prices are typically published in the late afternoon. Therefore, along with a forecast for

solar generation based on weather reports and other data, day-ahead prices could be used as an input for optimizing the use of solar generation to maximize revenue.

The stronger the correlation between day-ahead prices and real-time prices the better day-ahead prices are likely to perform as a forecasting tool. Figure 4-1 compares day-ahead prices (red lines) to real-time prices (black lines) during four selected weeks in 2005. The figure indicates that while the day-ahead prices do not capture all of the changes in real-time prices there is a clear correlation between the two. The real-time prices appear to have sharper changes from hour to hour throughout the day that are not reflected in the day-ahead prices. However, the two sets of prices often share the same peak hour. This coincidence of the peak hours is an important factor in the strength of the day-ahead prices as a forecasting input to the model.

## 4.2.2 Results

The optimization model was solved with the objective of maximizing revenue for the same 1 MW solar installation studied in the previous chapter. However, day-ahead prices were used to estimate the best use of energy storage instead of actual real-time prices. The day-ahead energy market was started in early 2003, so there are only two years of complete day-ahead energy price data available overlapping the available solar generation data (up to 2005). Therefore, the model was only solved for the years 2004 and 2005. The day-ahead prices are used only to schedule the use of energy storage in each hour. The resulting revenues are calculated using real-time prices; the photovoltaic system is still assumed to only sell electricity into the real-time wholesale energy market.

Table 4.1 displays the results of the revenue optimization using day-ahead prices. As expected, the magnitude of the increases in revenue using imperfect information (day-ahead prices) instead of real-time energy prices are smaller. The increases in revenue in 2004 and 2005 were 13.0% and 12.9%, respectively. The analogous increases using perfect information (real-time prices) were 19.5% and 19.3%.

These results indicate that simply using day-ahead prices in the optimization, with no other forecasting strategies, revenue increases approximately 2/3 of the maximum

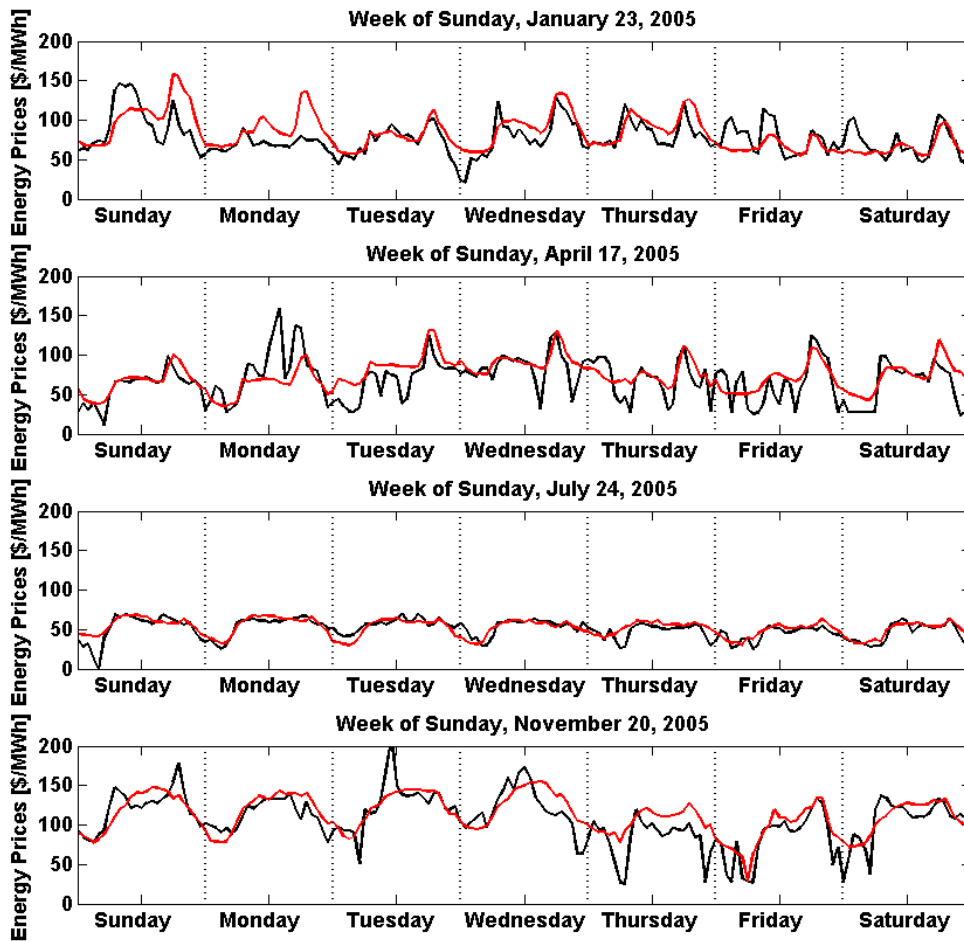


Figure 4-1: Real-time and day-ahead wholesale energy prices in selected weeks. The correlation between real-time energy prices (black) and day-ahead prices (red) is not perfect. However, the two prices do exhibit roughly the same shape and the peaks often align. Therefore, day-ahead prices are likely to help optimize energy storage use.

Table 4.1: Revenue and avoided emissions with energy storage, optimizing for revenue using day-ahead energy prices.

Quantity	Units	Year			
		2004	2005		
Total Revenue No Storage	\$	52013	N/A	75784	N/A
Total Revenue Perfect Information	\$	62137	+19.5%	90389	+19.3%
Total Revenue Imperfect Information	\$	58754	+13.0%	85530	+12.9%
Average Revenue No Storage	\$/MWh	56.41	N/A	82.30	N/A
Average Revenue Perfect Information	\$/MWh	67.40	+19.5%	98.16	+19.3%
Average Revenue Imperfect Information	\$/MWh	63.73	+13.0%	92.89	+12.9%
Total CO <sub>2</sub> Avoided Emissions No Storage	kg	644116	N/A	624089	N/A
Total CO <sub>2</sub> Avoided Emissions Perfect Information	kg	648483	+0.6%	631409	+1.2%
Total CO <sub>2</sub> Avoided Emissions Imperfect Information	kg	647788	+0.6%	621027	-0.5%
Average CO <sub>2</sub> Avoided Emissions No Storage	kg/MWh	699	N/A	678	N/A
Average CO <sub>2</sub> Avoided Emissions Perfect Information	kg/MWh	703	+0.6%	686	+1.2%
Average CO <sub>2</sub> Avoided Emissions Imperfect Information	kg/MWh	703	+0.6%	674	-0.5%
Total SO <sub>2</sub> Avoided Emissions No Storage	kg/MWh	1109	N/A	1004	N/A
Total SO <sub>2</sub> Avoided Emissions Perfect Information	kg/MWh	1047	-5.6%	986	-1.8%
Total SO <sub>2</sub> Avoided Emissions Imperfect Information	kg/MWh	1023	-7.8%	999	-0.5%
Average SO <sub>2</sub> Avoided Emissions No Storage	kg/MWh	1.20	N/A	1.09	N/A
Average SO <sub>2</sub> Avoided Emissions Perfect Information	kg/MWh	1.14	-5.6%	1.07	-1.8%
Average SO <sub>2</sub> Avoided Emissions Imperfect Information	kg/MWh	1.11	-7.8%	1.09	-0.5%
Total NO <sub>X</sub> Avoided Emissions No Storage	kg/MWh	423	N/A	473	N/A
Total NO <sub>X</sub> Avoided Emissions Perfect Information	kg/MWh	403	-4.8%	475	+0.2%
Total NO <sub>X</sub> Avoided Emissions Imperfect Information	kg/MWh	399	-5.7%	465	-1.7%
Average NO <sub>X</sub> Avoided Emissions No Storage	kg/MWh	0.46	N/A	0.51	N/A
Average NO <sub>X</sub> Avoided Emissions Perfect Information	kg/MWh	0.44	-4.8%	0.52	+0.2%
Average NO <sub>X</sub> Avoided Emissions Imperfect Information	kg/MWh	0.43	-5.7%	0.51	-1.7%

<sup>1</sup> Energy storage efficiency = 100%.



possible revenue increases can be achieved. It is likely that a more sophisticated forecasting strategy could yield results close to the theoretical maximum.

Figure 4-2 displays the results of solving the model with day-ahead prices using a range of storage capacity and power ratings. The shape of this plot is similar to the shape of the results figures discussed in the previous chapter. However, the magnitude of the revenue increases illustrated here are approximately 2/3 of the magnitude of revenue increases calculated using actual real-time energy prices.

Overall, the results using day-ahead prices in the place of real-time energy prices indicate that even a very simple price forecasting scheme can achieve well over half of the theoretically maximum revenue increases with storage. The use of day-ahead prices is clearly not a perfect forecasting strategy. However, the results indicate that more sophisticated forecasting schemes might be able to achieve revenue increases close to the theoretical maximum.

## **4.3 Emissions optimization with seasonal average emissions profiles**

Next, the optimization model was solved with the objective of maximizing avoided emissions of CO<sub>2</sub>. The same 1 MW solar installation that was studied in the previous chapter is assumed here. However, marginal emissions rates were assumed not to be known in advance. Instead, seasonal average daily emissions profiles were used to forecast the relative CO<sub>2</sub> emissions rates in each hour. The average marginal emissions rates were used only to schedule the use of energy storage in each hour. The magnitude of the resulting avoided emissions were calculated using actual real-time marginal emissions rates.

### **4.3.1 Seasonally averaged emissions rate profiles**

Seasonally averaged daily marginal emissions rate profiles were discussed in detail in Chapter 2. The CO<sub>2</sub> emissions rate was observed to exhibit two peaks each day:

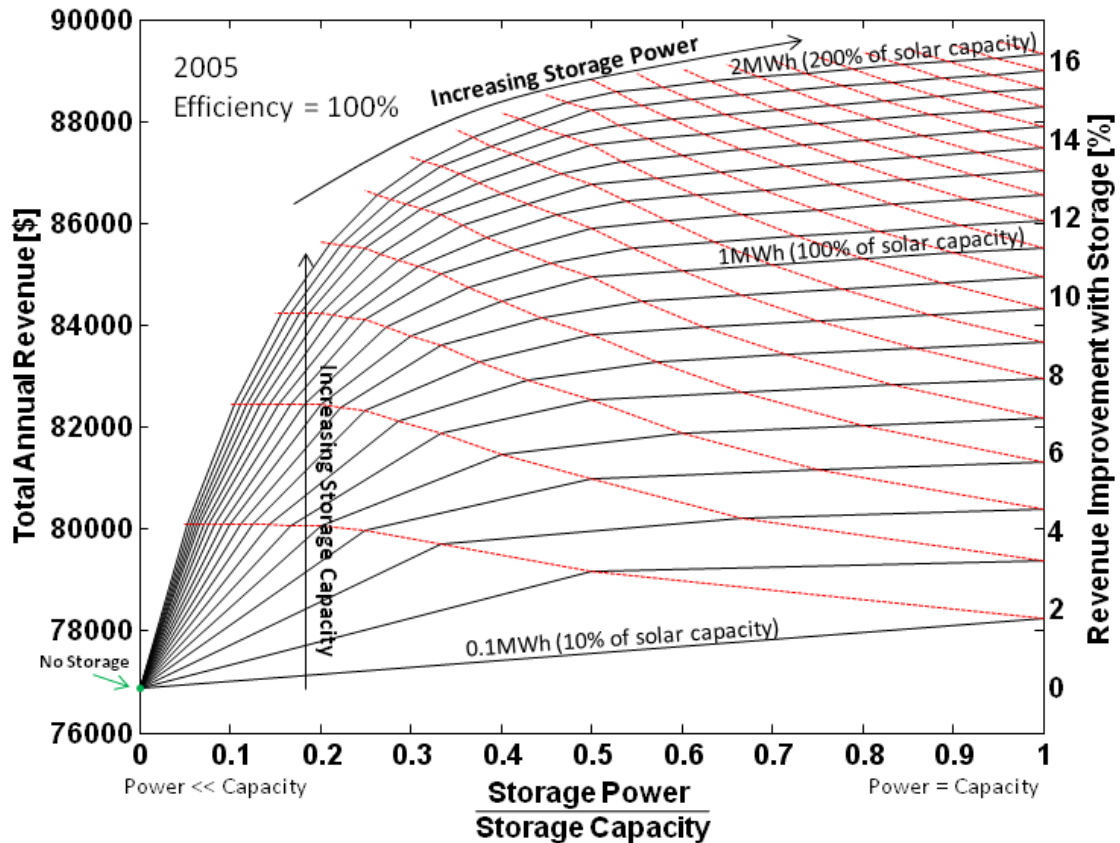


Figure 4-2: Revenue increases for photovoltaics with varying energy storage capacities and powers using day-ahead prices in revenue optimization. The base case revenue for photovoltaics with no energy storage is denoted by a green dot at the lower left. The black lines represent different energy storage capacities. The energy storage capacities vary from 0.1 MWh to 2 MWh (10% of the solar capacity to 200% of the solar capacity) each black line represents an increase of 0.1 MWh in capacity. The horizontal axis corresponds to the ratio of the energy storage power to energy storage capacity. Therefore, values along the right edge of the plot correspond to energy storage systems with matching values for power and storage (i.e., 0.5 MW and 0.5 MWh, 1 MW and 1 MWh, etc.) The red dotted lines represent constant energy storage power curves. The solar capacity is constant at 1 MW and the efficiency of storage is assumed to be 100%.

one peak during the 5th hour of each day (4:00 am to 5:00 am) and a second peak in the late evening. The early morning peak was consistent throughout the year while the evening peak shifted later during the summer months. The emissions rate profiles exhibited peak values approximately 1/3 greater than the rest of the days. For the purposes of this analysis, the year was divided into four seasons: (1) Winter: December 1 to February 28 (or 29 in the case of a leap year), (2) Spring: March 1 to May 31, (3) Summer: June 1 to August 31, (4) Fall: September 1 to November 31. The emissions rates for each day in each season were averaged for each hour of the day. In the results that follow, the daily average emissions rate profile was used as an input for scheduling the use of solar generation with energy storage.

### 4.3.2 Results

Seasonally averaged daily emissions profiles were less successful as a forecasting tool than the day-ahead prices used in the previous section. Optimizing the use of photovoltaics with energy storage using average emissions rates profiles in each season was successful at increasing the avoided emissions relative to photovoltaics alone. However, the increases were small compared with those calculated with perfect information on emissions rates. Table 4.2 displays the results of optimizing the use of energy storage using seasonally averaged CO<sub>2</sub> emissions rate profiles. The increases in avoided emissions for CO<sub>2</sub> were calculated to be between 11.4% and 20.7% during the study period. The corresponding increases with perfect information on marginal emissions rates were significantly higher, between 43.0% and 56.2%. The increases in SO<sub>2</sub> and NO<sub>X</sub> avoided emissions were also lower than the avoided emissions achieved with perfect information.

Seasonally averaged daily emissions profiles are a less sophisticated forecasting tool than day-ahead energy prices. Therefore, the difference in the results found here are not unexpected. It is likely that more sophisticated methods of estimating avoided emissions could be designed. This is an important area for future work.

Table 4.2: Revenue and avoided emissions with energy storage, optimizing for avoided emissions using seasonally averaged emissions rate profiles.

Quantity	Units	Year			
		2000	2001	2002	
Total Revenue No Storage	\$	42731	N/A	44812	N/A
Total Revenue Perfect Information	\$	37674	-11.8%	40393	-9.9%
Total Revenue Imperfect Information	\$	38913	-8.9%	40073	-10.6%
Average Revenue No Storage	\$/MWh	46.35	N/A	48.67	N/A
Average Revenue Perfect Information	\$/MWh	40.86	-11.8%	43.87	-9.9%
Average Revenue Imperfect Information	\$/MWh	42.21	-8.9%	43.52	-10.6%
Total CO <sub>2</sub> Avoid. Emiss. No Storage	kg	703139	N/A	688130	N/A
Total CO <sub>2</sub> Avoid. Emiss. Perfect Information	kg	1013692	+44.2%	984033	+43.0%
Total CO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg	783124	+11.4%	766946	+11.5%
Average CO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	763	N/A	747	N/A
Average CO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	1099	+44.2%	1069	+43.0%
Average CO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	849	+11.4%	833	+11.5%
Total SO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	2315	N/A	2223	N/A
Total SO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	2578	+11.4%	2562	+15.3%
Total SO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	2434	+5.1%	2379	+7.0%
Average SO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	2.51	N/A	2.41	N/A
Average SO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	2.80	+11.4%	2.78	+15.3%
Average SO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	2.64	+5.1%	2.58	+7.0%
Total NO <sub>X</sub> Avoid. Emiss. No Storage	kg/MWh	794	N/A	779	N/A
Total NO <sub>X</sub> Avoid. Emiss. Perfect Information	kg/MWh	971	+22.3%	936	+20.1%
Total NO <sub>X</sub> Avoid. Emiss. Imperfect Information	kg/MWh	861	+8.4%	827	+6.2%
Average NO <sub>X</sub> Avoid. Emiss. No Storage	kg/MWh	0.86	N/A	0.85	N/A
Average NO <sub>X</sub> Avoid. Emiss. Perfect Information	kg/MWh	1.05	+22.3%	1.02	+20.1%
Average NO <sub>X</sub> Avoid. Emiss. Imperfect Information	kg/MWh	0.93	+8.4%	0.90	+6.2%

Table 4.2: Revenue and avoided emissions with energy storage, optimizing for avoided emissions using seasonally averaged emissions rate profiles (continued).

Quantity	Units	Year			
		2003	2004	2005	
Total Revenue No Storage	\$	49983	52013	75784	N/A
Total Revenue Perfect Information	\$	46107	49296	70040	-7.6%
Total Revenue Imperfect Information	\$	44651	48145	68056	-10.2%
Average Revenue No Storage	\$/MWh	54.28	56.41	82.30	N/A
Average Revenue Perfect Information	\$/MWh	50.07	53.47	76.06	-7.6%
Average Revenue Imperfect Information	\$/MWh	48.49	52.22	73.91	-10.2%
Total CO <sub>2</sub> Avoid. Emiss. No Storage	kg	659389	644116	624089	N/A
Total CO <sub>2</sub> Avoid. Emiss. Perfect Information	kg	1005088	948593	975073	+56.2%
Total CO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg	785464	744826	753074	+20.7%
Average CO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	716	699	678	N/A
Average CO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	1092	1029	1059	+56.2%
Average CO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	853	808	818	+20.7%
Total SO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	1221	1109	1004	N/A
Total SO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	1423	1273	1174	+17.0%
Total SO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	1378	1182	1020	+1.6%
Average SO <sub>2</sub> Avoid. Emiss. No Storage	kg/MWh	1.33	1.20	1.09	N/A
Average SO <sub>2</sub> Avoid. Emiss. Perfect Information	kg/MWh	1.55	1.38	1.28	+17.0%
Average SO <sub>2</sub> Avoid. Emiss. Imperfect Information	kg/MWh	1.50	1.28	1.11	+1.6%
Total NO <sub>x</sub> Avoid. Emiss. No Storage	kg/MWh	540	423	473	N/A
Total NO <sub>x</sub> Avoid. Emiss. Perfect Information	kg/MWh	693	554	637	+34.6%
Total NO <sub>x</sub> Avoid. Emiss. Imperfect Information	kg/MWh	616	459	556	+17.6%
Average NO <sub>x</sub> Avoid. Emiss. No Storage	kg/MWh	0.59	0.46	0.51	N/A
Average NO <sub>x</sub> Avoid. Emiss. Perfect Information	kg/MWh	0.75	0.60	0.69	+34.6%
Average NO <sub>x</sub> Avoid. Emiss. Imperfect Information	kg/MWh	0.67	0.50	0.60	+17.6%

<sup>1</sup> Energy storage efficiency = 100%.

## 4.4 Summary

This chapter has discussed the impacts of adding energy storage to photovoltaics assuming perfect information about electricity prices and emissions rates are unavailable. These cases are closer to what might actually be achieved with a realistic system. The model was solved for the optimal use of energy storage with forecasted input values. First, day-ahead electricity prices were substituted for real-time prices to schedule the use of energy storage. Revenue increases of approximately 2/3 the maximum possible increases were achieved; day-ahead electricity prices are a good, but not perfect, forecast for real-time prices. Next, seasonally averaged daily emissions profiles were used in the model with the objective of maximising avoided emissions. The results revealed increases in avoided emissions of between 1/4 and 1/3 of the potential maximum increases. It is expected that these results could be improved significantly with more sophisticated forecasting methods.

# Chapter 5

## Discussion and Policy Implications

The results described previously indicate that it is possible to achieve increases in revenue or increases in avoided emissions by adding energy storage to photovoltaics. However, the results indicate that the two results may be mutually exclusive. This chapter discusses the policy implications of these findings and discusses the insights the results offer on the most important characteristics of energy storage including power, capacity, and cost. Finally, this chapter compares the short and long run implications of the results.

### 5.1 Policy implications

The results described in the previous chapters have several important implications for policies relating to energy storage. First, the results indicate that adding energy storage to photovoltaics is unlikely to offer additional greenhouse gas emissions reductions beyond those achieved with the photovoltaics alone without policies to incentivize emissions reductions (i.e., monetization of emissions reductions). When owners optimize the use of energy storage to maximize revenues, there is negligible change in avoided emissions with storage relative to with photovoltaics alone. In fact, in some instances, the magnitude of avoided emissions could actually be reduced when energy storage is added to photovoltaics. Therefore, policies that focus on expanding the use of energy storage such as tax credits, rebates, or other incentives to purchase

energy storage should not be expected to produce immediate emissions reductions. Policymakers whose primary goal is to formulate technology-based policies to reduce GHG emissions might be more successful by focusing on other technologies such as photovoltaics themselves.

Next, the results described in the previous chapters indicate that it is *possible* to achieve significant increases in emissions reductions from photovoltaics. In fact the potential relative increases in avoided emissions can actually be larger than the potential increases in revenue. When a large storage system is added to photovoltaics, the avoided emissions can increase by over 100%. However, these emissions reductions are unlikely to be achieved without well-designed policies. In order to achieve maximum emissions reductions with energy storage, policies must give generators economic incentives to optimize the use of photovoltaic generation with energy storage for emissions reductions.

A wide range of potential policy mechanisms are currently being proposed to value GHG emissions reductions including renewable energy credit schemes, carbon taxes, and cap and trade programs. Cap and trade programs for CO<sub>2</sub>, in particular, appear to be gaining significant traction. The details of establishing a successful cap and trade program are complex and beyond the scope of this thesis. However, the results here provide insight into the potential role for energy storage in such schemes. The results indicate that if avoided emissions are valued sufficiently, the additional reductions achieved from photovoltaics after adding storage could be significant.

The magnitude of the emissions reductions achieved are dependent on how the energy storage is actually dispatched. Therefore, in order to achieve large increases in avoided emissions, the payment for emissions reductions to photovoltaic generators should depend on how the owner uses the energy storage. If the owner sells most of the solar generated electricity during the daytime, significant emissions reductions are unlikely to be achieved. However, if the owner shifts solar generation to the late evening or early morning, reductions could be large. It is likely that renewable generators will have to be paid depending on what hour of the day they sell solar generation. Policies could be designed to pay owners flat rates for different periods



Table 5.1: Value of CO<sub>2</sub> avoided emissions necessary to incentivize emissions optimization.

	Units	Year					
		2000	2001	2002	2003	2004	2005
Revenue (Rev. Opt.)	\$	55758	58777	46400	59661	62137	90389
Revenue (Em. Opt.)	\$	37674	40393	34736	46107	49296	70040
$\Delta$ CO <sub>2</sub> (Em. Opt.)	metric ton	310.8	295.9	322.9	345.7	304.5	351.0
CO <sub>2</sub> value	\$/metric ton	58.19	62.13	36.12	39.21	42.17	57.97

of the day or could be established such that they try to estimate the actual emissions reductions achieved using data collected through a program similar to the EPA's CEM program. The infrastructure to calculate these payments could be costly.

Finally, the results offer some indication of the magnitude of the payments that would be necessary to give owners of photovoltaics with energy storage sufficient incentive to maximize emissions reductions as opposed to maximizing revenue from the direct sale of energy in higher price hours. With energy storage, photovoltaics owners can increase revenues simply by shifting power to higher priced periods. In order to give owners the incentive to instead maximize emissions reductions, the economic value of those greater emissions reductions must be greater than the value offered by simple energy arbitrage. The value (or price) of CO<sub>2</sub> emissions that would achieve the maximum possible emissions reductions can be calculated by dividing the difference in revenues under revenue optimization and avoided emissions optimization by the increase in CO<sub>2</sub> avoided emissions under emissions optimization.<sup>1</sup> Table 5.1 displays the values calculated from the results in Chapter 3.<sup>2</sup> The final row in the table is the value for carbon emissions that would need to be paid to a generator in order to make that generator indifferent between optimizing the use of energy storage for maximum revenue (via selling energy during higher priced periods) and optimizing

<sup>1</sup>The changes in avoided emissions when optimizing to maximize revenues were found to be negligible in Chapter 3. Therefore, they are not included in these calculations.

<sup>2</sup>The values calculated here refer to the net values to the photovoltaic generator after transaction costs are accounted for. Depending on the complexity of the cap and trade program, transaction costs could be significant.

for maximum avoided emissions.<sup>3</sup>

The values in Table 5.1 represent the price of CO<sub>2</sub> necessary to achieve the maximum achievable emissions reductions (assuming perfect optimization). These values are high compared to many of the prices currently being discussed in the context of cap and trade programs in the US. However, some researchers believe values in the \$40 to \$60 per metric ton of CO<sub>2</sub> emissions could be realized. These prices for CO<sub>2</sub> are not necessary to achieve additional emissions reductions from photovoltaics with energy storage. Owners of solar generation with energy storage will optimize the use of storage to maximize revenue regardless of where that revenue is derived. Therefore, while lower values for CO<sub>2</sub> emissions will not achieve all of the emissions reductions possible, some of the generation is still likely to be shifted to hours with higher emissions rates. Therefore, smaller increases in avoided emissions are likely to be achieved. Higher CO<sub>2</sub> avoided emissions values will yield larger increases in avoided emissions. However, if the value associated with CO<sub>2</sub> avoided emissions climbs higher than the values listed in Table 5.1 no additional avoided emissions would be possible.

## 5.2 Wholesale vs. retail electricity prices

The analysis in this thesis assumed owners of the photovoltaics sell the energy generated in the wholesale market for electricity. Therefore, the analysis and results refer to the economic benefits of photovoltaics with energy storage as revenue. However, in the case of smaller photovoltaics installations subject to net-metering, the owner may simply use the generated electricity locally in lieu of purchasing electricity from the grid. In these cases the economic benefits of coupling energy storage to photovoltaics would actually be in the form of savings instead of revenue.

In the case where solar generated power is used locally, as in a net-metering arrangement, the owner avoids the need to pay for transmission, distribution, and delivery costs associated with grid purchased electricity. The “savings” yielded by

---

<sup>3</sup>It is important to recall here that a central assumption in this thesis holds that the solar generation does not impact the power grid dispatch order or the market prices for electricity.

photovoltaics in these cases are equivalent to the retail price of electricity rather than the wholesale price. Historically, the additional costs associated with retail electricity (i.e., transmission, distribution, etc.) have constituted a significant portion of total electricity bills. Currently, the retail market for electricity is still evolving rapidly in New England. Reasonably complete data sets of hourly retail prices would be needed to perform the analysis in this thesis assuming savings against retail prices instead of selling energy at wholesale prices. Currently, relatively few consumers in New England are subject to time-varying retail prices (i.e., real-time hourly prices, time-of-use prices, etc.)

The difference between the wholesale and retail pricing results will depend on the specific retail pricing regime. For example, the revenue and emissions impacts of adding energy storage with time-of-use (TOU) retail pricing would depend on the specific time periods selected in the rate design process. If solar generation were to take place during the peak pricing period, adding energy storage would not increase revenue. However, if solar generation were to take place during a lower price time period, energy storage could add value by shifting that generation into the highest price time period. TOU pricing would likely amplify the importance of storage capacity over storage power as the peak price period would most likely be multiple hours in duration. The energy storage system could discharge over multiple hours without reducing revenue.

When energy storage is added to photovoltaics with hourly real-time retail pricing (RTP) the savings offered by photovoltaics could be somewhat larger than the revenue results discussed in this thesis. However, the relative increases in revenue/savings would be the same as those discussed with wholesale pricing; the costs associated with delivering electricity do not change on an hourly basis. The unchanging nature of these prices is subject to regulation. In principle, these costs could change on an hourly basis. In a regime where these costs change hourly, the increases in revenue possible with energy storage would likely increase.

Studying the impacts of adding energy storage to photovoltaics in the context of the retail price of electricity will become increasingly important as the retail market

continues to evolve and real-time or time-of-use retail-pricing becomes more common.

### **5.3 Most important characteristics of energy storage**

In Chapter 3, it was found that at a given storage capacity, the majority of the potential revenue increase can be achieved with relatively low storage power. This was found to be especially true for systems with high storage capacities relative to photovoltaic capacity. Storage power and storage capacity both experience diminishing returns with increasing size. However, it appears storage power saturates more quickly than storage capacity. The greater relative importance of energy vs. power would make energy storage technologies such as compressed air, flow batteries, and NaS batteries particularly attractive.

These observations are only relevant to discussions of the impacts derived from energy arbitrage using energy storage-coupled photovoltaics. For other applications, such as providing short term operating reserves or frequency regulation, high power storage would be more valuable. Therefore, the ideal balance of energy storage power to energy storage capacity will depend heavily on the anticipated application(s) for the energy storage. The results discussed in this thesis, focusing on the application of energy arbitrage, indicate that if the costs of storage capacity and storage power are similar, the ideal system would have higher storage capacity and lower storage power. A power to capacity ratio of approximately 0.3 to 0.4 appears ideal. Of course, as the relative costs of storage power and storage capacity change the ideal ratio between the two will also change.

### **5.4 The cost of energy storage**

Energy storage cost is a critical parameter in determining the potential impact of energy storage. While adding energy storage to photovoltaics can increase the revenues generated by photovoltaics, adding energy storage is not without cost. The costs of

different energy storage technologies vary widely. It is difficult to pin down specific costs for energy storage. For example, compressed air energy storage has been reported to cost approximately \$1-\$5/kWh of capacity while flow batteries are reported to cost approximately \$500-\$1300/kWh of capacity [10]. These costs are likely to fall rapidly given the increased attention from both the scientific and investment communities that storage has found recently. These costs are actually quite low relative to the cost of installing photovoltaics. Installed photovoltaics typically cost more than \$5000/kWh. Therefore, in instances where investments in photovoltaics and energy storage are being made simultaneously, it may make sense to reduce the size of the photovoltaics slightly and add energy storage capacity.

Since the cost of energy storage is a moving target that is very difficult to pin down, this thesis has avoided focusing on energy storage costs. However, the analysis would be incomplete without an attempt to consider the results in the context of energy storage costs. This section provides such an analysis.

One way to consider the results given here in the context of energy storage costs is to calculate the present value of adding energy storage to photovoltaics for a variety of energy storage costs. Present value is a way to calculate the current value of a series of future payments, discounted to reflect the time value of money. The calculation of present value and expected investment costs can be used to calculate the net present value (NPV) of a given investment. A positive NPV represents an investment that would net positive value and therefore should be considered. A project with a negative NPV represents an investment that should be rejected. In order to evaluate whether it is advantageous to add energy storage to photovoltaics, one should compare the cost of adding energy storage to the present value of the additional revenue derived from the storage over the life of the storage system.

Table 5.2 displays the present value of adding energy storage to photovoltaics under a variety of assumptions. In Chapter 3, adding a 1 MW/1 MWh energy storage system to a 1 MW photovoltaic installation was found to increase the revenue derived from the photovoltaics by an average of \$11,609 dollars per year. However, the range of revenue increases was from \$8,253 to \$14,605. Table 5.2 considers each

Table 5.2: Present value of adding 1 MW/1 MWh storage to 1 MW photovoltaics.

Project Lifetime	10 years		25 years		
	Discount Rate	5%	10%	5%	10%
Low Revenue	\$63,727	\$50,711	\$116,320	\$74,913	
Average Revenue	\$89,642	\$71,332	\$163,620	\$105,380	
High Revenue	\$112,780	\$89,741	\$205,840	\$132,570	

<sup>1</sup> Energy storage efficiency = 100%.

of these different revenue values throughout the life of the storage. The lifetime of storage technologies also varies widely. Therefore, the table includes calculations for an assumption of a 10 year lifetime and a 25 year lifetime. A 25 year lifetime is likely to be more compatible with photovoltaics installations that often have 20 or 25 year warranties.

The present values in Table 5.2 represent the maximum capital costs (for a 1 MW/1 MWh storage system) for which adding energy storage to photovoltaics would make economic sense. Dividing each of these numbers by 1000 yields the threshold capital costs in \$/kWh. The range of costs that must be achieved (depending on the assumptions used regarding lifetime and discount rate) is approximately \$50/kWh to \$205/kWh. The present value of the increases in revenue possible with energy storage do not appear high enough to justify the addition of energy storage to photovoltaics given the current high costs of storage. In locations where space constraints are not the key factor determining photovoltaic size, owners who wish to invest additional capital would likely be better off simply increasing the size of their photovoltaic installation. However, as the cost of energy storage falls, the net present value of adding energy storage to photovoltaics could become positive. It might also be possible to achieve effective cost reductions by fully integrating energy storage into a photovoltaic installation. For example, it might be possible to utilize the same power conversion equipment (i.e., inverter, meter, etc.) for both the photovoltaics and the energy storage. Innovations such as these could lower the barriers to adding energy storage to photovoltaics.

In reality, as discussed in Chapter 1, energy storage can provide a variety of services on the power grid. The combined revenues and collective present value of providing all of these services would determine the actual value of adding energy storage to photovoltaics. The revenue from energy arbitrage explored in this thesis is simply one piece of the total picture.

## **5.5 Short run vs. long run implications of results**

The results described in the previous chapters and discussed above are concerned only with the short run impacts of adding energy storage to photovoltaics. The results primarily deal with the economics of individual photovoltaic installations with energy storage. The economic analysis does not consider broader market-wide impacts. In fact, one of the primary and necessary assumptions in this analysis is that the energy storage-coupled photovoltaics do not impact the markets as a whole. The results indicate that, in the short term, adding energy storage to photovoltaic installations can be expected to have little GHG emissions impact above and beyond that already achieved with the photovoltaics alone. The increased revenues associated with adding energy storage to photovoltaics only consider energy storage's ability to enable arbitrage. Taken alone, these short run results underestimate the potential economic and environmental benefits of adding energy storage to photovoltaics.

There are a variety of additional ways energy storage can add value to photovoltaics. First, energy storage can smooth minute-to-minute variations in the power output of photovoltaics. Minute-to-minute variations can make it difficult to efficiently manage the power grid. The power variations can cause irregularities in both frequency and voltage requiring additional procurement of ancillary services by the grid operator. Ultimately, increased requirements for ancillary services will increase the costs of operating the power grid and in most cases will also increase emissions. Energy storage can reduce these requirements.

Energy storage can also enable photovoltaics to participate in markets that the photovoltaics alone would not be able to access. Many energy storage systems are

ideally suited to provide ancillary services such as frequency regulation and voltage support. In fact, in one analysis, it was found that the primary source of value for energy storage in the markets operated by the New York ISO was frequency regulation [18]. Energy storage could also allow photovoltaics to receive higher installed capacity payments in forward capacity markets. In New England, intermittent resources receive reduced capacity payments compared to traditional dispatchable generation sources. Energy storage that allows interday storage as opposed to the intraday storage considered in this thesis would allow photovoltaics to participate in day-ahead energy markets.

Further, energy storage capabilities can also be used to provide fast-start reserve capabilities. Used in this way, energy storage facilities can reduce the number of traditional fossil units that must be running to provide reserve capacity. This is another way that energy storage can provide environmental benefits. However, in many cases the infrastructure and market designs to allow energy storage to provide reserve capabilities are very much still in development.

Finally, if photovoltaics achieve large grid penetration levels, energy storage has the potential to enable additional photovoltaics installations. Many researchers believe there is a peak penetration level for photovoltaics that current power grids can handle without major upgrades or redesigns. By firming intermittency, energy storage could play an enabling role in allowing greater amounts of photovoltaics. In this role, the environmental benefits of energy storage are very strong.



# Chapter 6

## Conclusion

Energy storage technologies have the potential to alleviate some of the challenges associated with intermittent renewable generation sources. Solar resource variability and intermittency are important limiting factors in the deployment and growth of photovoltaics at large scale. As new storage technologies emerge and the costs of conventional storage technologies fall, energy storage has the potential to become an important complementary technology to photovoltaics.

### 6.1 Summary

This thesis has attempted to quantify some of the economic and emissions impacts of adding energy storage to photovoltaics in New England using historical solar generation, energy prices, and greenhouse gas emissions rates. Understanding these impacts in detail could be critical to designing the most effective policies to drive the growth and deployment of photovoltaics and/or energy storage with environmental motivations. In particular, this thesis has attempted to answer the following central question: Does coupling energy storage to photovoltaics enhance or reduce the economic and emissions benefits associated with small to mid-scale photovoltaic installations?

The results reveal that significant revenue increases can be achieved when energy storage is added to photovoltaics. The annual increases in revenue that photovoltaics installations could have achieved with energy storage capacity and power equal to the

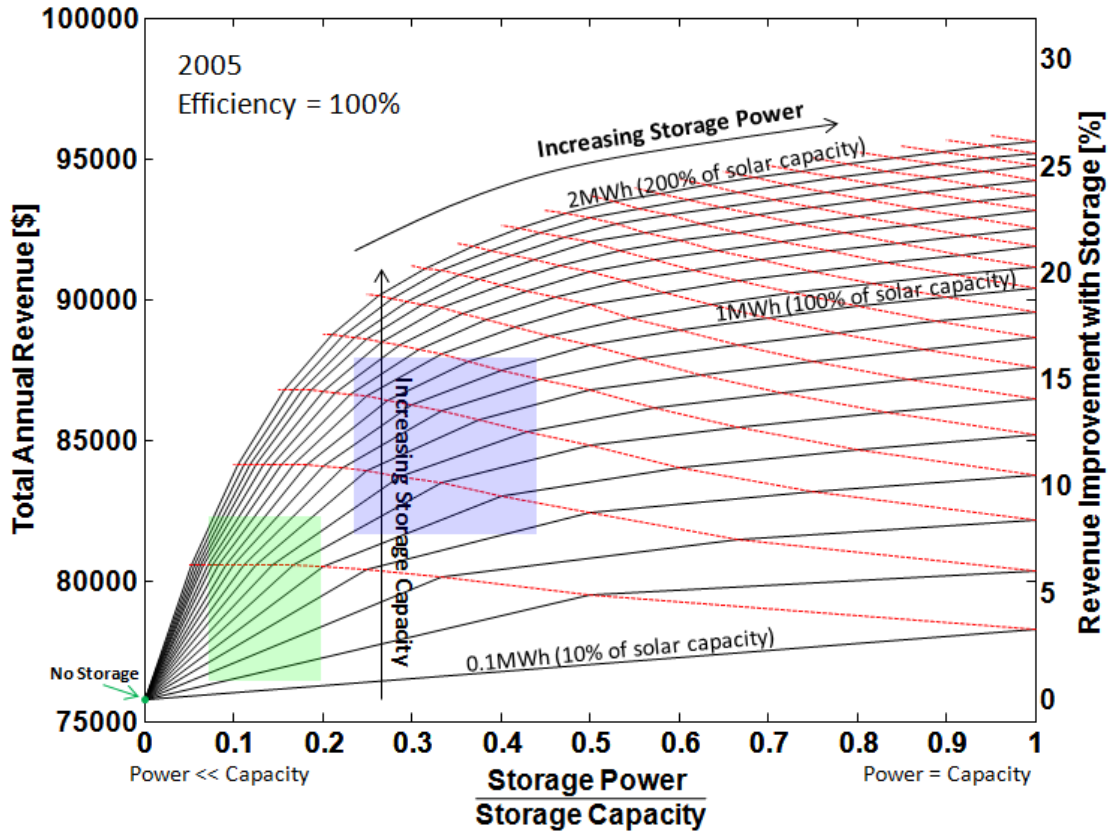


Figure 6-1: Revenue increases for photovoltaics with varying energy storage capacities and powers. The blue box corresponds to ideal energy storage system capacity and power combinations. The area covered by the green box indicates that significant revenue increases are possible even with relatively small investments in energy storage.

solar capacity between 2000 and 2005 were found to be between 19.3% and 31.1% with an energy storage efficiency of 100%. Unfortunately, the potential revenue increases were found to fall to between 9.1% and 21.3% with 80% efficient storage and between 3% and 14.5% with 60% efficient storage.

Figure 6.1, from Chapter 3, summarizes the revenue increases that are possible with varying energy storage capacities and powers. The blue shaded box in this figure corresponds to what are likely the ideal combinations of energy storage capacities and powers. The points within the blue box correspond to energy storage systems that achieve the majority of the increases in revenue possible while avoiding over-investments which would suffer from large diminishing returns to both capacity and power. Second, the green box in the figure indicates energy storage and power combinations for which significant revenue gains are possible even with relatively small investment. The slope of the lines in these regions are quite steep, indicating that even with relatively little investment in energy storage, large revenue increases are possible.

The results also indicate, however, that when owners utilize energy storage only to maximize revenue, the changes in avoided emissions with energy storage are negligible. Adding energy storage to photovoltaics does not yield additional environmental benefits beyond those achieved by the installation of photovoltaics alone.

However, the results also reveal that it is possible to achieve significant increases in the emissions offset by photovoltaics by adding energy storage. Adding energy storage with equivalent capacity and power to the capacity of the solar generation yielded maximum avoided CO<sub>2</sub> emissions increases of up to 56.2% with 100% efficient storage. With large storage installations, it was found that avoided CO<sub>2</sub> emissions could increase as much as 116%. This means that with large amounts of energy storage the CO<sub>2</sub> emissions offset by photovoltaics could be more than doubled depending on the efficiency of energy storage. However, in cases where energy storage is utilized to maximize emissions reductions, revenue is found to always decrease. The revenue reductions were found to be between 5% and 12% depending on the year.

Overall, these results indicate that there is a tradeoff between the economic and

environmental benefits that can be achieved when energy storage is added to photovoltaics. While it is possible to increase revenues with energy storage and it is possible to increase avoided emissions, these two objectives directly compete with each other. It is not possible to simultaneously achieve large increases in revenue and large increases in avoided emissions. Policy mechanisms that pay owners for verifiable CO<sub>2</sub> emissions reductions could overcome this trade-off. However, the value owners derive from CO<sub>2</sub> emissions reductions would have to be large enough to ensure the photovoltaics yield the same or greater revenue than if energy storage was used to maximize revenues without considering emissions reductions. The value of CO<sub>2</sub> emissions reductions that would be necessary to achieve the maximum possible CO<sub>2</sub> emissions reductions was found to be in the range of \$40 to \$60 per metric ton.

Finally, the results of the analysis in this thesis may also be of interest to energy storage researchers. The results indicate that for the application of adding energy storage to photovoltaics for energy arbitrage, storage capacity is a more important parameter than storage power. If the cost of capacity (MWh) and power (MW) for a given technology are similar, the ideal ratio of storage power to storage capacity, as indicated in Figure 6.1, is likely approximately 0.3 or 0.4.

## 6.2 Future work

“Finish each day and be done with it. You have done what you could.”

- Ralph Waldo Emerson

There are a number of areas of future work that would extend or complement the analysis in this thesis.

First, there are a number of ways in which the model formulated in this thesis could be extended. First, the model could be extended to consider inter-day storage use. Perhaps the most straightforward method of doing this would be to use the same model but to optimize over a 25 hour period. The 25th hour would have an artificial “transfer” price assigned to it which reflects the expected value of holding energy in storage until the following day. The energy used in the final hour at the transfer

price would not be counted in calculations of revenue but would instead be passed to the following day's optimization. This method of considering inter-day energy storage optimization would likely be consistent with the way actual energy storage installations would be optimized. Owners would likely pick a price threshold below which they would hold stored energy (assuming minimal losses) until the next day.

Multiple-day storage could also be studied by extending the optimization model to optimize the use of storage over multiple days, weeks, months, or even the entire year. The complexity of the model and the computation time required to find a solution grows very quickly as additional time is added. Extending the optimization time likely would only make sense if owners of photovoltaic installations with storage could be expected to also attempt to optimize storage use over extended periods of time. It is very difficult to forecast solar generation, energy prices, and emissions rates well into the future, limiting how far into the future owners would likely attempt to optimize the use of energy storage-coupled photovoltaics.

The model could also be expanded to consider day-ahead energy storage capabilities. The solar generation in a given day could be stored and used the following day. Optimization under these conditions would be significantly easier as the total energy available from storage would be known a day in advance. Considering day-ahead energy storage would also require a detailed analysis of how owners of photovoltaics with energy storage could also participate in day-ahead energy markets.

A second important area for future work is the detailed analysis of specific policy mechanisms that could be formulated to unlock the increase in avoided emissions that are possible when adding energy storage to photovoltaics. Giving owners the incentive to maximize emissions reductions would require both putting a value on CO<sub>2</sub> emissions and developing a detailed method of calculating and/or verifying hourly emissions rates. The current cap and trade policies being discussed to put a price on CO<sub>2</sub> emissions are unlikely to immediately have capabilities such as these.

Another important area for future work is in the development of advanced algorithms for forecasting solar generation, energy prices, and hourly marginal emissions rates. The results of the optimization of the use of energy storage with imperfect

information indicate the importance of good forecasting algorithms for these input parameters. The accuracy of forecasting tools could determine whether or not it is economically favorable to add specific energy storage technologies to photovoltaics. More accurate forecasting tools could also hasten the adoption of energy storage.

There are also many potential economic and emissions impacts associated with adding energy storage to photovoltaics that were not discussed in detail in this thesis. Ultimately, it was only possible to focus on a somewhat narrow set of potential impacts of adding energy storage to photovoltaics here. As discussed in Chapter 1, energy storage could enable photovoltaics to participate in a variety of additional electricity markets including markets for ancillary services, reserves, and/or capacity markets. Participation in each of these markets could have both economic and environmental impacts. Studying the role of energy storage-coupled photovoltaics in these markets is an important area for additional work.

Finally, the analysis in this thesis can be expanded to study the impacts of adding energy storage to other intermittent renewable generation technologies. While the trade-off between revenue enhancements and avoided emissions are likely to also be present for other renewable generation, the magnitudes of the potential changes could be different. Wind generation, for example, typically changes rapidly throughout the day and is often strongest during the overnight hours. Therefore, in the case of adding energy storage to wind generation, one might expect a reduction in avoided emissions when optimizing for revenue. Further, the duration of energy storage would likely be significantly longer than that required with photovoltaics. The delay between peak generation and peak prices is typically only a few hours for photovoltaics where it could be nearly a full day for wind. The intermittency of wind may also make multiple day storage optimization more important. Studying how easily the results of this thesis transfer to other renewable generation technologies is an important area for future work.

# Appendix A

## Solar Generation Data

### Normalization

Ideally, the analysis in this thesis would use actual historical measured values for solar generation. Unfortunately, measured data of solar generation is difficult to find and the data is often incomplete. Therefore, this thesis instead uses modeled hourly solar radiation data from the National Solar Radiation Database (NSRD) [35]. The data in the NSRD is given in units of  $\text{W}/\text{m}^2$  of solar radiation. Current photovoltaic systems, however, are only able to convert a fraction of this energy into electric power. System efficiencies vary widely based on photovoltaic device properties as well as installation location. The NSRD data must be normalized for use in this analysis. This appendix describes the normalization of the NSRD data for use in the optimization model formulated in Chapter 2.

The normalization described here impacts the absolute values of revenue and emissions increases found in the analysis. However, the relative changes in revenue and avoided emissions, the primary focus of the analysis, are not impacted by the selected normalization procedure.

In this study I used measured hourly PV generation data to normalize the radiation data in the NSRD. Unfortunately, measured generation data was only available for years prior to 2003 and, therefore, was insufficient to be used directly in the analysis. Measured data from five PV sites in New England were selected to perform

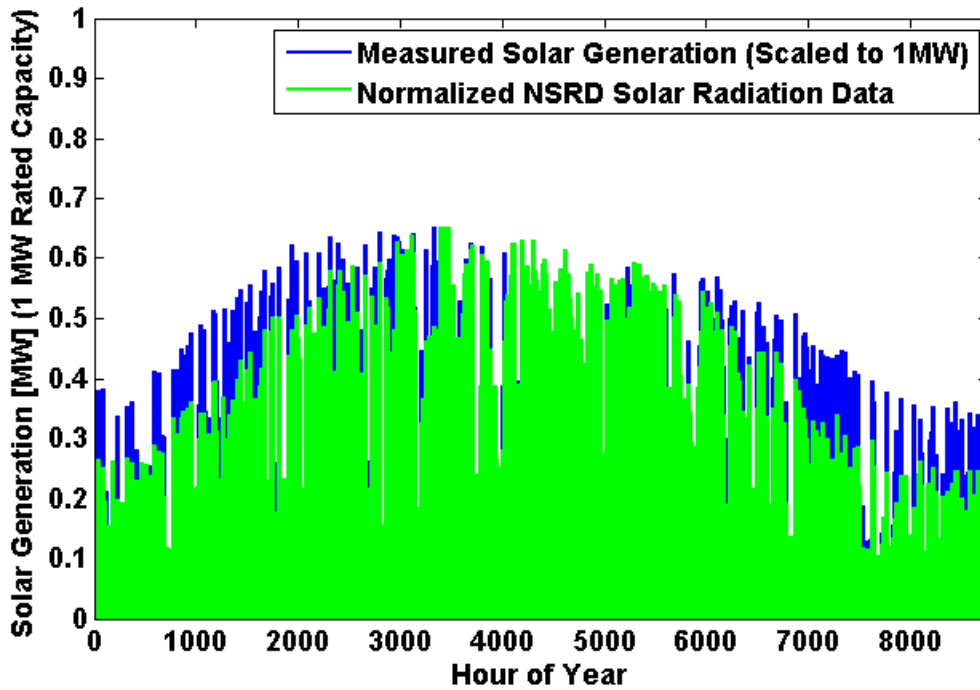


Figure A-1: Normalized hourly solar generation data.

the normalization. The five sites collected data during various periods during the the years 1998 to 2002. Two of the systems are located in North Dartmouth, MA with rated capacities of 14 kW and 1 kW. The other three systems are located in Cambridge, MA, Lynn, MA, and Middletown, RI with ratings of 23 kW, 5 kW, and 40kW, respectively. The systems were selected for their high data availability rather than their geographic distribution. While data was collected for these sites between 1998 to 2002, the dataset was most complete for the year 2002. Therefore, data from 2002 was selected to perform the normalization.

The measured data was used to quantify the expected capacity factor of actual installed PV systems. I first divided the sum of the measured generation from the sites described above in each hour by the sum of the sites' rated capacities. The result yields the sites' hourly capacity factor, or the sum of the actual generation in each hour divided by the sum of the sites' rated capacities. I then scaled the results to represent the generation that would be expected from a hypothetical site with a rated capacity of 1 MW.



Next, the solar radiation data from the 66 NSRD sites in New England were averaged in each hour [35]. The averaged data was then scaled uniformly in all hours such that the maximum value matched the maximum hourly capacity factor for a 1 MW system calculated from the measured generation data. The result is illustrated in Figure A-1. The green line in the figure represents the normalized NSRD data while the blue line represents the normalized measured generation data. A uniform normalization factor was applied to all of the NSRD data used in this study (2000 to 2005).

Interestingly, the difference between summer peak and winter peak generation appears to be smaller for the measured data relative to the data normalized from the NSRD solar radiation data. This same discrepancy was found when the same calculation was performed for data from 2000 and 2001. I considered trying to correct for this difference. However, for simplicity's sake, I decided to leave the normalized data as is. Therefore, the normalized solar generation data used in this thesis may make a conservative estimate of the magnitude of winter generation. This will impact the baseline values for revenue and avoided emissions from photovoltaic systems. However, this difference should have only a minimal impact on the relative changes in revenue and avoided emissions with energy storage.

Figure A-2 compares the normalized measured solar generation data with the normalized data from the NSRD. While there are some differences, the two datasets have similar shapes and magnitude in most days, indicating the normalization of the NSRD data is reasonable. Sometimes the normalized solar radiation data appears to over estimate the actual solar generation while in other hours the normalized dataset underestimates the actual solar generation. Some of these discrepancies may be due to the wider geographic distribution of sites in the NSRD.

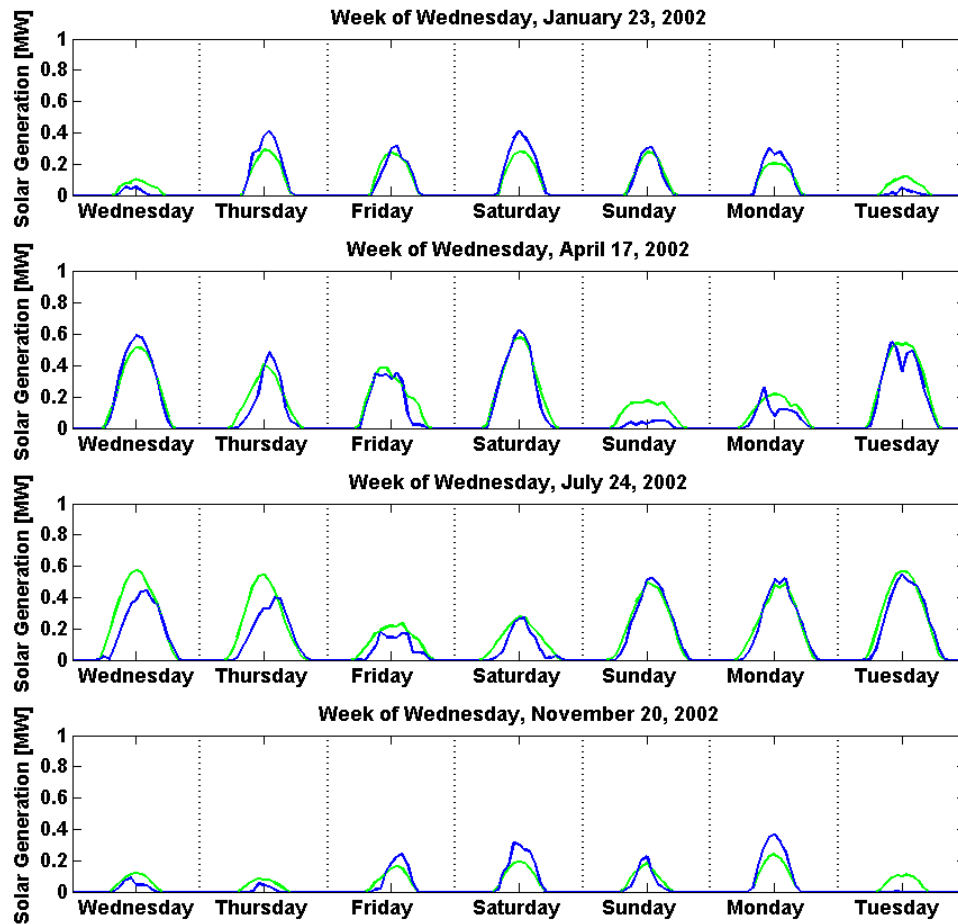


Figure A-2: Comparison of normalized NSRD solar radiation data to normalized measured solar generation data in selected weeks. The blue lines represents the normalized measured solar generation data while the green lines represent the normalized NSRD data.

# Appendix B

## GAMS Optimization Model

### Formulation

This appendix contains the source code for the optimization model used in this thesis. The model was formulated and solved using the General Algebraic Modeling System (GAMS). The input data and model parameters are passed to the model from MATLAB using the GAMS GDXMRW utility function. The GDXMRW utility allows MATLAB to read and write files in GAM's GDX file format. Once the model is solved, the results are returned to MATLAB for processing and plotting.

GAMS Code:

```
$title Energy Storage and Solar Revenue Maximization
$offsymxref

* The model optimizes the use of storage over a 24 hour period
sets t    scheduling hours / 1*24 /

* This code loads that data parameters from the file that MATLAB wrote
execute_load 'DataToGAMS.gdx' storagecapacity, storagepowercharge,
storagepowerdischarge,storageefficiency, price, newgen, CO2er,
SO2er, NOXer;

variables
    pstorage(t)    energy used from storage during hour t
    pstored(t)     solar energy stored during hour t
```

pused(t)                solar generation used directly during hour t  
 storedenergy(t)        the volume of energy in storage after hour t  
 revenue                total operating revenue during entire day  
 hourlyrevenue(t)      revenue generated in hour t  
 CO2emissionsreduction   total CO2 emissions reduction  
 hourlyCO2emred(t)    CO2 emissions reduction in hour t  
 SO2emissionsreduction   total SO2 emissions reduction  
 hourlySO2emred(t)    SO2 emissions reduction in each hour  
 NOXemissionsreduction   total NOX emissions reduction  
 hourlyNOXemred(t)    NOX emissions reduction in each hour

positive variables pstorage, pstored, pused, storedenergy;

\* The energy in storage cannot exceed the storage capacity  
 storedenergy.up(t) = storagecapacity;  
 storedenergy.lo(t) = 000;

\* The energy stored or used from storage in a single hour  
 \* cannot exceed the storage power  
 pstorage.up(t) = storagepowerdischarge;  
 pstored.up(t) = storagepowercharge;

\* The total power used directly each hour is given by the  
 \* new solar generation in that hour.  
 pused.up(t) = newgen(t);

equations

revfn                total revenue -- an objective fn  
 hourlyrev(t)        hourly revenue  
 CO2emfn    total CO2 emissions reduction -- an objective fn  
 hourlyCO2em(t)    hourly CO2 emissions reductions  
 SO2emfn        total SO2 emissions reduction  
 hourlySO2em(t)    hourly SO2 emissions reductions  
 NOXemfn        total NOX emissions reductions  
 hourlyNOXem(t)    hourly NOX emissions reductions  
 storeeq(t)        the balance in the storage tank  
 geneq(t)        generation must be used or stored  
 onefunc(t)        make sure the storage is only doing one thing

revfn..

revenue =e= sum(t, pstorage(t)\*price(t)+pused(t)\*price(t));

hourlyrev(t)..

hourlyrevenue(t) =e= pstorage(t)\*price(t)+pused(t)\*price(t);

```

CO2emfn..
CO2emissionsreduction =e= sum(t, pstorage(t)*CO2er(t)+pused(t)*CO2er(t));

hourlyCO2em(t)..
hourlyCO2emred(t) =e= pstorage(t)*CO2er(t)+pused(t)*CO2er(t);

SO2emfn..
SO2emissionsreduction =e= sum(t, pstorage(t)*SO2er(t)+pused(t)*SO2er(t));

hourlySO2em(t)..
hourlySO2emred(t) =e= pstorage(t)*SO2er(t)+pused(t)*SO2er(t);

NOXemfn..
NOXemissionsreduction =e= sum(t, pstorage(t)*NOXer(t)+pused(t)*NOXer(t));

hourlyNOXem(t)..
hourlyNOXemred(t) =e= pstorage(t)*NOXer(t)+pused(t)*NOXer(t);

storeeq(t)..
storedenergy(t) =e= storedenergy(t-1) - pstorage(t) +
  storageefficiency*pstored(t);

geneq(t)..
newgen(t) =e= pstored(t)+pused(t);

onefunc(t)..
pstorage(t)*pstored(t) =e= 0;

model ucom / all / ;

* The solve statement for revenue optimization
solve ucom using nlp maximizing revenue;

* The solve statement for emissions optimization
* solve ucom using nlp maximizing CO2emissionsreduction;

parameter hourlyrevenuesol(t);
parameter hourlyCO2emredsol(t);
parameter hourlySO2emredsol(t);
parameter hourlyNOXemredsol(t);
parameter endingstoragesol;
parameter hourlypusedsol(t);
parameter hourlypstoragesol(t);
parameter hourlypstoredsol(t);
parameter hourlystoredenergysol(t);

```

```
* These lines gather the data to be returned to MATLAB
hourlyrevenuesol(t) = hourlyrevenue.l(t);
hourlyCO2emredsol(t) = hourlyCo2emred.l(t);
hourlySO2emredsol(t) = hourlySO2emred.l(t);
hourlyNOXemredsol(t) = hourlyNOXemred.l(t);
hourlypusedsol(t) = pused.l(t);
hourlypstoragesol(t) = pstorage.l(t);
hourlypstoredsol(t) = pstored.l(t);
hourlystoredenergysol(t) = storedenergy.l(t);

* These lines write the results to a file to be read by MATLAB.
execute_unload 'DataFromGAMS.gdx' hourlyrevenuesol,
hourlyCO2emredsol, hourlySO2emredsol, hourlyNOXemredsol,
hourlypusedsol, hourlypstoragesol, hourlypstoredsol,
hourlystoredenergysol;
```

# Bibliography

- [1] Solarbuzz LLC. World pv industry report summary, Apr 2009. <http://www.solarbuzz.com/Marketbuzz2009-intro.htm>.
- [2] Staffan Jacobsson and Volkmar Lauber. The politics and policy of energy system transformation - explaining the german diffusion of renewable energy technology. *Energy Policy*, 34(2006):256–276, October 2004.
- [3] Ryan Wiser and Galen Barbose. Renewables portfolio standards in the united states. Technical Report LBNL-154E, Lawrence Berkeley National Laboratory, Berkeley, CA, April 2008.
- [4] Travis Bradford. *Solar Revolution: The Economic Transformation of the Global Energy Industry*. MIT Press, Cambridge, Massachusetts, 2006.
- [5] EIA. Renewable energy consumption and electricity preliminary 2007 statistics. Technical report, Energy Information Agency, Washington, DC, May 2008.
- [6] P. Denholm and R. Margolis. Very large-scale deployment of grid-connected solar photovoltaics in the united states: Challenges and opportunities. In *Conference Paper presented at Solar 2006, Denver, Colorado, 2006*.
- [7] Shimon Awerbuch. Investing in photovoltaics: risk, accounting and the value of new technology. *Energy Policy*, 28(14):1023–1035, November 2000.
- [8] Electricity Storage Association. Storage technology, Apr 2009. <http://www.electricitystorage.org/>.
- [9] Paul Butler, Jennifer L. Miller, and Paula A. Taylor. Energy storage opportunities analysis phase ii final report a study for the doe energy storage systems program. Technical Report SAND2002-1314, Sandia National Laboratories, Livermore, CA, May 2002.
- [10] Ying Wu, Jaideep Raje, Kristin Abkemeier, Eddie Krule, Samhitha Udupa, Michael Holman, and Matthew Nordan. Alternative power and energy storage, state of the market q2 2008: Making sense of the next big thing. Technical Report LPRI-SMR-08-01, Lux Research Inc., New York, NY, May 2008.

- [11] Ali Nourai. Installation of the first distributed energy storage system (dess) at american electric power (aep). Technical Report SAND2007-3580, Sandia National Laboratories, Livermore, CA, June 2007.
- [12] VRB Power Systems. The vrb energy storage system (vrb-ess): The multiple benefits of integrating the vrb-ess with wind energy - case studies in mwh applications. Technical report, VRB Power Systems, Richmond, BC, Canada, March 2007.
- [13] Peter J. Hall and Euan J. Bain. Energy-storage technologies and electricity generation. *Energy Policy*, 36(12):4352–4355, December 2000.
- [14] Roel Hammerschlag Christopher Schaber, Patrick Mazza. Utility-scale storage and renewable energy. *The Electricity Journal*, 17(6):21–29, July 2004.
- [15] H. Ibrahim, A. Ilinca, and J. Perron. Energy storage systems - characteristics and comparisons. *Renewable and Sustainable Energy Reviews*, 12(5):1221–1250, June 2008.
- [16] International Energy Agency. Empowering variable renewables. Technical report, International Energy Agency, Paris, September 2008.
- [17] Richard Baxter. *Energy Storage: A Nontechnical Guide*. PennWell Corp., Tulsa, Oklahoma, September 2005.
- [18] Rahul Walawalkar, Jay Apt, and Rick Mancini. Economics of electric energy storage for energy arbitrage and regulation in new york. *Energy Policy*, 35(4):2558–2568, April 2007.
- [19] SK Aditya and D Das. Battery energy storage for load frequency control of an interconnected power system. *Electric Power Systems Research*, 58(3):179–185, July 2001.
- [20] A. Oudalov, D Chartouni, and C Ohler. Optimizing a battery energy storage system for primary frequency control. *IEEE Transactions on Power Systems*, 22(3):1259–1266, August 2007.
- [21] S. Eckroad. Handbok of energy storage for transmission or distribution applications. Technical Report 1007189, Electric Power Research Institute, Palo Alto, CA, December 2002.
- [22] J. Svensson, P. Jones, and P. Halvarsson. Improved power system stability and reliability using innovative energy storage technologies. In *The 8th IEE International Conference on AC and DC Power Transmissions*, 2006.
- [23] Dan Ton, Charles Hanley, Georgianne Peek, and John Boyes. Solar energy grid integration systems - energy storage (segia-es). Technical Report SAND2008-4247, Sandia National Laboratories, Livermore, CA, July 2008.



- [24] A Oudalov, T. Buehler, and D. Chartouni. Utility scale applications of energy storage. In *IEEE Energy 2030 Conference*, November 2008.
- [25] Brian Parsons, Michael Milligan, Bob Zavadil, Daniel Brooks, Brendan Kirby and Ken Dragoon, and Jim Caldwell. Grid impacts of wind power: a summary of recent studies in the united states. *Wind Energy*, 7(2):87–108, May 2004.
- [26] Ramteen Sioshansi, Paul Denholm, Thomas Jenkin, and Jurgen Weiss. Estimating the value of electricity storage in pjm: Arbitrage and some welfare effects. *Energy Economics*, 31(2):269–277, March 2009.
- [27] Paul Butler, Joe Iannucci, and Jim Eyer. Innovative business cases for energy storage in a restructured electricity marketplace. Technical Report SAND2003-0362, Sandia National Laboratories, Livermore, CA, February 2003.
- [28] Pedram Mokrian and Moff Stephen. A stochastic programming framework for the valuation of electricity storage. In *26th USAEE/IAEE North American Conference*, Ann Arbor, MI, 2006.
- [29] Edwin Maesen, Johan Driesen, and Ronnie Belmans. Multi-objective valuation of electricity storage services. In *Proceedings of EESAT Conference*, September 2007.
- [30] Liliana Benitez, Pablo Benitez, and G. Cornelis van Kooten. The economics of wind power with energy storage. *Energy Economics*, 30(2008):1973–1989, March 2007.
- [31] G.N. Bathurst and G. Strbac. Value of combining energy storage and wind in short-term energy and balancing markets. *Electric Power Systems Research*, 67:1–8, 2003.
- [32] Wei-Fu Su, Shyh-Jier Huang, and Chin-E Lin. Economic analysis for demand-side hybrid photovoltaic and battery energy storage system. *IEEE Transactions on Industry Applications*, 37(1):171–177, 2001.
- [33] Jukka Paatero and Peter Lund. Impacts of energy storage in distribution grids with high penetration of photovoltaic power. *International Journal of Distributed Energy Resources*, 3(1):31–45, 2007.
- [34] Katherine Martin. The impact of large-scale solar photovoltaic adoption on prices and reliability the new england power pool. Master’s thesis, Massachusetts Institute of Technology, 2006.
- [35] NREL. National solar radiation database 1991-2005 update: User’s manual. Technical Report NREL/TP-581-41364, National Renewable Energy Laboratory, Golden, Colorado, April 2007.
- [36] New England Independent System Operator. Hourly historical data post-market, Apr 2009. [http://www.iso-ne.com/markets/hrly\\_data/index.html](http://www.iso-ne.com/markets/hrly_data/index.html).

- [37] Michael Berlinski and Stephen Connors. Economic and environmental performance of potential northeast offshore wind energy resources. Technical report, MIT Laboratory for Energy and the Environment, Cambridge, MA, January 2006.
- [38] Stephen Connors, Katherine Martin, Michael Adams, Edward Kern, and Baafour Asiamah-Adjei. Emissions reductions from solar photovoltaic (pv) systems. Technical report, MIT Laboratory for Energy and the Environment, Cambridge, MA, August 2005.
- [39] J.P. Connolly. Effect of real-time electricity pricing on renewable generators and system emissions. Master's thesis, Massachusetts Institute of Technology, 2008.
- [40] Tarek Rached. Communicating complexity and informing decision-makers: challenges in the data and computation of environmental benefits of renewable energy. Master's thesis, Massachusetts Institute of Technology, 2008.
- [41] US Environmental Protection Agency. Clean air markets, Apr 2009. <http://www.epa.gov/airmarkt/index.html>.
- [42] US Environmental Protection Agency. The emissions & generation resource integrated database (egrid), Apr 2009. <http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html>.
- [43] US Environmental Protection Agency. Continuous emissions monitoring data, Apr 2009. <ftp://ftp.epa.gov/dmdnload>.
- [44] Alberto Fabbri, Tomas Gomez San Roman, Juan Rivier Abbad, and Victor H. Mendez Quezada. Assessment of the cost associated with wind generation predictions errors in a liberalized electricity market. *IEEE Transactions on Power Systems*, 20(3):1440–1446, August 2005.
- [45] C.P. Rodriguez and G.J. Anders. Energy price forecastig in the ontario competitive power system market. *IEEE Transactions on Power Systems*, 19(1):366–374, February 2004.
- [46] P. Mandel, T. Seniyu, N. Urasaki, T. Funabashi, and A.K. Srivastava. A novel approach to forecast electricity price for pjm using neural network and similar days method. *IEEE Transactions on Power Systems*, 22(4):2058–2065, November 2007.