

Using Supply Chain Management Techniques to Make Wind Plant and Energy Storage Operation More Profitable

by

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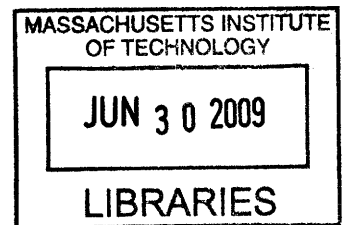
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Abstract

Our research demonstrates that supply chain management techniques can improve the incremental gross profits of wind plant and storage operations by up to five times. Using Monte-Carlo simulation we create and test scenarios that achieve incremental operating profits of up to 15 percent of base case revenue, and show pre-tax profit. We show that energy storage – specifically in the form of utility-scale batteries – can become economically-viable today when using supply chain management strategies under certain scenarios.

To achieve these results we have built a simulation model with three data inputs. First, we synthesized the output of a 120 MW wind plant in Maine for both summer and winter seasons. Second, we simulated New England ISO market pricing data for both the Day-Ahead and Real-Time markets in summer and winter seasons using Monte Carlo simulations. Third, using actual data from two existing battery companies, we incorporated the technical and cost specifications for two energy storage facilities. All of these data inputs feature adjustable parameters so we can test various plant configurations, market volatilities and storage capabilities, among other inputs.

Using our model, we then employed supply chain management network design strategies and daily operating policies to test profitability improvements on our wind plant-plus-storage operation. For example, we ran simulations for scenarios where our storage facility is either located in Maine next to our wind plant, or located in another state. Also, since storage can make wind generation a predictable capacity resource, we ran simulations to test results in both the Day-Ahead and Real-Time markets. In addition we developed four (4) inventory management policies with dynamic input (charge) and output (discharge) strategies for our storage units. For each policy, we had to conceptualize the policy – while considering planning horizon, lead time, holding costs, shortage costs, market pricing and storage capabilities – and then build functionality in our model to execute those strategies in dynamic pricing and wind plant output environments. The outcomes of our simulation model include incremental gross profit, operating profit and pre-tax profit for each of 54 scenarios, as well as 11 management insights for wind plant and storage operators, storage technology manufacturers and New England ISO leadership.

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Dedication

We thank our wives, Parul and Deirdre, and our daughters, Prateeti and Ruth, for their collective support, understanding and patience during our many days and nights of work on this project.

We dedicate this thesis to them.

-Prashant

-Clay

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1 Introduction and Motivation

Energy storage is a rapidly-evolving field that will transform the functioning of the electricity grid. Especially-promising energy storage technologies include modular utility-scale batteries whose grid-integrated applications could include multi-megawatt battery facilities providing power in cities, distributed systems of batteries powering fleets of electric vehicles, or batteries solving the intermittency issues of *Wind Plants*, among others. In each of these applications, effective management of the stored electricity in these batteries will greatly impact the extent of benefits realized.

We have chosen to explore the use of energy storage with a wind plant because research indicates that this pairing could represent a realistic economic opportunity for battery-based energy storage in the near term. Whereas vehicle-to-grid applications are still several years away, new wind plants are being built across the United States. Each new wind installation provides an immediate opportunity for the co-installation of a battery to help solve intermittency and pricing issues.

Wind power is among the fastest-growing energy sources in the world. In 2008, global wind power capacity grew by nearly 29%, increasing worldwide capacity to more than 121,000 *Megawatts* (World Wind Energy Association, 2008). Last year, the United States surpassed Germany to become the world leader with installed wind power capacity of 25,170 Megawatts. As a percent of total electricity generation, wind power accounts for approximately 1.5% globally and 1.26% in the United States (American Wind Energy Association, 2008). These figures are expected to increase to 12% and 15%, respectively, by 2020 if government production incentives and tax credits continue to be a driving catalyst for growth of the industry (World Wind Energy Association, 2008).

Despite rapid growth, wind power has inherent shortcomings that can limit its profitability. First, wind plants are often located in remote areas that have high wind speeds, but relatively low wholesale electricity prices. These wind plants must sell their energy at the prevailing wholesale electricity prices in these regions. Second, since electricity is an absolutely perishable resource (meaning it needs to be

consumed the moment it is produced, or be lost), wind plants are forced to sell at whatever wholesale price is prevailing in the market at the time of generation – even if that price is unprofitable for the wind plant. Third, wind power is classified as an intermittent resource due to variability of wind speed and direction. Due to this unpredictability (especially when compared to the daily consistency of coal-fired or nuclear generation) wind power is unable to participate in some wholesale electricity markets (e.g. Day-Ahead market) where prices on average are higher. Thus, wind plants earn less per KWh on average than other forms of generation because of locational pricing pressures and reliability constraints like those mentioned above. For example, while the nationwide average wholesale price paid for electricity in the United States in 2007 ranged from approximately \$0.040 to \$0.070 per KWh, the cumulative capacity-weighted-average price paid in the U.S. for wind electricity was under \$0.040 per KWh (Wiser & Bolinger, May 2008).

Energy storage technology has been proposed as a possible solution for overcoming the above-mentioned pricing issues and increasing the profitability of wind plants. Storage can help wind plant operators give their absolutely perishable product a longer ‘shelf life.’ For example, energy storage can allow wind plants to store their electricity output during periods of low prices and then sell that stored energy during hours of higher prices thereby increasing revenue and profit. Also, wind plant operators can use storage to increase the predictability of their *Wind Plant Output* thereby increasing the value of their electricity for buyers who pay a premium for reliability. Finally, wind plant operators can place *Linked* storage units near densely-populated areas where wholesale electricity prices are highest, thus effectively allowing wind plant operators to sell their clean, renewable energy closer to high-demand areas.

Despite the promise of energy storage as a useful application for wind plants, there are relatively few storage-wind plant installations currently up and running. In fact, just 2.5% of the total electricity delivered (or approximately 95 million Megawatt-hours (MWh)) in the United States passes through energy storage systems (Electric Power Research Institute and U.S. Department of Energy, 2003). The percentages in Europe and Japan are 10% and 15%, respectively. Almost all of these storage systems are

geographically-constrained *Pumped Hydroelectric Storage* facilities. The perceived limitations of other storage technologies such as battery storage are mostly to blame. Batteries are modular and scalable, yet the technology is still evolving and is not considered cost-effective. In fact, most existing research and industry reports suggest that battery storage will not become economically-viable for several years.

Our thesis takes aim at these existing claims that energy storage systems using utility-scale battery technologies are not economically-viable for a wind plant. Our research suggests that energy storage *can* be profitable. We demonstrate that by utilizing supply chain management techniques, such as network design and inventory management policies, energy storage can actually increase a wind plant's operating profit. We have accomplished this by building a supply chain model that uses synthesized Wind Plant Output, Monte Carlo market pricing simulations, and real-life battery technical specifications to calculate the incremental financial benefits of combining energy storage with a wind plant. Our results demonstrate that using supply chain management techniques can make a combined energy storage-wind plant operation more profitable.

We have chosen to focus our research on the New England region. We have done so for several reasons. First, New England has few wind plants built currently. Yet the region has rich wind resources and many new wind plants in development (Department of Energy, 2008). Thus New England provides a relatively uncharted landscape for research. Second, to the best of our knowledge, the New England Independent System Operator (ISO) has not had a research study conducted specifically to assess the use of utility-scale battery energy storage within the region. By comparison, other ISO regions such New York, California and Pennsylvania-Jersey-Maryland (PJM) have all had multiple studies conducted. To us, this presented a unique opportunity to investigate this topic. Third, because we are located in Massachusetts, we felt that choosing the New England region for our study would allow us to gain easier access to local utility representatives and industry experts. In fact, this has proven to be the case as we have been able to speak with a range of resources. Thus, we viewed the coupling of energy storage with a wind plant in New England to be an ideal situation for our academic exercise.

1.1 Background and Current Practices

We undertook this thesis project with little background or knowledge of the energy industry. Therefore, we had to start by learning the basics. To do this, we studied energy industry reports and research studies. We also contacted various industry experts and New England ISO representatives to engage them, ask questions and validate findings. Through this process we developed a working knowledge of the Electricity Grid, wind generation, electricity storage technology and wholesale electricity markets. We share these high-level findings below.

1.1.1 Wind Generation

The amount of installed wind generation capacity worldwide continues to rise dramatically. Meanwhile, the technology behind wind generation continues to evolve. In fact, development is happening so fast that the standard image of a wind turbine – i.e., a large, usually-white, 3-pronged blade spinning at the top of a tall pole – now serves only to oversimplify the level of complexity involved in modern wind generation, and veil the number of variables that contribute to make wind generation possible.

Despite all of these developments, wind remains an intermittent resource. Wind plant electricity output varies with wind speed. Moreover, if the wind speed is too low or too high, there is no electricity output at all. No matter the *Wind Power Class* (ratings go from 1 to 7, with 7 being the fastest winds), the turbine type (there are many models ranging from 1.5 to 6 MW in size), or the *Hub Height* (the altitude at which a turbine sits on a pole), wind is still dependent upon the unpredictable speed and direction of wind to operate.

Wind generation's intermittency manifests itself in a wind plant's *Capacity Factor*, which is the ratio of total energy the plant produced during a period of time over the energy the plant would have produced operating at full capacity. Wind plants have low Capacity Factors (average of about 33%) relative to other forms of generation (e.g., U.S. nuclear plants average 92%) (Renewable Energy Research Laboratory, University of Massachusetts at Amherst). Thus wind plant owners can never be sure that the wind will be

blowing during periods of high demand and high prices. Consequently, wind plant owners must sell whatever energy they generate in the spot market regardless of price. If wind plant owners could make their energy generation predictable and *Dispatchable* – even for just several hours a day – they could schedule a portion of their electricity sales to coincide with higher demand and higher prices.

1.1.2 Electricity Storage

As we began our research into energy storage, we quickly realized that there are many different technology options available. Choice of technology depends primarily on how one intends to use storage. For our research, we decided upon a strategy of using storage for *Time Shifting* which requires a battery that can dispatch energy for multiple hours on one charge. The most basic method of Time Shifting is arbitrage – storing electricity overnight (when prices are historically lower) and selling it the next day (when prices are historically higher). We chose to investigate Time Shifting for three reasons. First, existing research on energy storage confirms that Time Shifting is a fitting use of storage for wind plants. Second, the use of energy storage for Time Shifting presents scenarios where supply chain management techniques – such as network design and inventory management policies – can be applied to impact performance and profitability. Third, storage technologies exist for Time Shifting that can be purchased today.

Through research and interviews with industry experts we chose to use two technologies for our model: *Zinc Bromine* batteries (*ZnBr*) and *Sodium Sulfur* batteries (*NaS*). Both of these technologies demonstrate functional capabilities ideal for Time Shifting. For example, both technologies are modular and scalable; both can discharge many of Megawatts per hour for at least five hours; both can be charged and discharged – or “cycled” – many thousands of times before failure. We attained pricing information for each technology that we use in our model to calculate the incremental operational profit and incremental Pre-Tax Profit of each system under various scenarios.

1.1.3 Wholesale Electricity Markets and Electricity Grid

The New England Electricity Grid is a series of high-power transmission lines and “last mile” distribution lines that deliver energy to residential and commercial customers. Electricity generation is provided by a mixture of coal (15%), nuclear (28%), natural gas (41%), fuel oil (4%), Hydroelectric (5%), renewables (6.0%) and Other (1.3%) (Edison Electric Institute, 2009). Wind accounts for less than 1% of generation according to the New England Independent Service Operator (ISO-NE) which administers the electricity markets.

ISO-NE operates two wholesale electricity markets, the *Real-Time* and *Day-Ahead* markets. Buyers and sellers trade in these two markets much the same way that traders participate on the New York Stock Exchange. Sellers are typically electricity *Generators* who are looking to sell their electricity output. Buyers (or *Loads*) are organizations that need electricity for commercial or residential purposes. The Real-Time market is like a spot market. By comparison, Day-Ahead market trades are commitments to buy/sell electricity the following day at a specified hour.

The ISO-NE market features eight “Zones” and nearly 500 “Nodes.” Each zone or node has its own prevailing market price (or *Locational Marginal Price*) which can fluctuate dramatically. Prices vary by time of day, by season, and by location within the New England region. For example, while the price of electricity may be trading at \$63 per Kilowatt-hour in Cambridge Massachusetts, at the same hour the price could be \$58 in Maine. For example, in Cos Cob Connecticut, while *summer* electricity prices can range from \$3 to over \$300 per Kilowatt-hour in a single day, *winter* prices may only top out at \$270. This extreme price variability of the ISO-NE electricity market can create arbitrage opportunities for Generators. However, as noted earlier, intermittent generation resources such as wind plants cannot take advantage of these arbitrage opportunities. Instead, intermittent resources can only sell into the Real-Time market where advance commitments are not required. These Generators simply sell whatever energy they produce at any given hour.

1.1.4 Supply Chain Management

There are several parallels between the Electricity Grid and a physical supply chain. For example, a wind plant is like a manufacturing plant that produces a product – in this case a highly-perishable product, electricity. A storage battery is like a warehouse that inventories product in anticipation of future demand. Electricity Grid power lines are like roads/railways that move product. Drawing these parallels allowed us to begin to conceptualize supply chain policies for our wind plant-plus-storage system. Specifically, we charted out *Network Design Decisions* such as facility role, facility location, capacity allocation, supply allocation and market allocation (Chopra & Meindl, 2004).

Next we set out to develop *Daily Operating Policies* (equivalent to inventory control policies) for our stored electricity. To do this, we attempted to identify common products in the physical world that have perishability characteristics similar to those of electricity and looked at the supply chains of those products. We identified blackberries as a product that has such characteristics. Blackberries are among the most perishable of fruits. They can turn soft, mushy, and moldy within 24 hours if not consumed at the peak of their ripeness. Harvested blackberries become less valuable by the hour (Fernandez & Ballington, 1999). Given their perishable nature, blackberries are often sold locally at prevailing market prices. However, higher prices can be earned if the shelf life of the fruit is extended and the fruit can be safely transported at a distance to other markets (Boyette, 1995).

The blackberry case gave us a useful perspective for devising Daily Operating Policies for stored electricity. First, we realized that energy storage could bring significant value to electricity by extending its shelf life of electricity from zero to 24 hours or more. Second, we realized that our operating policies needed to address the problem of holding costs (*Standby Losses* incurred through heat loss of a charged battery) faced by stored electricity. Third, we decided to set our policy's planning horizon for selling our stored electricity to one day by using elements of a *Single Period Problem* (or *Newsvendor*) within our Time Shifting strategy. Fourth, we examined prices and demand in various New England regions to find new markets for our wind plant to sell its stored electricity at higher prices. Finally, we made sure to

consider transportation costs as we sought new markets to sell our stored electricity. Table 1-1 below captures the lessons we learned from the blackberry case study:

Table 1-1: Blackberry Supply Chain Lessons for Electricity

Blackberry fruit: product and supply chain characteristics	Wind electricity	Key learning for our electricity supply chain
Cold transportation– reduces spoilage rate	Battery storage – extends shelf life	Use storage
Even with cold transportation - quick spoilage	Even with storage - Standby Losses	Product value decreases by hour – incorporate in holding costs
1-day shelf life	1-day planning horizon (using Time Shifting)	Apply concepts from Single Period Problem (Newsvendor Problem)
Higher prices if transported to markets farther away from source	Higher prices if sold in high-demand areas	Find locations with higher prices + design network accordingly
Transportation damages (due to delicacy of fruit)	Transmission losses over wires (reflected in Locational Marginal Price)	Factor high transportation costs as reflected in different Locational Marginal Price

With this foundation for understanding of how supply chain concepts could be applied to our wind plant-plus-storage system and stored electricity, we continued to make Network Design Decisions and develop operating policies.

1.2 Research Question, Objectives and Scope

We began with the following research question: “Can the use of supply chain management techniques make a wind plant-plus-energy storage operation in New England more profitable?” In answering this question, our objective is to extend existing research in the emerging field of energy storage. While our Literature Review (see Section 1.4) has extensive reviews of existing research, it is worth noting here that none of the existing research explores the use of supply chain management techniques to the operation of a wind plant-plus-storage system. Nor do these studies focus on the New England ISO. By demonstrating that supply chain management techniques can improve profitability of a wind plant-plus-storage system, we believe we will establish a solid base for further research in this area.

Our scope was defined by existing research in the field as well as our own goals for the project. We used existing research and models for synthesis of wind plant electricity output, simulation of electricity prices and evaluation of storage technology and customized it for our context. We did not seek to extend

research in these fields by developing new methods; we simply applied existing methods to generate inputs for our model. These inputs were used to create a realistic environment of Wind Plant Output, electricity prices, and storage characteristics that we used to test different supply chain management techniques. We also did not conduct a system wide study for the Electricity Grid, nor did we examine numerous other possible applications of storage beyond Time Shifting.

1.3 Literature Review

We conducted a review of literature related to our topic by surveying reports, journals and websites in the field of wind energy, electricity markets, energy storage, and supply chain management. This review of literature helped us to gain a fundamental understanding of the related fields of wind energy, storage and electricity markets to which we applied established supply chain management techniques. In this section we begin by discussing documents that helped us to establish a basic understanding of these fields in Section 1.4.1. Then, in Section 1.4.2 we discuss existing studies and reports on large scale commercial electrical energy storage and on combining wind energy plants with storage. Finally we conclude in Section 1.4.3 by a quick review of established research in the field of supply chain management that we have used.

1.3.1 Literature on Wind Energy, Storage and Electricity Markets Fundamentals

In this section we discuss some of the resources that we used to develop a fundamental understanding of the fields of wind energy, energy storage and electricity markets and the manner in which we used them to develop our model.

Due to a combination of technology improvements, policy incentives and public focus on renewable energy alternatives, wind energy is one of the fastest growing energy sources in the United States and in the world. The growth and future potential of the wind energy industry is extensively reported in reports published by the Global Wind Energy Council, (Global Wind Energy Council, May 2008) American Wind Energy Association and the US Department of Energy (U.S. Department of Energy, Energy

Efficiency and Renewable Energy, May 2008). We used these sources to develop a basic understanding of the wind energy industry. In addition, we combined some of the characteristics of wind speeds such as the Power Law profile (Manwell, McGowan, & Rogers, 2002) and correlation factors for spatial distribution of wind speeds (Wan, December 2005) used in wind energy modeling with specific values for our wind speed data to model and synthesize the Electricity Output from our wind plant.

Energy storage is also a rapidly evolving field. The Electric Power Research Institute (EPRI) published in 2003 a handbook of energy storage for transmission and distribution applications (Electric Power Research Institute and U.S. Department of Energy, 2003). This report was followed in 2004 by a supplement in 2004 that discussed energy storage for grid connected wind energy applications (Electric Power Research Institute, December, 2004). These resources have comprehensively evaluated almost all the available storage technologies and served as the foundation of our research on energy storage. We used them to evaluate and select storage technologies for our application. However, as energy storage technology is evolving rapidly we also checked the costs and technical specifications of the shortlisted technologies with the principal investigators of the EPRI report and also storage companies.

The New England Independent Service Operator (ISO-NE) “oversees” and “administers” the wholesale *electricity markets* in the New England region. We used the training material available on their website to understand the different electricity markets and then selected the Day-Ahead and Real-Time markets for our model application. We used the historical pricing data available on the ISO-NE website (www.iso-ne.com) as the basis for simulating prices in our model. Some of the rules about participation of energy storage units in the electricity markets are still not completely clear. So, we also held detailed discussions with personnel in the ISO (Peet, Supervisor, Customer Support, 2009) to discuss and evaluate the various options that we were discussing.

1.3.2 Literature on Combining Wind Energy with Storage

In this section we review research done on economic viability and optimization of a combined wind energy and storage facility. Studies on combining wind energy with storage can be classified into two broad sets. The first set of studies survey and evaluate several different storage technologies for a specific transmission and distribution application from a technical and economic point of view. The second set of studies conduct a more detailed economic viability evaluation for a selected group of technologies under different operating and design conditions. Our review, thus confirmed that there is no existing research that applies supply chain management techniques to the operation of wind plants and energy storage. In addition, there was no other study focusing on the New England region. We also strengthen existing research by using more robust and realistic assumptions on prices and characteristics of storage technologies.

The first set of studies that we reviewed conduct a survey of several storage technologies and evaluate different technologies from an economic and technical point of view. For example, Nourai (2002) provides guidelines for identifying energy storage technology that is suitable for large-scale energy management applications such as Time Shifting. He presents ten technologies and compares them based on *Full-Power Discharge Time*, energy density, efficiency, *Cycle Life*, operating temperature and siting requirements. He finds the two most appropriate technologies to be flow batteries (including ZnBr) and NaS batteries. Similarly, Schaber, Mazza, & Hammerschlag (2004) argue that in order for widespread renewable energy to become a reality, it must be coupled with energy storage to match variable supply with demand. They evaluate the pros and cons of different technologies and amongst the technologies that they recommend for longer term energy discharge are NaS and ZnBr batteries. Along similar lines, Spahi, Balzer, Hellmich, & Munch (2007) survey several storage technologies for suitability of use with a 100 MW wind plant in Germany. They conduct a technical analysis and project the economic analysis to the year 2030, to show that it is in principle economically viable to use storage. Their results suggest that compressed air energy storage, Pumped Hydroelectric Storage and NaS batteries amongst the most

suitable technologies. The results from all of the studies that we reviewed confirmed our choice of NaS batteries and ZnBr batteries as the most suitable technologies for our application.

The other set of studies that we reviewed, develop a detailed economic assessment of wind plant plus storage facility under different operating and design conditions. Several studies including (Eyer, Iannucci, & Corey, December 2004), (Eyer & Brown, March 2007) and, (Castronuovo & Pecas Lopes, August 2004) develop algorithms to optimize revenue by assuming “perfect knowledge” i.e. they use a historical time series of prices. Thus, at any given point of time the price at all the other times is known. This approach is good for estimating the theoretical maximum potential benefit of storage. In reality, of course, the price at a later time is not known and the decision maker has to decide a policy for charging and discharging in advance. Other studies have extended this “perfect knowledge” approach by formulating the optimization model as a stochastic joint optimization problem considering two random parameters market prices and wind generation (García-González, Moraga, Matres, & Mateo, June 2004). The authors establish that the “joint operation selling and buying” where the wind plant and storage work in tandem - jointly bidding in the Day-ahead market, maximizes revenue. They conduct sensitivity analysis for different sizes of storage and establish that there are diminishing returns as the size of the storage facility increases. Some authors have examined the optimal time frame for maximizing revenue from storage. For example, some authors examine three charge/discharge policies viz. “base-load” (where storage constantly charges and discharges at a steady rate over long periods of time to smooth intermittent wind generation), “mid-merit” (where storage charges at night and discharges during the day), and “peak” (where storage discharges only during 6 hours of highest demand and highest prices) under different time frames (Feeley, Bryans, Nyamdash, Denny, & O'Malley, *The Viability of Balancing Wind Generation With Storage*, 2008). Most of these studies also make simplistic assumptions on the costs involved. For example, some authors do not consider the opportunity costs of storage i.e. they have not considered the revenue foregone by the wind plant by not selling the energy into the electricity market (Eyer, Iannucci, & Corey, December 2004). They simply state the cost of wind generations as \$0.03/KWh, which is

approximately the cost of wind generation. Similarly, García-González, Moraga, Matres, & Mateo (June 2004) ignore the operating and maintenance costs of storage. Several of these optimization studies are focused on Pumped Hydroelectric facilities (e.g. (Castronuovo & Pecos Lopes, August 2004), (García-González, Moraga, Matres, & Mateo, June 2004) (Benitez, Benitez, & van Kooten, July 2008)) given that such facilities have already been in operation for a long time. However, Pumped Hydroelectric facilities have severe geographic limitations and cannot obviously be located in densely populated areas. Lastly, we found studies focused on a specific region for example Walawalkar & Apt (July 2008) focus on the New York Independent System Operator and the region covered by the PJM Interconnection, García-González, Moraga, Matres, & Mateo (June 2004) focus on the Spanish market, Distributed Utility Associates and The E Cubed Company (March 2007) have studied the New York city power system and, Spahi, Balzer, Hellmich, & Munch, Wind Energy Storages - Possibilities (July 2007) have examined a case in Germany. However, we did not find any study for a wind plant-plus-storage system in the New England region of the U.S.

Hence, we extend the existing studies by removing the constraint of “perfect knowledge”, using more robust assumptions of cost and electricity market prices, doing sensitivity analysis for the best size of storage relative to the wind plant, examining storage technologies for densely populated areas and conducting the study for the New England region.

1.3.3 Summary of Relevant Concepts from Supply Chain Management

We seek to apply concepts from the field of supply chain management to managing a wind plant plus storage facility. The details of how supply chain management concepts have been applied are provided in Section 3. In this section we provide a summary review of these concepts and literature. We examine the similarities and differences between a physical product supply chain and the electricity supply chain. For this examination we have used supply chain management concepts at two different levels, viz. Network Design Decisions including defining facility role, facility location, capacity allocation, market allocation

and supply allocation (Chopra & Meindl, 2004) and Daily Operating Policies that are similar to traditional replenishment systems for managing individual item inventories of physical products (Silver, Pyke, & Peterson, 1998, pp. 147-404). In addition, we have considered a daily planning horizon and given the fact that even stored electricity is a highly perishable item, it becomes a case suitable for applying the Single Period Problem (Silver, Pyke, & Peterson, 1998, pp. 382-420). In addition, due to the unique characteristics of electricity we have also examined extensions of the newsvendor problem. For example, Raafat (1991) reviews literature for the extension of the Single Period Problem for perishable items with a random lifetime, where inventory on hand deteriorates at a constant rate. Chung & Ting (1994) investigate a perishable item system with a specific pattern of variable demand and develop a good heuristic for the amount of inventory to order. We have used the learning from such studies to develop our Daily Operating Policies. Further details of these supply chain management concepts and how they are applied to our model are discussed in detail in Section 3.

2 Methodology: Model Overview and Inputs

Our hypothesis is that wind plant operators can make their wind plant operation more profitable through the use of supply chain management techniques and energy storage. To test this hypothesis, we have built a model to assess the impact of supply chain management techniques on the profitability of wind plant and energy storage operations. Our model creates a realistic replication of the operation of a wind plant and storage unit in the New England electricity market.

With our simulation model built, our first step was to create a “Base Case” scenario against which we could benchmark all subsequent policy iterations using the following metric: expected incremental revenue generated above and beyond our Base Case. Our Base Case was a wind plant with no access to storage that sells its electricity directly into the Real-Time market at prevailing prices. We ran 10,000 simulations for each of the 95 summer days and 95 winter days of the Base Case to find our benchmark.

The next step was to run various simulations for a wind plant with access to energy storage technology (what we call our “wind plant-plus-storage system”). We used our model to apply different supply chain management techniques, such as Network Design Decisions and Daily Operating Policies to improve our results beyond the Base Case. We also extended our scenarios to test the operations in the Day-Ahead electricity market which requires firm commitment of electricity output a day in advance. For each scenario, we calculated the expected incremental revenue and profits that could be generated over the Base Case.

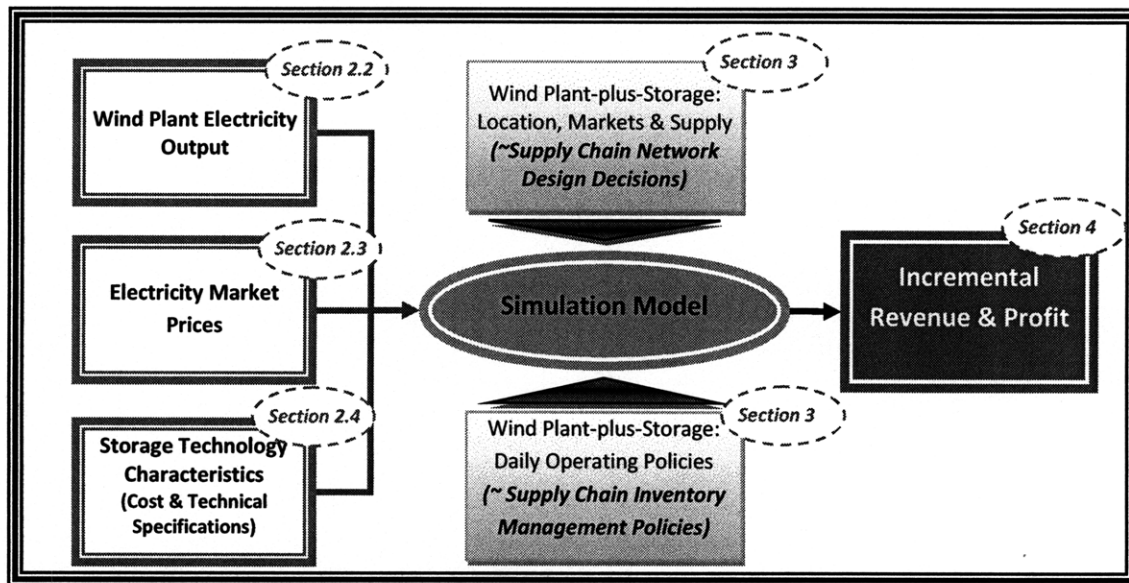
In the remainder of this section we will discuss the different input components of the model in detail, starting with a pictorial overview of the model in Section 2.1. In Section 2.2, we review our synthesis of the electricity output from a wind plant. In Section 2.3, we discuss the different electricity markets and our method for simulating electricity market prices. Then we evaluate different storage technologies in Section 2.4 and discuss important characteristics for the technologies that we have used in our model. In Section 3, we discuss in detail the supply chain management concepts that are relevant for our model and

describe in detail our process of arriving at Network Design Decisions and Daily Operating Policies that we tested. Finally in Section 4, we bring all of this together by describing the various *Model Input Configurations* (Configuration) and how they can be varied using a *Dashboard* in our model. We follow that with a discussion on our method for calculating the incremental revenue and profits over the Base Case for all the different simulated scenarios.

2.1 Overview of Simulation Model

The following graphic provides an overview of the simulation model that we have developed. Also highlighted are the sections in which the different components of the model are discussed:

Figure 2-1: Schematic Representation of the Simulation Model



As depicted above, there are three main external inputs to our model:

1. *Wind plant electricity output*: We tried to collect actual wind plant electricity output data by contacting existing wind plants in the New England. However, as this is an extremely competitive and nascent industry, the wind plant operators were not willing to share this data. Hence, we

synthesized the Wind Plant Output by using publicly available wind speed data at a chosen location in Maine. The details of the synthesis of Wind Plant Output can be found in Section 2.2

2. ***Electricity market prices:*** Based on the location that we choose for our wind plant and /or storage unit, we would be required to participate in different electricity markets. We have studied in detail the relevant electricity markets for different locations within the New England region that we chose and used historical pricing data for these locations and markets to create simulated market conditions in our model. The details of the market price simulation are discussed in Section 2.3
3. ***Storage technology characteristics:*** Electrical energy storage is a very rapidly evolving field with several different technologies and companies vying for techno-commercial viability and adoption. We surveyed the various different technologies through secondary sources and also by contacting premier research institutes (e.g. Electric Power Research Institute) and storage companies (the names are withheld due to confidentiality reasons) and selected two technologies for our model. The technical specifications and costs parameters of these technologies were used as inputs to our model. Our study of storage technologies are discussed in Section 2.4.

Also, as depicted above, there are two primary Supply Chain-related decisions that are used in our model:

1. ***Network Design Decisions:*** These decisions include (Section 3.1):
 - a. What role should storage play?
 - b. Where should the storage unit and wind plant be located?
 - c. Which markets should we participate in?
 - d. Should the supply of electrical energy into the storage unit be limited only to the output from the wind plant?
2. ***Daily Operating Policies:*** These are similar to supply chain inventory management policies and include decisions like (Section 3.2):
 - a. What should be the policy for input to storage (charging)?

- b. What should be the policy for output from storage (discharging)?
- c. What costs are relevant in deciding input / output policies?
- d. What assumptions do we have to make in evolving these policies?

Finally, as depicted above, the output of our model is a calculation of *incremental revenue and profits* for our wind plant-plus-storage unit which is measured against our Base Case.

Choice of simulation model

As explained in Sections 1.2.1 and 1.2.3, both the electricity output from a wind plant (which depends on the wind speed) and prices in the electricity markets (which are determined dynamically by demand and supply) are extremely variable, and difficult to predict. In case *perfect information* about the Wind Plant Output and future electricity prices is available, then it is possible to formulate a deterministic optimization problem to find the best policy for operating a wind plant-plus-storage system. In fact, Castronuovo & Pecos Lopes (2004) have followed this approach for a wind plant and Pumped Hydroelectric Storage unit by performing independent deterministic optimizations for different scenarios sampled by Monte-Carlo simulation. However, as García-González, Muela, Santos, & González (2008) mention in the context of participation in Day-Ahead market the wind plant and storage decision maker has to make “here and now” decisions i.e. does not have perfect information about prices and Wind Plant Output. They have used a two-stage stochastic programming model to decide on optimal bids for the Day-Ahead market as “here and now” decisions, while the optimal operation of the facilities are recourse variables. However, for our model we do not confine our operation to the day-ahead market nor do we make the assumption of perfect information. Hence, given the limiting assumptions required for using optimization in this case, we consider a simulation approach based on real data for wind speeds, and market prices as the best suited approach for testing our hypothesis and generating meaningful managerial insights. Thus we have chosen to develop a simulation model for our analysis.

2.2 Wind Plant Electricity Output

In this section we discuss the “Wind Plant Electricity Output” portion of our model.

To test our hypothesis that supply chain management techniques can make wind plant and energy storage operation more profitable, we needed electricity output data from a wind plant. At first, we attempted to contact wind plants in New England to request data. For example, we contacted First Wind (Jacobs, 2009) the company that operates the Mars Hill Wind Farm in Maine to understand their operation and also to get wind plant electricity output data. We also contacted the other wind plants in Maine. However, we quickly learned that obtaining actual wind plant electricity output data is extremely difficult. Wind plant owners prefer not to divulge their proprietary performance data because the wind power industry is nascent and competitive. Plus, New England wind plants are especially tight-lipped about their operations given that this region does not currently have a high penetration of wind power. Thus, we could not find a wind plant that was willing to provide us with data.

With actual wind plant data unavailable, we decided to create our own fictional wind plant for which we could synthesize electricity output data. We began synthesizing this fictional wind plant by first asking basic questions:

- Where in New England will we locate our wind plant?
- What are the prevailing wind speeds in this location?
- What should be the capacity of our wind plant and how many wind turbines will the wind plant have? What size and brand of wind turbine will we use? How high will each turbine be off the ground? (i.e. Hub Height)
- How will we convert wind speed data to electricity output from the wind turbine?
- How will we use this data to generate the electricity output from the wind plant, while taking into account spatial variations in wind speed?

Knowing the questions that we needed to answer, we set forth to create our synthesized wind plant using established industry techniques. Our goal was to create Wind Plant Output that is realistic and credible. Section 2.2.1 provides an overview of the specifications of our synthesized wind plant and a summary of the wind plant electricity output. Later in section 2.2.2 we explain in greater detail all the steps we followed to construct our fictional wind plant electricity output.

2.2.1 Brief Description of Wind Plant

We opted for a location in Presque Isle, Maine where we were able to obtain wind speed data captured by anemometers installed by the Renewable Energy Research Laboratory. (An anemometer is a device used to measure wind speed.) We obtained data for 95 winter days and 95 summer days. This region of Maine is a realistic location for a wind plant because several existing wind plants are already operating within this region. Plus, there is a nearby utility Node – or, Electricity Grid connection point – through which our synthesized Presque Isle wind plant can be connected to the Electricity Grid.

We chose to create a 120 MW wind plant given that this is the average-sized wind plant in the United States (US Department of Energy - Energy Efficiency and Renewable Energy, May 2008). We chose to install GE 1.5 MW turbines because this is the most prevalent wind turbine size installed in the U.S. (Thresher, Robinson, & Veers, 2007) This turbine model requires installation 80 meters above ground, so we used that Hub Height for our turbines altitude. We chose to extrapolate our wind data into Class 3 winds. Our wind plant achieved a Capacity Factor of 38% in winter and 28% in summer – for an average of 33%, which is consistent with the 33% average for wind plants in the U.S. as reported by (US Department of Energy - Energy Efficiency and Renewable Energy, May 2008). This served as a validation for the Wind Plant Electricity Output portion of our model.

2.2.2 Steps for Synthesizing Wind Plant Output

Specifically, synthesizing our fictional wind plant's output involved the following steps:

1. Identify and select wind plant location

2. Collect wind speed data for selected location
3. Select size of wind plant and type of wind turbine
4. Transform wind speed data based on Hub Height and Wind Power Class
5. Use transformed wind speed data to generate wind turbine Electricity Output
6. Validate Wind Plant Output synthesis results

These steps are discussed in detail in the following pages:

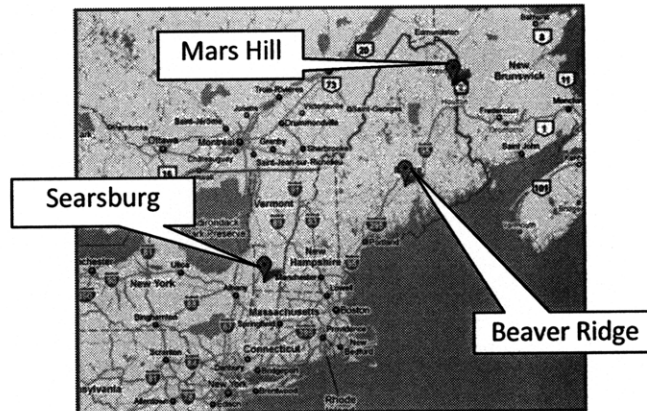
Step 1: Identify and select wind plant location

We have considered the New England ISO (Independent Service Operator) region for the scope of our study. The New England Wind Forum provides an updated list of all existing and proposed wind projects in the New England region on their website. (U.S. Department of Energy Energy Efficiency and Renewable Energy, 2008) From this list we found that there are three *wind plants* currently operating in the New England region:

Table 2-1: Wind Farms in New England

S.No.	Wind Farm Name	Location	Installed Capacity (MW)
C	Beaver Ridge Wind Project	Freedom , ME	4.5 MW
B	Mars Hill Wind Farm	Mars Hill, ME	42 MW
A	Searsburg Wind Power Project	Searsburg, VT	6.6 MW

Figure 2-2: Wind Farms in New England



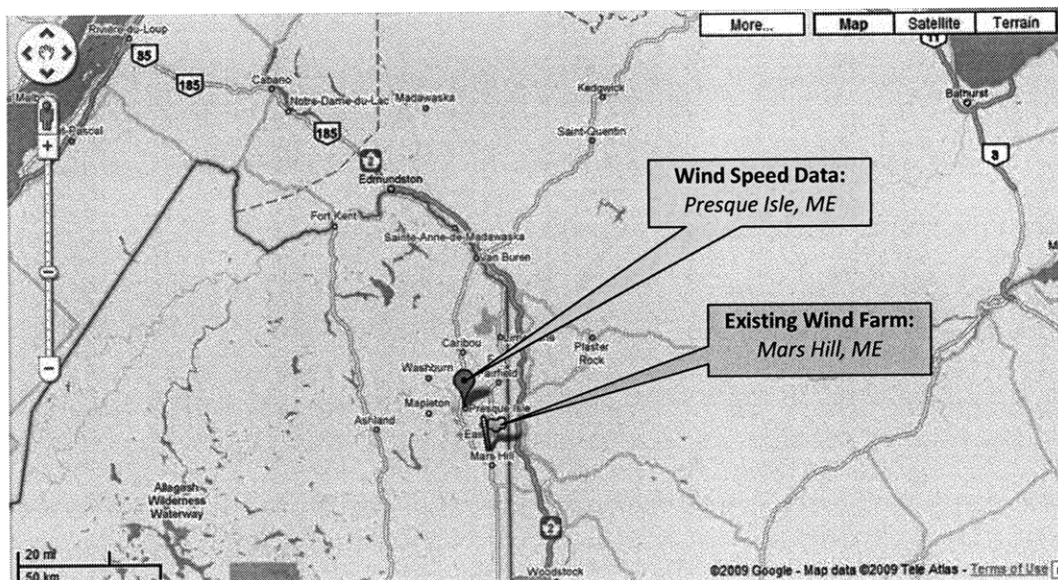
Source: (U.S. Department of Energy Energy Efficiency and Renewable Energy, 2008)

Since two of the existing wind plants in New England are located in Maine, we chose Maine as our location too. We contacted all three wind plants in the table above. However, none of the wind plants were willing to share the plant output data. Having selected a location for our wind plant, we now needed to obtain recorded wind speeds in the Maine region in order to synthesize our wind plant's output.

Step 2: Collect wind speed data for selected location

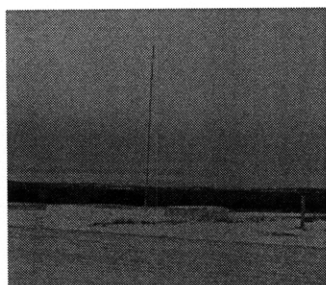
The Renewable Energy Research Laboratory (RERL) of the Center for Energy Efficiency and Renewable Energy at the University of Massachusetts Amherst gathers wind data around New England and has published historical wind data sets on its website (Renewable Energy Research Laboratory, 2008). We examined all the locations for which historical wind speed data was available and selected Presque Isle, ME as the location for wind speed data due to its proximity to the existing Mars Hill wind plant.

Figure 2-3: Presque Isle and Mars Hill on Map



Wind speed data was collected by anemometers and wind vanes (the device used to measure wind direction) at different heights on a 40-meter pole on the site. The picture of the data tower as installed is shown below:

Figure 2-4: Wind Data Collection Tower, Presque Isle



Source: (Henson, Manwell, Rogers, & Ellis, FINAL WIND DATA REPORT-Presque Isle, July 25, 2006)

Seasonal Wind Speed Variance

Wind speeds show significant intra-day and seasonal variation. In general, the wind speeds for the Presque Isle site showed significant difference between the average and maximum speeds between summer and winter months:

Table 2-2: Average and Maximum Wind Speeds – Summer and Winter

Season	Average Wind Speed (mph)	Max. wind speed (mph)
Summer Months (Jul, Aug)	8.3 mph	27.1 mph
Winter Months (Dec, Jan)	10.1 mph	32.2 mph

Source: (Henson, Manwell, Rogers, & Ellis, WIND DATA REPORT, Presque Isle, December 1, 2004 – December 1, 2005, January 9, 2006)

Hence, we chose to do our analysis for winter and summer months separately. This represents two extremes and gives us an estimate of the range of Wind Plant Output over the course of the year.

The wind speed data sets available on the RERL website have been filtered by the RERL quality control software. However, there were a few occasions where data was missing due to reasons such as icing or wet snow events. If the data was missing for a short duration (few hours) we filled in the data using interpolation. This is consistent with the approach followed by (Berlinski & Connors (2006). For cases where the data was missing for a large number of hours or for whole days, these days were completely excluded from the analysis. Thus we were able to create the following data sets for wind speeds in summer and winter.

Table 2-3: Dates for Wind Speed Data

Season	Dates	Number of days (datasets)
Winter	01-Dec-04 to 10-Dec-04; 16-Dec-04 to 31-Jan-05; 01-Dec-05 to 24-Dec-05; 18-Jan-06 to 31-Jan-06	95
Summer	01-Jul-05 to 31-Jul-05; 01-Aug-05 to 31-Aug-05; 04-Jun-06 to 06-Jul-06	95

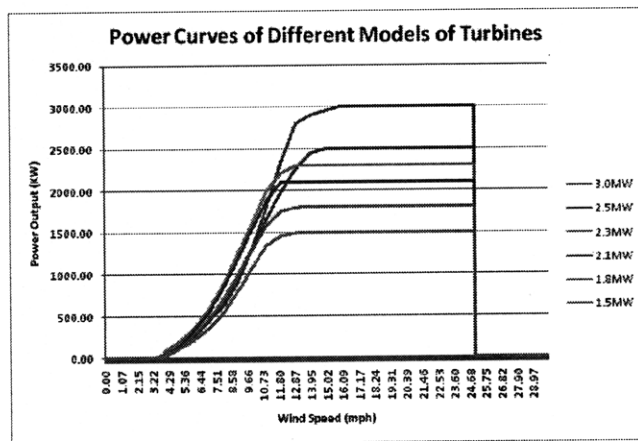
The wind speed data from the RERL website are for 10 minute intervals and were collected at heights of 10m, 30m and 39m. For the purpose of our synthesis we used the data at 39m height. For each hour we had 6 data points, thus providing 144 (=24 hours * 6 data points / hour) wind speed data points for each day and 13,680 (= 95 seasonal days * 144 data points / day) wind speed data points for each season.

Step 3: Select size of wind plant and type of wind turbine

The average size of a wind plant installed in the U.S. in 2007 (the most recent year for which a report was available at the time of developing the model) was 120 MW (US Department of Energy - Energy Efficiency and Renewable Energy, May 2008). Also the typical wind turbine installed in the U.S. was of capacity 1.5 MW (Thresher, Robinson, & Veers, 2007). Hence for the purpose of our analysis we have considered a wind plant of 120MW installed rated capacity and turbine size of 1.5 MW. Thus our Presque Isle wind plant has $80 \left\{ \frac{120 \text{ MW (plant capacity)}}{1.5 \text{ MW (capacity of 1 turbine)}} \right\}$ wind turbines. However, we have built into our model the flexibility to vary the wind plant capacity from 40MW to 300MW (in steps). Also we have built in the option of choosing wind turbines sized at 1.5, 1.8, 2.1, 2.3, 2.5 or 3.0 MW.

Wind turbine manufacturers specify different technical parameters for the performance of their turbines. These include parameters like *Cut-In Wind Speed* (lowest speed below which the wind turbine does not produce any electricity output), *Cut-Out Wind Speed* (highest speed above which the wind turbine does not produce any Electricity Output), and recommended Hub Height (the altitude at which a turbine sits on a pole). Most wind turbine manufacturers also provide the *Power Curve* which specifies the expected electricity output from the wind turbine at different wind speeds. The Idaho National Laboratory (INL) has developed Excel Wind Analysis software that incorporates the Power Curve for different wind turbines (Idaho National Laboratory, 2007). We have used the Power Curves for the 1.5, 1.8, 2.1, 2.3 and 2.5MW turbines from the INL Excel Wind Analysis software. The INL Excel Wind Analysis software does not have the Power Curve data for the 3MW wind turbine, so we incorporated the Power Curve for the 3MW turbine from the technical specifications provided by the manufacturer (GE Energy, 2005). The Power Curves for the different models and ratings of wind turbines in our model are shown below.

Figure 2-5: Power Curves for Different Models of Turbines



Sources: (Idaho National Laboratory, 2007) & (GE Energy, 2005)

Table 2-4: Wind Turbines Power Rating, Manufacturer and Model

MW Rating	Manufacturer	Model
1.5 MW	GE	GE 1.5 S
1.8 MW	Vestas	V80-1800 II
2.1 MW	Suzlon	S.88/2000
2.3 MW	Nordex	N90-2300
2.5 MW	Nordex	N80-2500
3.0 MW	GE	GE 3.0s



Step 4: Transform wind speed data based on Hub Height and Wind Power Class

As mentioned earlier the wind speed data on the RERL website was recorded at a height of 39 meters. However, technical literature provided by the manufacturer of the 1.5MW turbine that we have used in our model recommends Hub Heights of 64.7m / 80m / 85m / 100m for the turbine (GE Energy, 2008). For the purpose of our model we have thus assumed Hub Height of 80m. Hence, we had to project wind speeds from 39m (given in the data) to 80m. Wind speeds can be projected to different heights using either the Logarithmic profile (Log law) or the Power Law profile (Manwell, McGowan, & Rogers, 2002). The RERL wind fact sheet and report for Presque Isle wind data suggests using the power law profile equation with a coefficient of **0.32** (Henson, Manwell, Rogers,

& Ellis, July 25, 2006). Wind speeds typically increase non-linearly with height above the ground. This change in wind speed with height is called wind shear. The Power Law equation characterizes the wind shear by the coefficient, α as given below:

$$V = V_{\text{ref}} \left(\frac{z}{z_{\text{ref}}} \right)^{\alpha} = V_{\text{ref}} \left(\frac{80}{39} \right)^{0.32}$$

where V is the wind speed at the height (z) of interest (say, Hub Height = 80m in our model), and V_{ref} is the speed actually measured at another height z_{ref} (= 39m in our case). As mentioned earlier, the RERL data for Presque Isle has a suggested coefficient (α) of **0.32**. Hence the multiplication factor of $1.26 \left\{ \left(\frac{80}{39} \right)^{0.32} \right\}$ is used to transform wind speeds to a height of 80m.

Different locations in Maine are classified into different Wind Power Classes based on the Wind Power Density (Watt/sq. m.) and Average Wind Speed (Mph) at height of 50 meters by the National Renewable Energy Laboratory (NREL) of the U.S. Department of Energy (National Renewable Energy Laboratory, 2007). The average wind speed at a height of 39 meters for the Presque Isle wind data is 10.04 miles per hour (Henson, Manwell, Rogers, & Ellis, July 25, 2006). Projected to a height of 50 meters using the Power Law given above this becomes 10.87 mph. This average speed suggests that the wind speed data at Presque Isle belongs to a Wind Power Class of one. However, the NREL resource map suggests that the wind plants in Maine will most likely be located in a Wind Power Class of three. Based on the lower limit of the wind speed range in the different power classes we used a correction factor of 1.32 for transforming the wind speeds at Presque Isle (Class 1 Wind Power Class) to Class 3 Wind Power Class. (National Renewable Energy Laboratory, 2007)

Step 5: Use transformed wind speed data to generate wind turbine electricity output

We thus obtained the *transformed wind speed data* (Hub Height = 80m; Wind Power Class = 3) in miles per hour for 13,680 ten minute intervals for both the winter and summer seasons. The *Power*

Curve of the GE 1.5s wind turbine obtained from the INL Excel wind analysis software was used to generate the electricity output (in MW) from a single wind turbine for each ten minute interval based on the transformed wind speed data.

The next challenge was to use this electricity output of a single turbine to generate the output of our entire Presque Isle wind plant (120 MW installed rated capacity) of 80 turbines. We needed to take into account the spatial variation of wind speeds and wind power output. Meaning in the case of a wind plant with 80 turbines, each turbine would be located approximately 25 meters apart over a one-square mile expanse of land. Over this land expanse, there would be different wind speeds hitting each turbine. (Wan, December 2005) provide data to suggest that the correlation coefficient for electricity output from different wind turbines in a small wind plant ranges from 30.9% to 90.3% for a 10-minute output series. Hence we have used a correlation coefficient of 60% (approximately the mid-point of 30.9% and 90.3%) for using the power output of a single turbine to the power output of 80 spatially distributed turbines. Thus using this coefficient of 60% were able to assign limits for the maximum and minimum electricity output from any of the 80 turbines, given that we had generated electricity output from one turbine using the ten-minute wind speeds and the Power Curve. We then used random numbers to generate output from each of the 80 turbines within these limits determined by the correlation coefficient. Adding up this output from each of the 80 turbines for each 10-minute interval we were able to synthesize the electricity output (in MW) for our Presque Isle wind plant.

Our 10-minute wind plant power output was then averaged over each hour to obtain 24-hourly Wind Plant Output data sets for each of the 190 days over both the seasons (summer and winter).

Step 6: Validate Presque Isle Wind Plant Output synthesis results

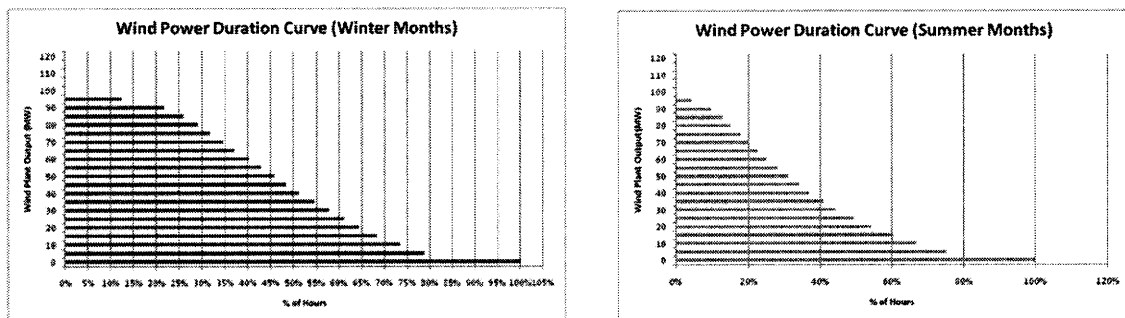
To validate our assumptions and methodology for Wind Plant Output synthesis, we calculated the Capacity Factor (see List of Terms) for our synthesized Presque Isle wind plant. Our synthesized

Wind Plant Output gives a Capacity Factor of 38% for winter and 28% for summer. Hence the average annual *Capacity Factor* for the Presque Isle wind plant is 33%

(US Department of Energy - Energy Efficiency and Renewable Energy, May 2008) reported that the average Capacity Factor for all the wind plants installed in the U.S. for 2006 was around 33% (with a range from 18% to 48%) Hence, this value of Capacity Factor is consistent with Capacity Factor of our synthesized Presque Isle wind plant and served as a validation of our method of synthesizing the output.

The *Wind Power Duration Curve* for our synthesized Wind Plant Output during winter is shown in the graph below. This graph shows the percentage of the total operating hours (shown on the horizontal axis) during which the wind plant was generating a given power output in MW (shown on the vertical axis). This once again is consistent with Wind Power Duration Curve reported in literature (Wan, December 2005) and serves as a validation of our wind plant synthesis model.

Figure 2-6: Wind Power Duration Curve (Summer & Winter Months)



Thus we were able to synthesize validated electricity output data for our fictional wind plant in Maine.

2.3 Simulation of Electricity Market Prices

In this section we discuss the “Electricity Market Prices” portion of our model.

After creating 190 days of Presque Isle Wind Plant data (95 winter days and 95 summer days), we set out to simulate a dynamic market pricing environment in which to run our wind plant. Unlike our unsuccessful efforts compiling actual wind plant data, we were successfully able to collect actual electricity market pricing data. In fact, we were able to access two years of hourly data through the website of the New England Independent System Operator, the organization which operates and monitors the electricity market in New England. Ultimately, we used this actual data to simulate batches of 10,000 pricing scenarios (for both winter and summer) using Crystal Ball simulation software. In Section 2.3.1 we provide a brief description of our pricing simulation techniques. Then in Section 2.3.2 we explain in greater detail all the steps we followed to simulate realistic market prices.

2.3.1 Brief Description of Pricing Simulation Model

The simulated ISO-NE electricity market prices are an important input to our model. One of our project's most important goals was to test the business case for locating storage units separately from wind plants (i.e. at a distance, and in different U.S. states) in Zones and Nodes with historically higher prices. To do this, in our model we test a scenario where our storage unit is located in Connecticut (near the "CosCob" utility node) where prices are higher while our wind plant continues to be located in Presque Isle, Maine (near the "Lakewood" utility node) where prices are lower. To simulate prices, we first downloaded actual ISO-NE pricing data from the past two years (2007 and 2008) and calculated the average price for each of the 24 hours of the day, thus getting 24 separate averages, one for each hour for both the locations. Next we used Crystal Ball software to fit the best probability distribution curve to each hour's pricing data. Based on our research into industry best practices for simulating electricity market pricing (these are discussed later in this Section) and our curve fitting results we chose a lognormal probability distribution for our simulation. With our historical hourly averages calculated, and our distribution curve established, we then used Crystal Ball to establish the mean, standard deviation and location values for the fitted Lognormal curve for each pricing hour. Finally, we used Crystal Ball to simulate pricing scenarios in batches of 10,000 for each day of Wind Plant Output.

2.3.2 Steps for Simulating Market Pricing

Here are the steps that we followed to simulate ISO-NE market pricing scenarios for our model:

Steps:

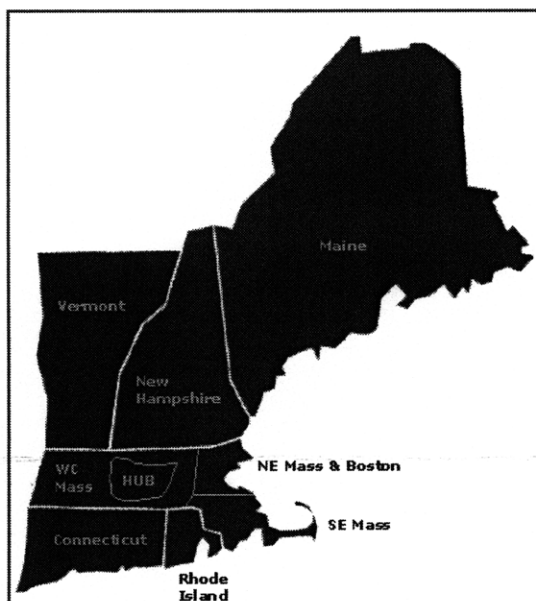
1. Identify ISO-NE's eight (8) Load Zones and nearly 500 Nodes
2. Find Load Zone and Node closest to our wind plant location in Presque Isle, Maine
3. Analyze actual historical pricing at each Zone and Node
4. Identify New England Zones/Nodes with highest average Real-Time and Day-Ahead LMP prices
5. Identify the best-fitting curve and simulate prices

These steps are discussed in detail in the following pages:

Step 1: Identify ISO-NE's eight Load Zones and 500 Nodes

The ISO-NE has the eight Load Zones depicted in the map below: Maine, New Hampshire, Vermont, WC Mass, NE Mass & Boston, SE Mass, Connecticut and Rhode Island

Figure 2-7: New England ISO Different Load Zones



Source: New England ISO

As stated previously, each of the eight Load Zones contains many Nodes, which are physical points in the ISO-NE market where electricity prices are calculated and set for buying and selling electricity. This dynamic pricing by region can create arbitrage opportunities – especially wind plant operators who operate storage units in different Load Zones and Nodes away from their wind plants.

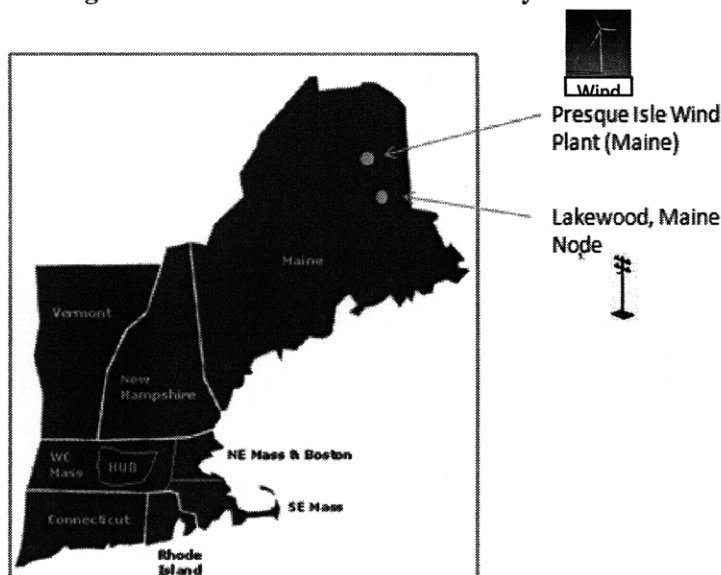
Step 2: Find Load Zone and Node closest to our wind plant location in Presque Isle, Maine

As we identified and became familiar with the various Load Zones and Nodes within the ISO-NE, we were able to identify the Load Zone and Node most suitable for our model. Our Presque Isle, Maine wind plant is located in the Maine Zone and near the “*Lakewood*” Node in Maine.

Note: Since there is no Node in Presque Isle Maine, we searched for the closest Node on the New England Electricity Grid and found the Lakewood Node. It is important to note that the Lakewood Node is approximately 200 miles from Presque Isle. In fact, any generation assets in the Presque Isle area actually sell their electricity into the New Brunswick (Canada) Electricity Grid, which then sells it back to New England. However, for our research exercise, since we are measuring incremental profit beyond our Base Case scenario, the specific location of the Node within a few hundred miles is not relevant.

We quickly scanned through historical pricing at the Maine Zone and Lakewood Node to understand the market dynamics at these locations. Knowing the historical pricing in these locations would be important as we test the business case for wind plant owners to locate storage units separately from their wind plants (i.e. at a distance, and in different U.S. states). Thus, we would need to find Zones and Nodes within the ISO-NE market *with higher prices than those in the Maine Zone and Lakewood Node* for our storage units.

Figure 2-8: New England ISO Wind Plant and Electricity Market Node Location



Step 3: Analyze actual historical pricing at each Zone and Node

Our goal was to identify Zones and Nodes with electricity prices that are higher on average than those in the Maine Zone and Lakewood Node.

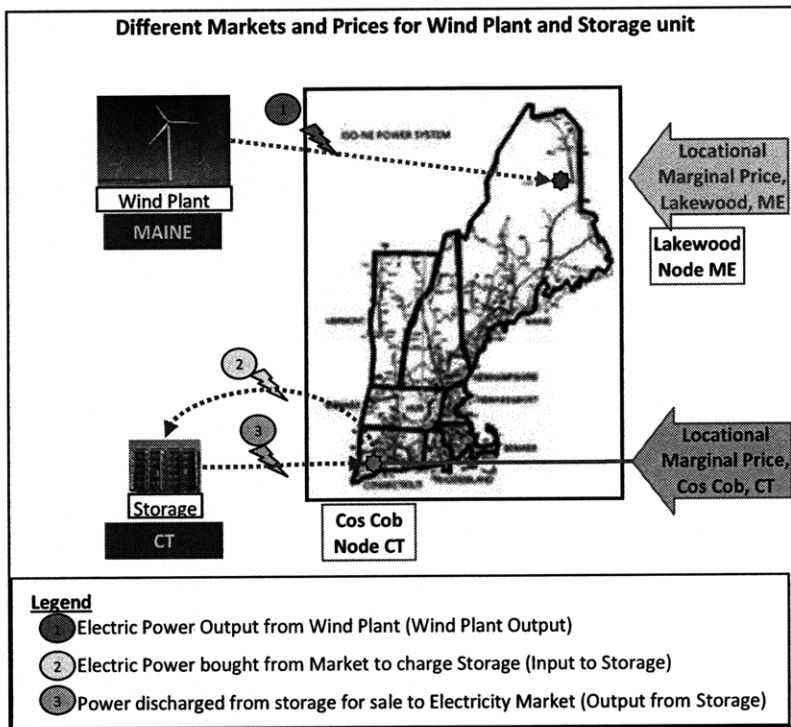
In order to gain a greater understanding of pricing complexities and trends in the ISO-NE market, we analyzed historical pricing using the ISO-NE's pricing databases. These databases, which are available on the www.iso-ne.com website, offer all historical pricing for every Load Zone and every Node for the past two years. Our research strategy was to scan through various Zones and Nodes in search of areas/regions with the highest prices and the greatest price fluctuations.

This process, though long and cumbersome, was very instructional. As mentioned in Section 1.2.3, ISO-NE electricity prices can be quoted in either the Real-Time or Day-Ahead markets. Within each market, prices are set for each Load Zone (the "Zonal Prices") and each Node (the "Nodal Prices"). These Zonal and Nodal prices are referred to as the Locational Marginal Price. Buyers (or Loads that wish to consume electricity) buy at Zonal LMP Prices only, while sellers (Generators that wish to sell electricity) sell at Nodal LMP Prices only. That said, since storage units are *Dispatchable Asset Related Demand* (DARDs) assets, these units both buy and sell electricity at the Nodal LMP price.

So unlike traditional demand customer which buy electricity at Zonal LMP prices, and unlike traditional electricity generating units which only sell electricity at Nodal prices, DARDs buy *and* sell at Nodal prices.

To further clarify how ISO-NE market pricing works, let us use our Base Case example where our wind plant is in Presque Isle, Maine (located near the Lakewood Node) and our storage unit is located near the CosCob, Connecticut) Node. The diagram below demonstrates how the ISO-NE's buying and selling prices operate:

Figure 2-9: Different Location Markets and Prices for Wind Plant and Storage

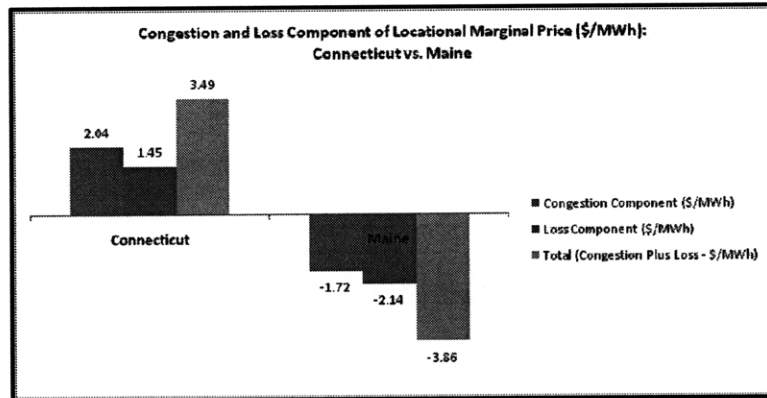


Whether a Zonal or a Nodal price in the Real-Time market or Day-Ahead market, Locational Marginal Prices in the New England electricity market fluctuate due to three dynamic components that comprise electricity prices: Energy Price, Loss Component, and *Congestion Component of LMP* (ISO New England, 2008, pp. 23-24). Each of these three factors affects overall electricity pricing. These three components are profiled below:

- i. **Energy Component:** This represents the basic price of electricity traded in the whole of the ISO NE market. The Energy Component of the LMP is the same across all locations at any given point of time. The energy price is thus determined by the overall demand-supply position in the market and also reflects the overall cost of generation (based on fuel prices)
- ii. **Loss Component:** The loss component of the Locational Marginal Price reflects the result of physical losses that happen as electricity travels through the transmission lines (big overhead wires used to carry electricity over long distances). If the demand at a location is higher than the generation available at that location, then electricity will have to be transported to that location to meet the demand. When electricity is ‘transmitted’ over wires, losses occur due to the resistance in the wires primarily in the form of heat. The price at such a location that needs a lot of electricity transported in from outside Generators will consequently be higher to reflect the losses incurred to transmit electricity to the location. This is equivalent to losses / damage to goods during transportation. The cost of the goods will thus need to be adjusted upwards to reflect the losses occurred during transportation.
- iii. **Congestion Component:** If at a particular location there is inadequate transmission capacity to carry the required amount of electricity in from a cheap outside source, then a local expensive Generator might be required to fulfill the demand. This inadequacy of transmission capacity is called “Congestion” and locations that suffer Congestion consequently have higher prices. This is reflected in a positive Congestion component (higher LMPs) of the prices for locations with transmission constraints. Similarly locations with excess transmission capacity have a negative Congestion component to reflect availability of excess transmission capacity.

As an illustration the average Congestion and Loss Component of the LMPs for Connecticut and Maine Load Zones are shown in the figure below. From this it is evident that the LMPs in Connecticut are higher due to the high cost of Congestion and losses. Moreover, we can see that Maine has more than sufficient transmission capacity, reflected in the negative Congestion and Loss Component of the prices.

Figure 2-10: Average Day-Ahead Loss and Congestion Component – Maine and CT



Source: Average Day-Ahead Price data for year 2007, (ISO New England, 2008, p. 55)

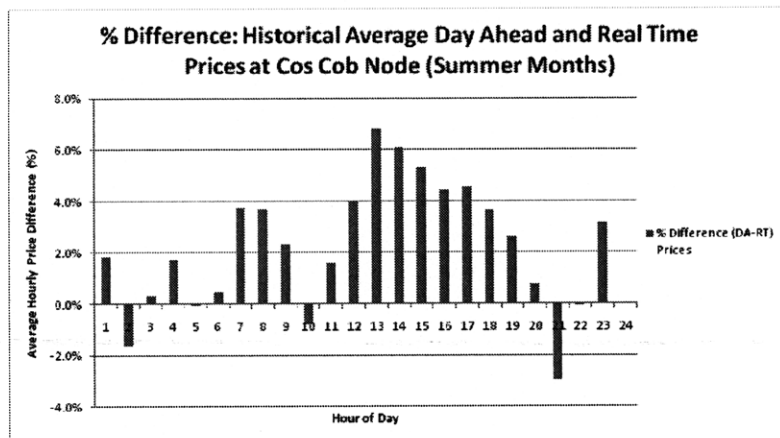
Step 4: Identify New England Zones/Nodes with highest average Real-Time and Day-Ahead

LMP prices

Our analysis of ISO-NE historical pricing revealed several trends:

1. Day-Ahead prices on average were as much as 2.1% higher than Real-Time prices in certain Nodes. For example, in the graph below, we show the % difference between the average Day-Ahead and average Real-Time prices for each hour at the Cos Cob node for the summer months. In most hours the Day-Ahead price is higher than the Real-Time price. In some hours (close to the peak hours) it is as much as 6-7% higher.

Figure 2-11: % difference (Average Day-Ahead – Average Real-Time prices)

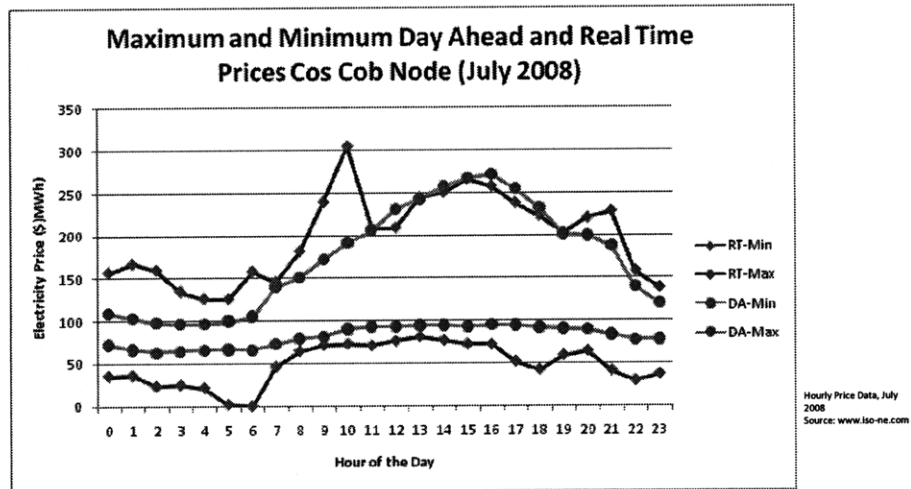


Winter Months: Dec'07, Jan'08, Dec'08, Jan'09
 Summer Months: Jul'07, Aug'07, Jul'08, Aug'08
 Source: www.iso-ne.com

2. Real-Time prices had much greater variability than Day-Ahead prices. As shown in the graph below where we have plotted the maximum and minimum prices over the course over a

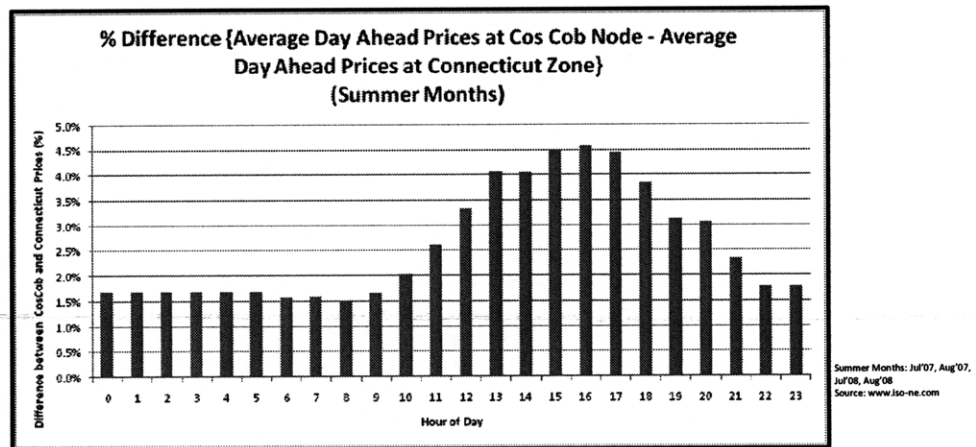
month (July 2008) the Real-Time prices fluctuate a lot more as compared to the Day-Ahead prices.

Figure 2-12: Range of Variation of Day-Ahead and Real-Time prices



- Nodal prices on average were as high as 2.7% higher than Zonal prices in certain regions. For example, we show in the graph below the % difference between the Average Day-Ahead Price at the Cos Cob node and the Average Day-Ahead Price in the Connecticut Zone. As is evident from the graph, the Cos Cob node prices can be 4% to 4.5% higher during the peak hours.

Figure 2-13: Percentage Difference between Cos Cob Node and Connecticut Zone prices



Each of these initial observations revealed possible arbitrage opportunities that we could explore further later on. Now knowing that our model would require both Zonal and Nodal pricing, as well as

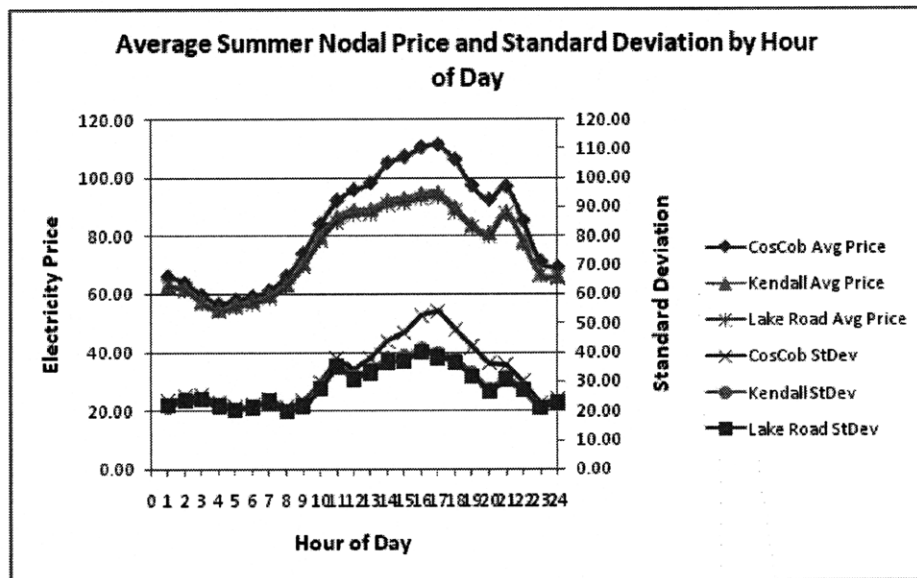
Real-Time and Day-Ahead pricing, we began to analyze ISO-NE pricing databases in search of Nodes with the highest average Day-Ahead prices and the highest variability.

We eventually identified three Nodes that fulfilled our requirements of consistently high, volatile prices:

- ✓ the “Kendall” Node in Cambridge, Mass
- ✓ the “Lake Road” Node outside Providence RI
- ✓ the “CosCob” node in southwestern Connecticut

Of these three Nodes, we chose CosCob because it had the highest average prices and the greatest standard deviation by hour of day:

Figure 2-14: Average Nodal Prices and Standard Deviations - Cos Cob, Kendall and Lake Road



We downloaded hourly historical Real-Time and Day-Ahead pricing for the Cos Cob, CT as well as the Lakewood, ME Nodes for the following winter and summer months:

- (1) Winter: January 2008, January 2009, December 2008, December 2009
 - (a) 124 days of Winter data (4 months * 31 days)
 - (b) 24 price points per day (one for each hour)
- (2) Summer: July 2007, July 2008, August 2007, August 2008

(a) 124 days of Summer data (*4 months * 31 days*)

(b) 24 price points per day (*one for each hour*)

Step 5: Simulate pricing

Having downloaded relevant historical pricing data for 248 total days (124 winter and 124 summer) that match the Winter and Summer months of our wind speed data, we set out to use this data to simulate dynamic market pricing conditions for our model. Our goal for our market pricing simulation was to accurately capture the temporal trends of ISO-NE prices (e.g. afternoon prices are higher on average than nighttime prices) as well as the potential hour-to-hour variability of ISO-NE pricing (e.g. prices can jump by more than \$100 in one hour in some cases). The resulting simulated pricing output would then create a realistic environment in which we could test the business case for using energy storage and supply chain management techniques to make a wind plant more predictable and profitable.

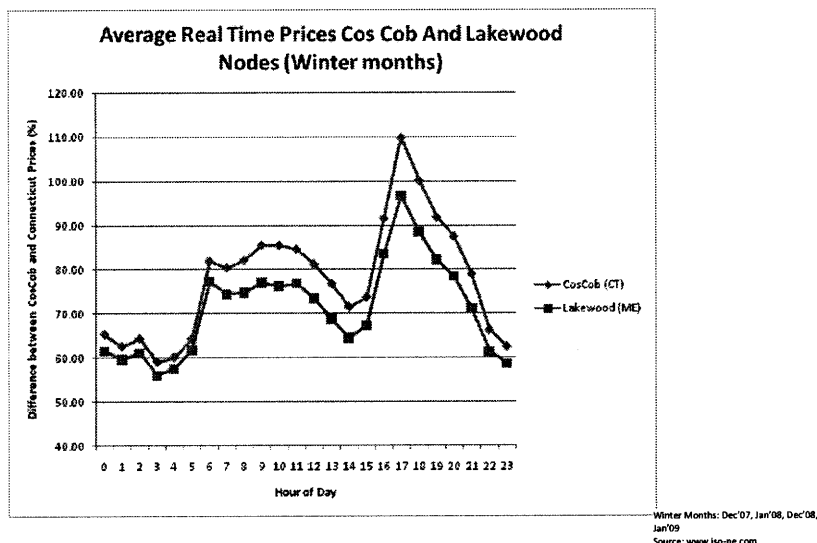
Our approach for simulating market prices followed the same process for both Winter (using 124 days of pricing data) and Summer (using 124 days of pricing data). Below are the details of this approach:

1. Calculate Hourly Average

We calculated the average price for each of 24 hours of the day using all 124 data points. For example, for Hour 1 we have 31 Hour 1 price points for Dec-07, 31 Hour 1 price points for Dec-08, 31 Hour 1 price points for Jan-08, 31 Hour 1 price points for Jan-09 – for a total of 124 price points which we used to calculate the average for Hour 1. For Hour 2 we have 31 Hour 2 price points for Dec-07, 31 Hour 2 price points for Dec-08...and so on.

Thus we get 24 separate averages, one for each hour. These average Real-Time prices for the Lakewood, Maine Node and the CosCob, Connecticut Node during the winter months are shown in the graph below. Notice that CosCob's prices are vastly higher than Lakewood's:

Figure 2-15: Hourly Average Real-Time Prices Cos Cob, CT and Lakewood, ME Node



The chart above also reveals a definitive temporal aspect for the change of electricity price from one hour to the next. We feel this has been preserved by using the average for each hour over all the 124 data points for the hour.

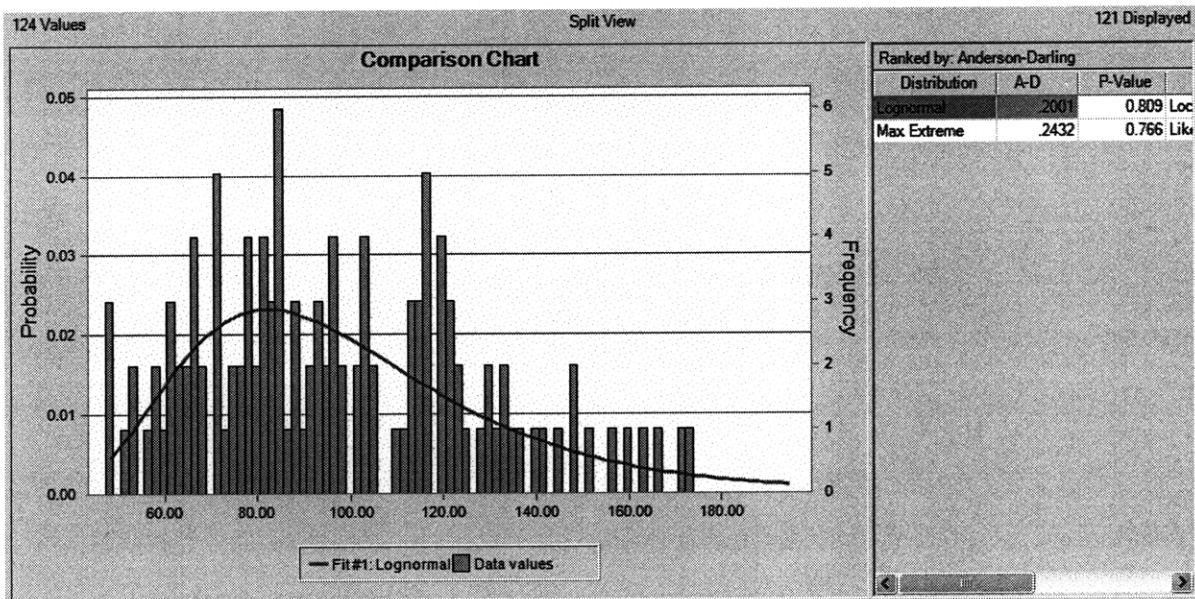
2. Fit Distribution Curve

For each hour's 124 pricing data points (31 days * 4 months) we used Crystal Ball software to fit a probability distribution curve. Crystal Ball revealed that the Lognormal Distribution curve was among the best-fitting curves for each hour. (Crystal Ball also identified Max Extreme as another possible distribution curve.) We chose to use a lognormal curve based on our research into best practices for simulating electricity market pricing. For example, Chapman, Faruqui, Hansen, & Holmes (2001) have shown that a three parameter Lognormal distribution gives accurate results when used to simulate Electricity Spot Prices. Also, Vehviläinen & Keppo (2003) have used lognormal prices to simulate spot electricity prices. Vehviläinen & Keppo (2003) show that the use of a lognormal distribution is not a perfect approximation for spot electricity. However, in the numerical calculations if we use average values to describe the spot prices of discrete time periods, the lognormality assumption holds better. The Energy Information Administration of the US Department of Energy has also used

Lognormal Distribution in simulation of electricity prices (Appendix B - Details of Present Net Value Calculation, 2002).

The figure below is a sample screen shot of our distribution curve fitting efforts for Real-Time pricing in Hour 19 at the CosCob Node. Here Crystal Ball has fitted a lognormal curve over the frequency distribution for historical pricing with a P-Value of 0.809 for the Anderson-Darling test statistic. The relatively high P-Value of 0.809 (1.00 is the highest) means we can safely accept the hypothesis that a lognormal curve fits the distribution of the historical pricing for Hour 19 at the CosCob Node.

Figure 2-16: Historical Pricing Curve Fitting With Crystal Ball



3. Establish Mean, Standard Deviation and Location for Pricing By Hour

With our historical hourly averages calculated, and our distribution curve established, we then used Crystal Ball to fit the lognormal curve for each hour of pricing data and established the three parameters (mean, standard deviation and location) values for the best-fitting lognormal curve for each pricing hour. An example of these lognormal values is set forth below for Real-Time, Winter pricing by hour at the CosCob Node:

Table 2-5: Lognormal Curve Fitting Parameters – Cos Cob, Real-Time prices, Winter

CosCob Node, Real-Time, Winter			
Curve Chosen: Lognormal			
Hour	Mean	Std. Dev.	Location
1	65.31	25.13	-129.01
2	62.61	24.06	-36.29
3	64.15	30.30	-17.14
4	59.02	24.89	-32.44
5	60.06	23.98	-22.97
6	64.35	26.92	2.60
7	81.72	39.47	-24.22
8	80.42	36.48	-52.54
9	82.26	29.44	14.39
10	85.79	31.13	24.02
11	85.43	29.06	-35.08
12	84.92	32.13	24.77
13	81.21	27.86	-30.46
14	76.72	26.17	-48.38
15	71.47	23.75	-20.12
16	73.74	25.93	0.69
17	91.80	35.56	32.79
18	109.85	43.52	25.73
19	100.21	35.06	16.42
20	91.92	31.42	19.08
21	87.63	30.52	17.56
22	78.93	27.05	-3.31
23	66.27	22.67	-28.87
24	62.41	21.45	-87.73

4. Simulate Pricing

With the best-fitting lognormal curve parameters established for each location and market, we used Crystal Ball to simulate dynamic pricing scenarios for all the cases that we wanted to test our policies for. We simulated 10,000 pricing scenarios for each case.

Thus we were able to simulate electricity market prices for input to our model.

2.4 Evaluation and Selection of Storage Technologies

In this section we discuss the “Storage Technology Characteristics” portion of our model.

Substantial research exists about using energy storage technologies in Electricity Grid applications.

However, since energy storage is such a rapidly-developing field, a portion of the data cited in earlier research is outdated, incomplete or inconsistent between studies. Therefore, as we undertook our research

into storage, we contacted both energy industry experts as well as energy storage manufacturers directly to confirm product information cited in existing research.

As discussed in Section 1, our strategy for improving revenue and profits for the wind plant-plus-storage facility is Time Shifting. Given that we had identified Time Shifting as our strategy, we took the following steps to evaluate and choose storage technologies:

1. Surveyed which storage technologies are currently available for Time-Shifting
2. Chose ZnBr and NaS technology for use in our model

Below is greater detail about each of these two (2) steps. Section 2.4.1 details the specific steps involved in evaluating the storage technologies. Section 2.4.2 discusses the technical specifications and costs of Alpha Battery and Beta Battery.

(NOTE: There are many existing research studies that exhaustively evaluate the suitability and technical requirements of using specific energy storage technologies in specific Electricity Grid applications. Our thesis references these research studies to describe our choice of ZnBr and NaS batteries for our model. For further information on other available storage technologies in these existing research studies, the reader can refer to the Bibliography at the end of this document.)

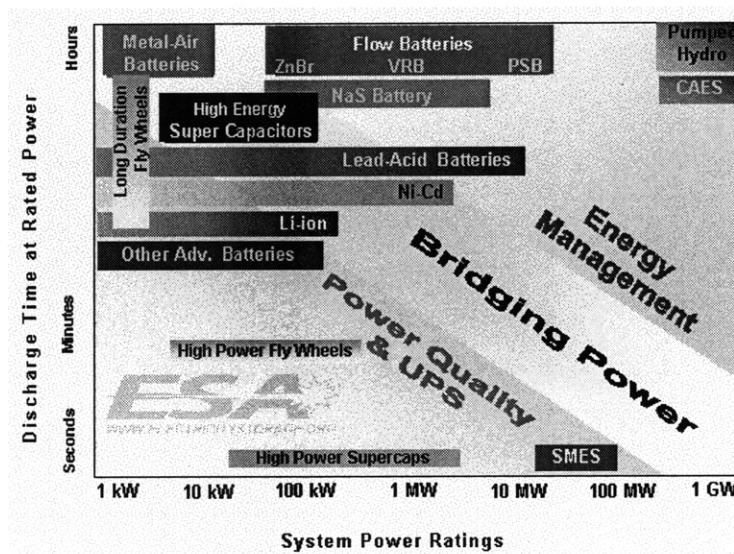
2.4.1 Storage Technology Evaluation Steps

Step 1 – Surveyed which energy storage technologies are currently available for Time-Shifting

Time Shifting requires certain capabilities from storage technologies. For example, storage must have high *Round-Trip Efficiency* and low Standby Losses to ensure that most of the electricity stored in the unit is available to sell during peak periods, among other characteristics. Also, as mentioned in the introduction to Section 2.4, storage used for Time Shifting must have high *Maximum Continuous Power Ratings* (or Power Ratings) and long Full-Power Discharge Times (or Discharge Times at Rated Power) to provide high *Energy Capacity* – meaning the units can discharge many hundreds of Megawatts of

power over many hours. The figure below shows that NaS and ZnBr batteries have high Maximum Continuous Power Ratings and long Full-Power Discharge Times relative to other battery technologies:

Figure 2-17: Full-Power Discharge Time vs. Rated Power of Storage



Source: (Electric Storage Association)

Several sources, including Spahi, Balzer, Hellmich, & Munch (2007), and Walawalkar & Apt (2008) have surveyed and identified technologies suitable for Time Shifting application. These technologies include: Pumped Hydroelectric Storage (PHES), compressed-air storage (CAES), nickel cadmium batteries (Ni-Cd), vanadium redox batteries (VRB), NaS batteries and ZnBr. We present in Appendix 1 a table adapted from Walawalkar & Apt (2008) that evaluates these storage technologies in detail.

Step 2 – Chose ZnBr and NaS technology for use in our model

Based on our review we eliminated the following technologies from consideration for the reasons provided:

Pumped Hydroelectric Storage – A PHES installation typically requires a mountain, a source of water, a nearby connection to the Electricity Grid, and environmental approval. Finding this combination of project drivers is difficult (Eyer & Brown, March 2007). Therefore, we eliminated Pumped Hydroelectric from consideration for our model due to these geographic and environmental limitations.

CAES – CAES requires the presence of geological formations (caves), a nearby connection to the Electricity Grid, and environmental approval. Finding this combination of project drivers is difficult (Spahi, Balzer, Hellmich, & Munch, 2007). Therefore, we eliminated CAES from consideration for our model due to these geographic limitations.

Note: While CAES is difficult to install given the necessity of below-ground caves, **above-ground CAES** – where air is compressed into pipes and tanks – could become a viable option for our model in the future. Above-ground CAES is an early-stage technology that stores compressed air in long tube formations, which negates the need for a large, natural underground cavity for storage. As this new technology evolves it could become a viable option in the future for modular energy storage applications in densely-populated areas.

Ni-Cd – We eliminated Nickel Cadmium batteries from consideration due to environmental concerns and resulting questions about the future use of these batteries for Electricity Grid applications based on research by Schaber, Mazza, & Hammerschlag (2004) and Walawalkar & Apt (2008).

VRB – We eliminated Vanadium Redox batteries from consideration after learning that the leading manufacturer of this technology went out of business in January 2009. Without the ability to confirm accurate pricing and technical specifications, we decided to remove it from consideration (VRB Power, 2009).

Lead Acid – We eliminated Lead Acid batteries from our consideration due to their short Cycle Life and high maintenance costs (Nourai, 2002).

After eliminating the above technologies from consideration, we focused on NaS batteries and ZnBr batteries, which several sources suggest have the best mixture of cost-effectiveness, performance, availability, price, modularity and scalability. Schaber, Mazza, & Hammerschlag (2004) suggest that storage technologies be evaluated by looking at energy efficiency, environmental impact, location

dependence, Cycle Life, economics and space and weight requirements. Among the technologies recommended by the authors for longer-term energy discharge are NaS and ZnBr batteries. The authors particularly mention that ZnBr have cheaper installation cost, relatively high efficiencies, and deep discharge capabilities – all of which make them ideal for cost-efficient energy storage. Similarly, Nourai (2002) presents 10 possible storage technologies and concludes that the two most appropriate technologies are flow batteries (including ZnBr) and NaS batteries.

The industry experts and manufacturers we spoke with confirmed that both of these technologies demonstrated the following functional capabilities that are suitable for Time Shifting:

(See the List of Terms for further definitions of the **highlighted terms** listed in the steps below.)

- 1) Have long **Replacement Interval**, meaning the units have a life expectancy of at least fifteen (15) years
- 2) Have high **Cycle Life**, meaning the units can be charged and discharged – or cycled – many thousands of times before failure
- 3) Have high **Depth of Discharge**, meaning the units have a high Cycle Life even when discharging up to 90% of stored energy in each cycle.
- 4) Have high **Maximum Continuous Power Rating**, meaning a single unit can discharge at least 0.5 MW of electrical power and units can be combined for the whole storage facility to have a higher power rating
- 5) Have **Full-Power Discharge Time** per cycle of at least five (5) hours, meaning the technologies can discharge electricity for at least five (5) hours
- 6) Have high **Energy Capacity**, meaning the units can discharge many hundreds of Megawatts of power over many hours
- 7) Have **Round-Trip Efficiency** of at least 75%, meaning that for every 100 MWh of electricity stored, at least 75 MWh can be discharged (with just 25 MWh being lost)

- 8) Have **Standby Losses** of less than 2%, meaning a storage unit does not lose more than 2% of its stored energy for each hour that it is in *Standby* mode awaiting charge/discharge cycles throughout the day
- 9) Are **modular and scalable**, meaning the units are standardized and can be used in parallel in flexible multi-unit clusters
- 10) Are **shippable**, meaning they can be easily shipped and installed within densely-populated areas, and are not bound by geographic limitations
- 11) Are **available** to purchase now

We confirmed these battery technical specifications and costs with two companies, and used their information to construct two battery facilities – Alpha Battery and Beta Battery – for use in our model. (We have code-named the two battery technologies at the requests of the two companies that provided us with proprietary technical and cost information.)

Our choice of energy technology was subsequently validated when we learned that several battery-based storage facilities were already in operation for Time Shifting:

- 1.) **Long Island NaS Facility** – Since 2008, a NaS battery system with the capacity of 1 MW and 7.2 MWh has been using off-peak energy for power during peak periods on Long Island in New York State. The primary application has been to supply up to 1 MW of power to a natural gas compressor for six to eight hours per day (Department of Energy, 2009).
- 2.) **American Electric Power NaS Facilities** – American Electric Power (AEP), an electric utility that operates in Midwestern and Southern states, now has six Megawatts worth of storage in three locations using this NaS battery technology (Lamonica, 2009).
- 3.) **Futamata NaS Facility** – Since May 2008, Japan Wind Development has been operating a 51 MW wind plant that incorporates a 34 MW NaS battery system at its Futamata, Japan wind plant (Yomogita, 2008).

2.4.2 Technical Specifications and Costs of Alpha Battery and Beta Battery

Each of our synthesized battery facilities, Alpha Battery and Beta Battery, is composed of a string of battery units operating in parallel. The facilities are marked by their modularity and scalability, as well as their suitability for installation in urban areas where land availability can be scarce.

2.4.2.1 Alpha Battery and Beta Battery Technical Specifications

We synthesized the Alpha and Beta Battery facilities to have similar technical capabilities. For example, each facility has the same minimum Round-Trip Efficiency (75%) and recommended Depth of Discharge (90%). Table 2-6 below lists the technical specifications of each battery facility:

Table 2-6: Alpha Battery and Beta Battery Technical Specifications

Technology Type		Beta		Alpha	
Minimum Round Trip Efficiency	%	75.0%	^Δ	75.0%	^Δ
Minimum Discharge Time per Cycle	hrs	5	^Δ	5	^Δ
Replacement Interval (lifespan)	years	30	^Δ	15	^Δ
Cycle Life (Adjusted for Depth of Discharge)	#	10950	^φ	5700	*
Recommended Depth of Discharge	%	90.0%	^Δ	90.0%	^Δ
Standby Loss per Hour	%	1.19%	**	1.19%	**
Modular and Scalable		Yes	^Δ	Yes	^Δ

^Δ Company information

^φ Battery units have unlimited # of cycles over 30 years, according to company. We assume one cycle per day for 30 years.

* **Alpha Cycle Life** – The company technical literature quotes 4500 cycles at 90% Depth of Discharge for 6-hours Full-Power Discharge Time, or 6500 cycles at 65% Depth of Discharge for 6-hour Full-Power Discharge Time. Since our application has a 5-hour Full-Power Discharge Time, we calculated a Cycle Life of 5700 cycles.

** **Standby Loss Per Hour** – This is calculated based on the EPRI Report (EPRI, 2003) and subsequent conversations with storage expert (Kamath, 2009)

2.4.2.2 Alpha Battery and Beta Battery Costs

While the technical profiles of Alpha Battery and Beta Battery are alike, the batteries' costs are different. The cost of a storage facility is dependent on the exact configuration of the unit and the operating conditions. The estimates of costs vary widely. Our research showed that the handbook released by the Electric Power Research Institute (EPRI, 2003) was the most widely-used source for comparing the costs

of different storage technologies. However, as that report was released in 2003, several cost numbers had changed since then. So we contacted the principal investigators of the report (Kamath, 2009) and (Gotschall, 2009) and storage companies to get updated cost numbers. Based on their inputs, we calculated the operating and capital *Cost-per-Cycle* for the two technologies for our Time Shifting application. The details of these calculations can be found in Appendix 2. The summary costs are shown in the Table 2-7 below:

Table 2-7: Alpha Battery and Beta Battery Costs (for 60MW storage facility)

Cost Category	Alpha Battery	Beta Battery
Operating Cost-per-Cycle (\$/cycle)	\$2,466 / cycle	\$5,918 / cycle
Capital Cost-per-Cycle (\$/cycle)	\$25,263 / cycle	\$5,479 / cycle

From these cost calculations it is evident that while Beta Battery has higher operating and maintenance costs, Alpha Battery has higher capital costs (as it has a much shorter Cycle Life as compared to Beta Battery). Since these costs vary widely depending on the assumptions and the exact configuration of the storage unit, these costs were used in our model to arrive at range estimates of the costs. Also, the calculated costs for our battery facility fall within the ranges cited by other authors (Walawalkar & Apt, July 31, 2008) on a per-MW basis. In addition, we learned that storage manufacturers can offer capital cost discounts (of approximately 25%) with volume battery purchase of at least 20 MW. These have been incorporated into our model cost calculations.

We then used the capital and operating costs and the number of cycles in the life of the battery to calculate the Cost-per-Cycle. Cost-per-Cycle is an important economic measurement for storage because each cycle represents an opportunity to monetize the unit and earn revenue (Hassenzahl & Schoenung, July 2007). Given that there are only few periods per day when profit can be made, storage units that offer greater revenue-earning opportunities can break even faster. To test profitability, both our capital and operating Costs-per-Cycle were then used in our Incremental Revenue and Profit model to calculate

Incremental Operating Profit and *Pre-Tax Profit* using our *Incremental Gross Profit* numbers as explained in Section 4.3.

Thus having identified the technical and cost characteristics of the storage units to be used in our model, we focus on the supply chain decisions for our model in the next section.

3 Supply Chain Management Techniques

In this section we discuss the “Supply Chain Network Design Decisions” and the “Supply Chain Daily Operating Policies” portions of our model.

As discussed in Section 1, we have examined the similarities and differences between the electricity supply chain and physical product supply chains. For this examination we have used supply chain management concepts at two different levels. We have identified Network Design Decisions and Daily Operating Policies as defined below:

A. **Network Design Decisions** that include (Chopra & Meindl, 2004):

1. Facility Role: What processes are performed at each facility?
2. Facility Location: How many facilities? Where should facilities be located?
3. Capacity Allocation: How much capacity should be built and allocated to each facility?
4. Market Allocation: What markets should each facility participate in?
5. Supply Allocation: Which supply sources should feed each facility?

B. **Daily Operating Policies** that include:

1. Input Policies (for charging storage units, in our case)
2. Output Policies (for discharging from storage units, in our case)

We have applied decisions at these two levels to test our hypothesis that supply chain management techniques can make wind plant and energy storage operations more profitable. For each level, we explored the implications of the decisions on both the wind plant and the storage unit(s).

Our Network Design Decisions are discussed in Section 3.1. We have approached these decisions from the perspective of designing our wind plant-plus-storage system as a physical supply chain. Our Daily Operating Policies are explored in Section 3.2. We have approached these operating policies from the perspective of a traditional replenishment system for managing individual item inventories.

3.1 Network Design Decisions

Chopra & Meindl (2004) have identified five main Network Design Decisions in supply chain management. These decisions involve defining facility role, facility location, capacity allocation, market allocation and supply allocation. We will analyze each of these decisions for our combined wind plant–storage operation.

3.1.1 Facility Role: What processes are performed at each facility?

In our combined wind plant-storage operation, each facility plays a role:

- Wind Plant – The wind plant ‘consumes’ the kinetic energy in the wind and converts it to electrical energy. This energy (if not stored) must be sold immediately to the Real-Time electricity market to earn revenue.
 - Note: The above description is the “*Base Case*” of our model – a 120 MW wind plant in Presque Isle, Maine that has no access to storage and sells electricity directly into the Real-Time electricity market at the prevailing market price.
- Storage Unit – The storage unit is an additional capital investment for a wind plant operator that also requires ongoing operation and maintenance activities. The storage unit is meant to charge up when electricity prices are low. The stored electrical energy can then be later sold into the market when the prices are higher, thus increasing revenue that the wind plant could have generated in the Base Case (i.e. without storage). This application is called “Time Shifting” (EPRI, 2003). See Section 1 for further explanation of Time Shifting.

3.1.2 Facility Location: How many facilities? Where should facilities be located?

Wind plants are typically located in areas with rich wind resources. However, often these wind-rich areas are sparsely-populated and remote, with low electricity demand and low wholesale electricity prices. Thus wind plants are bound to selling their generation output at the prevailing lower wholesale electricity

prices in these areas. Our Base Case – our 120 MW wind plant located in Presque Isle, Maine – fits these parameters.

However, strategically-located energy storage – when combined with Time Shifting policies – can offer wind plants a way to sell their electricity at dramatically higher electricity prices. By locating storage close to densely-populated areas with high demand, wind plants can gain access to higher prices. This scenario demonstrates that facility location can be a key decision for a wind plant-plus-storage system.

To test our hypothesis that it may be more profitable to locate the storage unit away from the wind plant at another location where the electricity prices are significantly higher, we have built our simulation model to offer two options for the location of our energy storage units:

- Co-Located – Storage facility is located on same premises as the wind plant (i.e. in Presque Isle, Maine)
- Located – Storage facility is physically separated from the wind plant, preferably in a high-demand urban/suburban area with high average electricity prices. Specifically, in our simulation model we offer the option of choosing to locate our storage facility near any of the following three Nodes:
 - Cos Cob (Connecticut)
 - Lake Road (Rhode Island)
 - Kendall (Massachusetts)

Each of these Nodes has among the highest average prices within the New England ISO Electricity Grid, making them ideal locations for energy storage units.

3.1.3 Capacity Allocation: How much capacity should be built?

With our wind plant in Presque Isle, Maine sized at 120 MW, the next question is: What size storage facility should I build?

The topic of determining the appropriate size of storage (relevant to wind plant size) has been explored in existing research. García-González, Muela, Santos, & González (2008) shows that as the size of storage increases relative to wind plant size that incremental benefits decrease. Without establishing or recommending a specific size, this study suggests that storage facilities that are smaller than wind plant size have better returns on investment. Other studies of storage applications in Japan suggest that the optimal size of a storage unit is at 20% of the installed wind plant capacity if input into storage is confined to Wind Plant Output (Haresh Kamath, 2009). Furthermore, other reports (EPRI, 2003) have found different optimal sizes for storage depending on how the storage unit is used. For example, optimal storage size can change if it is used for multiple applications during its lifespan (e.g. Time Shifting and Frequency Regulation, etc.).

We plan to focus on Time Shifting strategies. Within Time Shifting we will test two scenarios. First, we will confine input into storage to Wind Plant Output. We call this our *Linked* scenario. (See Section 3.1.5 for further explanation.) Secondly, we will allow input into storage to come from both Wind Plant Output and the Electricity Grid. We call this our *Hybrid* scenario. (See Section 3.1.5 for further explanation.) We have constructed our model so we can test any storage facility size relative to wind plant size. Our goal is to identify the optimal size of storage in both Linked and Hybrid scenarios by testing storage sizes relative to wind plant size from 10% to 100%.

3.1.4 Market Allocation: What markets should each facility serve?

As explained in Section 2.3, there are several electricity markets in the New England ISO where electricity is bought and sold. We have confined the scope of our simulation model to the Real-Time (RT) and Day-Ahead (DA) markets. As explained in Section 1, the RT market is similar to a ‘spot’ commodity market where buyers and sellers transact in an hour-by-hour manner. By comparison, the DA market requires parties to commit to buy/sell pre-determined amounts of energy for each hour of the following day at given prices. Our goal is to examine if participation in one market is more profitable than participation in the other market.

Currently, wind plants in the New England ISO region participate only in the RT market as they are classified as intermittent generation resources due to variable wind speeds and direction (LaPlante, October 27-29, 2004). However, by incorporating storage units into its operation, wind plant operators can increase the predictability of their plants' electricity output. Having this predictability can allow a wind plant to participate in the DA market.

There are possible advantages and disadvantages to participating in either the RT or DA markets.

Market	Higher Volatility	Higher Average Prices	Penalties for Default
Real-Time (RT)	✓		
Day-Ahead (DA)		✓	✓

For example, one possible advantage of the DA market is that prices are 2% higher on average than prices in the RT market (ISO New England, 2008). However, a disadvantage of the DA market is penalties exist if a Generator defaults on a commitment. If that Generator is not able to supply the committed amount of energy at the designated hour, then the Generator must buy in the RT market at that hour and immediately re-sell in the DA market. If volatile RT prices are extremely high at that hour, then that Generator risks a significant loss. In addition that Generator must pay a penalty for every unit of energy short.

In our simulation model we offer the option of choosing to participate in the following electricity markets:

- Real-Time
- Real-Time and Day-Ahead (even if Day-Ahead commitments are made for certain hours of the day, a Generator can also participate in the Real-Time market during other hours of the day)

Again, our goal is to examine if participation in one market is more profitable than participation in the other market. Also, we plan to test different supply chain management techniques and policies for each market to identify any trends or management insights.

3.1.5 Supply Allocation: Which supply sources should feed each facility?

In our wind plant-plus-storage system, each facility needs a supply source. Our Maine wind plant's supply source is the wind. The wind plant uses a supply of wind to produce electricity. Our energy storage facility also needs a supply source for charging. This supply of electricity can come from either the wind plant alone (our Linked scenario), or wind plant *and* Electricity Grid (our Hybrid scenario). These two scenarios are described and evaluated below:

Linked: In this scenario the energy storage unit is charged solely using wind plant electricity whereby the input into storage can never be more than the Wind Plant Output for any given hour. When the wind plant and storage unit are co-located in Maine this Linked scenario is straightforward. However, if the storage unit is located in a different location (for example, in Connecticut), then the Linked scenario requires further explanation:

Linked, Co-Located (Maine): The storage unit can be charged only from Wind Plant Output. When the storage unit is being charged output from the wind plant up to the Maximum Continuous Power Rating input of storage is diverted to the storage unit. Any Wind Plant Output in excess of the input to storage is sold to the Real-Time electricity market. Once the storage unit is charged to capacity, then the wind plant operator resumes selling to the electricity market through the Lakewood Node in Maine.

Linked, Located (for example, in Connecticut): This scenario creates a virtual coupling between a Maine wind plant and a Connecticut-based storage unit even though there is no direct physical link (other than the connection through the Electricity Grid). At certain hours of the day, whenever the Maine wind plant is producing electricity and selling into the Lakewood Node, the energy storage unit in Connecticut buys an equal amount of electricity from the electricity market in Cos Cob, CT. The input into Connecticut storage can never be more than the Maine Wind Plant Output for any given hour. In other words, the charging of the storage unit in Cos Cob for

any given hour is constrained by the electricity output of the wind plant located in Maine. Even though the wind plant and storage unit may be separated by hundreds of miles, they can act in tandem in this Linked, Located scenario.

Note: In the Linked, Located example above, a “bilateral contract” – a forward contract between a buyer and seller in the electricity market – could be used to structure the purchasing of electricity by the storage unit in Connecticut and the selling of electricity by the wind plant in Maine. In addition, simple wireless technology would likely be needed to synch the input-output cycles of each facility. (Without knowledge of the cost of this system, we have not accounted for it in our model.)

Hybrid: In this scenario the storage unit can be charged using electricity from wind plant and from the Electricity Grid. Thus, input from the Electricity Grid will be used to help charge the storage unit whenever Wind Plant Output is lesser than the Maximum Continuous Power Rating of the storage unit during the designated charging hours. (For example, if there is little wind overnight, then the storage unit can charge itself by buying electricity from the electricity market.) The objective is to maximize the utilization of a storage unit by always charging power equal to the Maximum Continuous Power Rating of storage during the designated charging hours. Whether Co-Located (in Maine) or Located (for example, in Connecticut), the storage unit in the Hybrid scenario uses electricity from both wind plant and Electricity Grid to charge.

If Wind Plant Output is lesser than the power *Capacity of Storage* during the designated charging hours, the entire Wind Plant Output is used up in charging the storage. However, if Wind Plant Output is greater than the power Capacity of Storage during the designated charging hours, a portion of the Wind Plant Output equal to the power Capacity of Storage is used up to charge the storage unit, while the remaining Wind Plant Output is sold to the Electricity Grid at the prevailing Real-Time price.

Note: When operating in Hybrid scenario, our wind plant-plus-storage system may need a simple power control system to monitor the connection to the Electricity Grid so the storage unit could be charged by either wind plant or Electricity Grid. (Without knowledge of the cost of this system, we have not accounted for it in our model.)

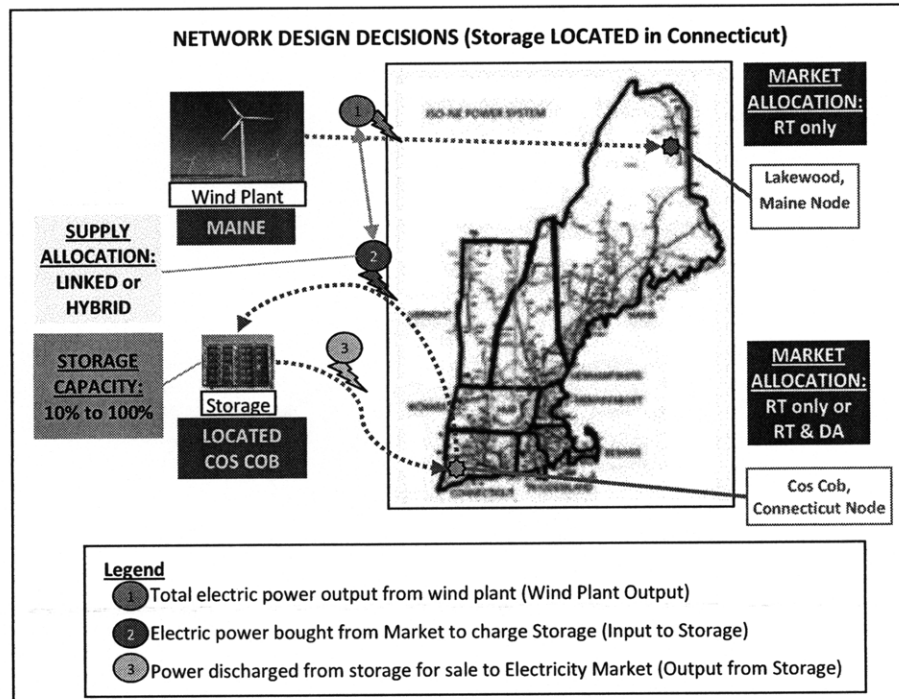
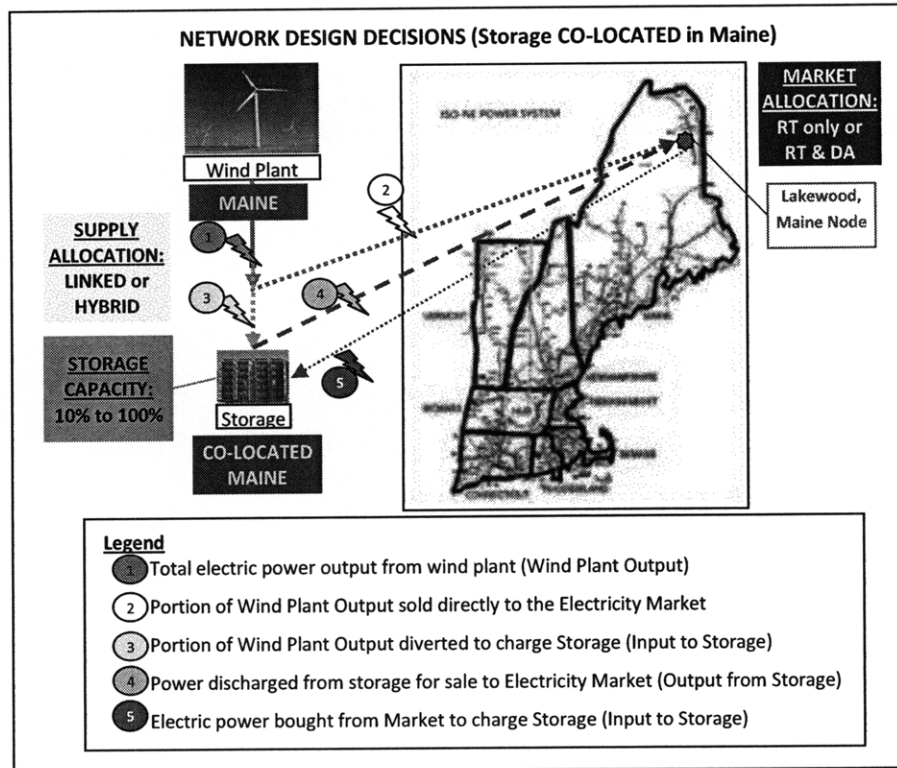
We use our model to assess revenue and profits for both the Linked and Hybrid scenarios as discussed in the Section on Incremental Revenue & Profit (Section 4.3).

3.1.6 Summary of Network Design Decisions

The Network Design Decisions for our model are summarized and represented below pictorially in Figure 3-1:

Figure 3-1: Network Design Decisions

DESIGN DECISIONS				
Facility Role	Facility Location	Capacity Allocation	Market Allocation	Supply Allocation
<u>Wind Plant:</u> Generate electricity	Wind Plant: Maine	Wind Plant: 120 MW	Real-Time (RT) only	Storage Input LINKED to Wind Plant Output
<u>Storage:</u> Time Shifting	<u>Storage:</u> 1. Maine (CO-LOCATED) OR 2. Cos Cob, CT (LOCATED)	<u>Storage:</u> % of Wind plant capacity: • From 10% to 100%	OR Real-Time(RT) & Day-Ahead (DA)	OR Storage Input Wind Plant Output + Electricity Grid HYBRID



3.2 Daily Operating Policies

Having factored for macro-level network design, we next considered Daily Operating Policies. In developing Daily Operating Policies for wind-generated electricity stored in batteries, we treated electricity as a physical product with a unique set of characteristics. (Section 3.2.1) Then we consulted literature on traditional replenishment systems for managing individual item inventories of physical products (henceforth called Traditional Inventory Control Systems) to begin to think about supply chain strategies we could employ for electricity (Silver, Pyke, & Peterson, 1998, pp. 147-404). Next we explored the incremental costs incurred by operating electricity storage units and compared these costs to the components of the total cost function used to arrive at decision rules for Traditional Inventory Control Systems (Silver, Pyke, & Peterson, 1998). (Section 3.2.2) Then we identified relevant Daily Operating Policies from Traditional Inventory Control Systems and highlighted similarities and dissimilarities for our wind plant-plus-storage system. (Section 3.2.3) Finally, we employed the criteria used to determine operating policies in Traditional Inventory Control Systems to develop a range of operating policies for optimizing revenue on the sale of stored electricity. (Section 3.2.4) Four of those policies – Simple, Cost-Based, Max Peak and Rapid Arb – are discussed in Section 3.2.5. These policies are supported with detailed flowcharts for the various policies in Appendix 3.

3.2.1 Electricity Product Characteristics and Inventory Control Model Assumptions

In thinking about applying Traditional Inventory Control System to electricity storage, we had to first identify the distinctive characteristics of electricity. We also had to make some assumptions for our model that are in line with the assumptions made for Traditional Inventory Control Systems. These are discussed in detail in this section.

- A. ***Electricity is absolutely perishable:*** The first thing that struck us was the fact that electricity in the absence of storage is an absolutely perishable product, meaning electricity must be consumed the moment it is generated, or be lost. The entire Electricity Grid has to be maintained in a state of

constant balance (or dynamic equilibrium) such that the amount of electricity being consumed should be exactly equal to the amount of electricity being generated at every instant. Even momentary imbalances between the demand and supply of electricity from the Electricity Grid could lead to a collapse of the whole system.

With the availability of storage, electrical energy can be stored and does not perish instantaneously. Hence, with storage it becomes possible to think of stored electricity as an inventory of units of electrical energy (measured in Megawatt-hours (MWh)). However, as explained in (Section 2.4) when the storage unit is in Standby (i.e. connected to the power system and actively waiting to either charge or discharge) it continues to lose the stored electrical energy as heat. As discussed in Section 1.2.4, this is called Standby Loss and is a measure of the perishability of the stored product i.e. electrical energy in storage. We have incorporated Standby Loss (as a % based on the choice of a particular storage technology) into our model.

- B. ***Demand and Prices:*** Electricity prices in New England fluctuate dramatically due to supply and demand, weather, time of day and season, among other reasons. This price variability is discussed in detail in Section 2.3. In approaching our inventory policy creation for our simulation model, we have made several assumptions. We have assumed that there is a significantly large demand, i.e. it is possible to sell all the electricity output that we intend to sell in the market at any given hour. Also, we have assumed that the demand is not influenced by the availability of electricity output from our wind plant or storage unit. Finally, we have assumed that the prices prevailing in the electricity markets will not be influenced by the slight increase in supply due to our wind plant. This is a reasonable assumption because the total generation output from our synthesized wind plant represents approximately 2.5% of the of the total electrical generation for the Maine zone based on 2007 data (ISO New England, 2008, p. 33).

Note: Annual Output from Wind Plant = 120 MW * 24 hrs/day * 365 days * 28%
Capacity Factor = 294,000 MWh approx.; Electrical Energy Demand in Maine =
approximately 11,000,000 MWh.

Hence, in our model we have assumed that the demand is relatively large compared to the Wind Plant Output but it does vary in a continuous random manner. We have also used the random variation in market prices simulated in our model to be caused by and thus reflect the variation in demand.

- C. **Lead Time:** In Traditional Inventory Control Systems lead time refers to the time between placing an order and receiving that order and transferring it to inventory, when it becomes available for consumption. *For our model, the lead time is the time it takes to charge the storage unit.* Lead time can be constant or variable.

Storing electricity can only happen at a certain maximum rate determined by the technical specification of the unit. (This is the Maximum Continuous Power Rating of storage as explained in Section 2.4). If the storage unit is being charged at this maximum rate, it takes a finite amount of time for the storage unit to charge to its capacity (Energy Capacity as described in Section 2.4). Thus, if the storage unit is being charged at its Maximum Continuous Power Rating then there is a finite constant lead time for the storage unit to be fully charged. However, if the storage unit is *not* being charged at its Maximum Continuous Power Rating (such as in a Linked scenario were the Wind Plant Output may be higher or lower than the Maximum Continuous Power Rating) then the Lead Time to fully charge the unit is variable.

- D. **Review Period:** In Traditional Inventory Control Systems one of the fundamental issues to be resolved is, How often should inventory status be determined? (Silver, Pyke, & Peterson, 1998, p. 235). Determining the status of inventory requires resources (labor, computer time, etc.). Plus, as the period for determining inventory status increases, so does the susceptibility to unforeseen variations in demand. Inventory control models are thus classified as either Continuous Review, whose

inventory status is always known, and Periodic Review, whose inventory status determined at a fixed interval (Silver, Pyke, & Peterson, 1998, p. 236).

For an electricity storage unit, it is technically possible to know at any given instant the amount of stored electricity (inventory) through a power control and monitoring system attached to the storage unit. However, while setting the Daily policies for charging and discharging, it may not always be possible to do an instantaneous review to decide when to charge or discharge. Hence in our model we tested different policies over 24-hour periods, where the status of the storage unit (in terms of the amount of energy inventory available in the unit) is determined every hour. Based on the amount of energy inventory available at the beginning of each hour a decision is taken whether to charge or discharge in that hour depending on the input or output policy chosen (Section 3.2.5 on charging and discharging policies).

In the strictest sense all our models are Periodic Review models (with a periodicity of review of 1 hour). However, for practical purposes we treat our model as a continuous review model as the status of energy inventory is determined 24 times every single day.

- E. ***Capacity of Resource:*** Most common Traditional Inventory Control Systems assume that the resources have infinite capacity (Silver, Pyke, & Peterson, 1998). It is possible to construct inventory control models where capacity can be a constraining factor in two different ways: 1) the capacity of the resource producing the item is limited; or 2) the capacity of the storage facility holding the inventory is limited.

For the purpose of our model, two different capacities impact our inventory of stored electrical energy. The capacity of the storage unit itself (Energy Capacity) that puts a limit on the maximum amount of energy that can be stored in the unit. In addition, the storage unit has a power capacity in terms of the maximum rate at which it can charge/ discharge (Maximum Continuous Power Rating).

As discussed earlier, this capacity determines the Lead Time to charge up the storage unit with stored electricity.

- F. **Planning Horizon:** Traditional Inventory Control Systems are based on either a finite or infinite planning horizon. For our model, we have assumed a single day planning horizon. This means the storage unit starts at a state of minimum charge every day, then goes through charge/discharge cycle(s) during the day, and ends the day at the same state of minimum charge that it began with. Our policies are designed to increase revenue for the wind plant-plus-storage system over the course of the day.

3.2.2 Total Cost Function for Wind Plant-plus-Storage Unit

In developing inventory management policies for our wind plant-plus-storage system, we also analyzed our network's costs and compared them to the costs considered in Traditional Inventory Control Systems. The existing costs of wind plant operation are not relevant to our decision. That is because the Base Case in our model is the wind plant operating without storage selling electricity output to the Real-Time market at the prevailing price. Thus, the only costs relevant for our model are the incremental capital and operating costs for a storage unit.

The Total Costs Function used in Traditional Inventory Control Systems is (Silver, Pyke, & Peterson, 1998, pp. 44-48):

$$\text{Total Cost} = \text{Unit Variable Cost} + \text{Inventory Carrying Cost} + \text{Ordering or Setup Cost} + \text{Shortage Cost}$$

We now discuss each component of this Total Cost equation and discuss how it applies to our wind plant-plus-storage unit model.

A. Unit Variable Costs

For Traditional Inventory Control Systems the unit variable cost of an item is expressed in \$/unit and represents the price (including transportation) paid to the supplier including any cost incurred to make the

item ready for sale. For our wind plant-plus-storage system, the following costs need to be considered for the Unit Variable Costs of electricity (which we call *Input Energy Unit Variable Cost*) in our simulation model:

- i. For a Co-Located scenario (where the storage unit is located next to the wind plant, as discussed in Section 3.1.2) when the storage input is directly from the Wind Plant Output (co-located), the unit variable costs of each unit of energy stored can be thought of as being equal to the opportunity cost foregone by not selling the electricity output from the wind plant directly to the Real-Time electricity market at the prevailing Location Marginal Price.
- ii. For a Located scenario (where storage located in Connecticut as discussed in Section 3.1.2) when the storage input is not coming from the Wind Plant Output, the unit variable costs of each unit of energy stored is simply the price paid per unit to buy the electrical energy from the Real-Time Energy market at Cos Cob the prevailing Location Marginal Price.

In both cases the Input Energy Unit Variable Cost (IC) can be represented as

$$IC = \frac{\sum_{i=H_{cStart}}^{i=H_{cEnd}} E_i * P_i}{\sum_{i=H_{cStart}}^{i=H_{cEnd}} E_i}$$

Where IC: Input Energy Unit Variable Cost; H_{cStart} : Hour to start charging; H_{cEnd} : Hour to end charging; E_i : Energy input to storage in hour i ; P_i : Market Price of Energy prevailing in hour i .

For the co-located case P_i is the price of electricity at the Lakewood node and for the case when storage is not co-located P_i represents the price at the Cos Cob node.

Note: While thinking about Unit Variable Costs for Electrical Energy it is important to consider the distinctive nature of Transportation Costs for electricity. Electrical energy is ‘transported’ over the Electricity Grid through wires. This transportation does not require any vehicles or fuel but it does result in transportation *losses* (called transmission and distribution losses, which result as electric current flows through wires) and also causes

Congestion if there is not enough transmission capacity to carry the electricity over a certain portion of the Electricity Grid. Therefore, the cost of transportation for electricity can be interpreted in terms of the ‘Loss’ and ‘Congestion’ component of the Location Marginal Price. In fact it is this “transportation cost” as represented by the ‘Loss’ and ‘Congestion’ charges that results in different prices of electricity for different locations on the Electricity Grid. Hence, when we use the Location Marginal Price to calculate unit variable costs for electrical energy we have included the transportation costs in the price.

B. Inventory Carrying Costs

For Traditional Inventory Control Systems, the inventory carrying costs include the opportunity cost of money invested, the expense incurred in running a warehouse, handling and counting costs, the costs of special storage requirements, deterioration of stock, damage, theft, obsolescence, insurance and taxes (Silver, Pyke, & Peterson, 1998, p. 45). As explained below the only cost relevant as carrying costs for stored electricity in our model is the cost associated with Standby Losses. This is equivalent to carrying costs caused by deterioration of stock, damage, theft or obsolescence in Traditional Inventory Control Systems.

As explained in Section 2.4, when the storage unit is in Standby (i.e. connected to the power system and actively waiting to either charge or discharge) it continues to lose its stored electrical energy as heat. This is called Standby Loss. We have incorporated Standby Loss (as a % based on the choice of a particular storage technology) into our simulation model. This represents an inventory holding cost expressed as a % of the stored energy that is lost for every hour that the storage unit is in standby (i.e. connected to the Electrical Power system and ready to charge or discharge).

Note: For stored electricity, we could have looked at the opportunity cost of money invested in the form of stored electrical energy. However, in our model the planning horizon is only one day (as discussed in Section 3.2.1) so the electrical energy remains stored (as inventory) for only a few hours. Hence, the opportunity costs of money invested in stored energy is negligible.

C. Ordering / Setup Costs

For Traditional Inventory Control Systems, the ordering and setup costs represents the fixed costs associated with each replenishment cycle. Ordering cost can include the costs of order forms, postage, telephone calls, authorization, typing of orders, receiving, inspection, following up on unexpected events, and handling of vendor invoices. Setup costs can include the cost of interrupted production, and the components included in ordering costs (Silver, Pyke, & Peterson, 1998, p. 46).

For the wind plant-plus-storage system, a cost similar to ordering/setup cost is the cost associated with the loss that happens in each charge-discharge cycle of storage. This is measured by the Round-Trip Efficiency (described in Section 2.4) and represents the ratio of the output energy to the input energy in each charge-discharge cycle. Thus $(1-RTE)$ represents the loss of energy associated with every charge discharge cycle and this 'round trip loss' can be treated as a cost (loss) that is incurred in every charge discharge cycle. Note that the magnitude of this energy loss is constant if the storage unit is charged up to the Energy Capacity in every cycle. However, the cost (\$ value) of the loss in each cycle will vary depending on the average cost of energy during that cycle. In case the storage unit is not charged up to the full Energy Capacity in each cycle, even the magnitude of energy loss with each cycle will be different. Each storage technology that we considered for use in our model has a Round-Trip Efficiency factor, some being higher than others.

Note: We have considered the capital cost of investment in the storage facility and also the daily cost of operating and maintaining the storage facility for the purpose of calculating the profitability of the wind plant-plus-storage unit. These costs are determined by our Network Design Decisions and are not affected by our choice of daily operating policy. Hence, these costs are not factored into ordering/setup costs.

D. Shortage Costs

In Traditional Inventory Control Systems, the shortage costs are expressed as either the cost of avoiding a stockout (i.e. material available in inventory is not sufficient to meet demand) or the cost (in the form of a

penalty) that is incurred when a shortage takes place. These costs are typically expressed in one of the following forms (Silver, Pyke, & Peterson, 1998, pp. 244-245):

- a. Specified fixed cost per stockout occasion;
- b. Specified fractional charge per unit short;
- c. Specified fractional charge per unit short per unit time;
- d. Specified charge per customer line item short.

For our wind plant-plus-storage system, shortage costs are incurred only if we participate in the Day-Ahead (DA) market. As explained in Section 2.3, in the DA market, Generators must commit to sell a pre-determined amount of energy for each hour of the following day at a given price. If that Generator is not able to supply the committed amount of energy at the designated hour, then the Generator must buy in the RT market at that hour and immediately re-sell in the DA market. If volatile RT prices are extremely high at that hour, then that Generator risks a significant loss. In addition that Generator must pay a penalty for every unit of energy short.

There are no shortage costs when our wind plant-plus-storage system participates in the Real-Time market.

3.2.3 Relevant Operating Policies

Based on our study of Traditional Inventory Control Systems we have identified two commonly-used approaches for inventory management that are relevant to our wind plant-plus-storage system:

- A. Single-period policy for style goods and perishable items, such as:
 - a. Newsvendor
- B. Inventory control policies for individual items with probabilistic demand with an infinite planning horizon, such as:
 - a. Order-Point, Order-Quantity (**s,Q**) System;
 - b. Order-Point, Order-Up-to-Level (**s,S**) System;
 - c. Periodic-Review, Order-Up-to-Level (**R,S**) System;

d. (R,s,S) System.

We discuss below the salient features of these approaches and how they apply to our model.

A. Single Period Problem (Newsvendor)

In order to analyze how the inventory management of stored electricity relates to a Single Period Problem, it is helpful to consider the situation faced by a newsstand owner who sells Boston Globe newspapers.

Each morning, a newsstand owner must decide how many Boston Globe newspapers to buy. The decision of what quantity to buy is important because the newsstand owner only has one day – ***a single period*** – to sell whatever inventory he buys. Yesterday’s newspaper has little or no value. While there may be one or more opportunities for replenishment after the initial order is placed, the newsstand owner must commit to buy most of his inventory before he knows demand. Plus, forecasts of daily demand are unreliable. The newsstand owner knows that if total demand in a 24-hour period is less than the stock he has available, he will be long inventory resulting in a ***cost of overage***, or the loss he takes by discounting or discarding his inventory. The newsstand owner also knows that if total demand in period exceeds his stock available, the vendor is short inventory resulting in a ***cost of underage*** in the form of lost sales. So how many Boston Globes does he buy each morning?

The above example is an example of a single-item, Single Period Problem, otherwise known as a “Newsvendor” problem (Silver, Pyke, & Peterson, 1998, pp. 382-420). On the surface, our stored electricity inventory situation resembles a Newsvendor problem. Below is a list of similarities:

1. **Perishability**: As discussed in Section 3.2.1, electricity is a ***perishable item*** – much like a style good or perishable item – so it needs to be sold within a specific time period;
2. **Single Period**: Our wind plant-plus-storage system is operating on a 24-hour, daily cycle, and so all of our stored energy needs to ***discharge completely by the end of every day***;

3. Cost of Overage: We have a *cost of overage*: if we have energy remaining in the storage unit by the end of the peak hours then we must sell this energy at the prevailing market price, which might be lower than the input cost of electricity;
4. Cost of Underage #1: We have a *cost of underage*: if the storage unit does not have enough amount of energy stored to sell during the peak hours when prices are high, there is a loss of revenue;
5. Cost of Underage #2: Another *cost of underage* occurs if we participate in the Day-Ahead market (see Section 2.3). There is a penalty for not being able to supply the committed amount of electricity.

Given these similarities to a Newsvendor problem, we need to identify the ideal amount of energy input to and output from storage at different hours, to maximize profits by the end of the day.

While on the whole this system seems similar to an SPP in Traditional Inventory Control Systems, there are two important characteristics of our situation that make it dissimilar to the traditional newsvendor problem:

1. Impacts of Variable Costs, Variable Prices and Infinite Demand: Unlike the Single Period Problem (Newsvendor) where the selling price and purchase costs is fixed and demand is variable, in our model the cost of electricity input to storage and the selling price for electricity discharge from storage is not fixed and depends on the daily price fluctuations in the electricity markets. Also we assume infinite demand so we can always sell all the electrical energy available in storage. Our review of literature on the extensions to the SPP suggests that such an extension of the SPP has not yet been widely studied (Khouja, 1999);
2. Impact of Standby Losses: In a Single Period Problem (Newsvendor), the product being sold continues to retain its value until the end of the single period after which it has to be sold at the salvage value. However, with stored electricity, the product loses value throughout the single

period due to Standby Losses at a fixed rate. This is similar to the extension of the SPP for perishable items with random lifetime, which analyze cases where the inventory on hand deteriorates at a constant rate. Raafat (1991) reviews literature on this area. Chung & Ting (1994) investigate a perishable item system with a specific pattern of variable demand and develop a good heuristic for the amount of inventory to order. We have not incorporated any such heuristic into our model, but we do propose that future research could extend our model by incorporating finding from these SPP extension research.

Despite these dissimilarities, we still sought to incorporate Newsvendor characteristics into our Daily Operating Policies.

B. Inventory control policies with an infinite planning horizon

In our model, we have assumed the planning horizon of a day. However, it is possible to extend our model and think about policies that consider revenue and profit opportunities over the course of several days (i.e. an infinite planning horizon). It is possible to carry over the energy stored one day for use in the following day. Hence, it is instructive to examine common inventory control policies for an infinite planning horizon. There are four (4) forms of inventory control policies most commonly used in Traditional Inventory Control Systems with an infinite planning horizon (Silver, Pyke, & Peterson, 1998, pp. 237-241). These are:

a) Order-Point, Order-Quantity (s,Q) System

This is a continuous review system, where a fixed quantity Q is ordered whenever the inventory position (inventory position is equal to the sum of the stock on hand in the warehouse and the quantity on order) drops to reorder point s or lower. This is often called a “two-bin system.” The main advantages for this system are that it is quite simple to understand and implement, errors are less likely to occur and production requirements for the supplier are predictable;

b) Order-Point, Order-Up-to-Level (s,S) System

This is also a continuous review system, where an order is placed to raise the inventory position up to level S whenever the inventory position drops to reorder point s or lower. This is also called the “min-max system”. (s,S) systems in general can lead to lower costs than (s,Q) systems and are frequently encountered in practice;

c) Periodic-Review, Order-Up-to-Level (R,S) System

This is a periodic review system where every R units of time enough is ordered to raise the inventory position up to level S . This is also called the “replenishment cycle system” and is in common use, particularly in companies not utilizing computer control;

d) (R,s,S) System

This is a combination of (s,S) and (R,S) systems. There is a periodic review every R units of time. If the inventory position is above s then nothing is done, else an order is placed to raise inventory position up to level S . The (R,s,S) system can in general condition produce the lowest costs from amongst all the four systems. However, it does involve significant computational effort and is difficult to understand.

For our wind plant-plus-storage system, as discussed in section 3.2.1, we have set up an hourly review so we get to know the amount of energy stored (inventory position) every hour and it seems at first glance, like a continuous review system. However, in case we pre-specify only certain hours within which charging or discharging is allowed, then although we have information on level of energy stored at each hour yet we can charge or discharge only during the pre-specified hours and the system becomes more like a Periodic Review (R) system. Also the storage system can never store more than the Energy Capacity, so it is like having an order-up-to level S . Hence, our input policy resembles an (R,S) policy at a basic level. However, there are important differences from the traditional (R,S) policy:

1. Storage Input Constraints: The actual amount of energy input into the system (order received) during any hour also depends on:

- a. The Maximum Continuous Power Rating of the storage unit that sets a limit on the size of input in any hour (shipment size capacity limitation);
 - b. The Wind Plant Output in case the storage input is Linked to the Wind Plant Output. As the Wind Plant Output is variable, this can be treated as an extension of the simple Traditional Inventory Control Systems, where the quantity of shipment received from the supplier is unpredictable and variable. Extensions of the Periodic Review Inventory policies dealing with uncertainty in supply have been studied by Li, Xu, & Hayya (2004), who derive bounds for the optimal policy in such a case. We have not incorporated such results into our model, but we do propose that future research could extend our model by incorporating extensions of periodic review models;
2. Variable Lead Time: In addition, within the pre-specified hours for charging and discharging, input to storage to charge up to the Energy Capacity level can be received at any later hour as well. Hence, this can be treated as a case of variability in replenishment lead time for Traditional Inventory Control Systems. The topic of incorporating variable lead time into Traditional Inventory Control Systems has been researched widely (Silver, Pyke, & Peterson, 1998, p. 284) (Magson, 1979). We propose in further research that the learning from these models can be extended to our wind plant-plus-storage system.

3.2.4 Criteria for Operating Policies for Energy Storage

Based on our assessment of the operating policies of a traditional inventory control system as they relate to management of an energy storage system, we developed criteria for our operating policies in our simulation model. An inventory management system needs to resolve three fundamental issues (Silver, Pyke, & Peterson, 1998, p. 235):

- 1) How often should the inventory status be determined?
- 2) When should a replenishment order be placed?

3) How large the replenishment order should be?

From the three questions above, it is clear that Traditional Inventory Control Systems focus heavily on monitoring and replenishing inventory levels in a system. Thus, these Traditional Inventory Control Systems were very helpful as we created our “input policy” (i.e. policy to charge storage) in our simulation model for our wind plant-plus-storage system. However, we realized that we needed to also create dynamic operating “output policies” for storage (i.e. discharge from the storage unit) to optimally sell to the electricity market. We discuss the salient criteria used to create our input and output policies in this section.

A. Criteria for Input Policies (for charging storage)

In designing our input policies for our simulation model, we have considered all of the issues identified by Silver, Pyke & Peterson (1998) for Traditional Inventory Control Systems:

How often should the inventory status be determined? As discussed in Section 3.2.1, we evaluate the status of the storage unit (in terms of amount of energy stored, i.e. inventory position) at the beginning of each hour. Strictly speaking this is a *periodic review* system, but for all practical purposes this can be treated as a *continuous review* system.

When should a replenishment order be placed? For our wind plant-plus-storage system, the input policy determines the hours during which the storage system is charged i.e. when a replenishment order can be placed. The storage input policy can be based on either the hour of day (i.e. charging is allowed only during certain pre-designated charging hours) or on the price prevailing during the hour (i.e. charge only if the price prevailing in the hour is lower than a certain pre-designated minimum price).

How large the replenishment order should be? There are three factors that determine the size of the replenishment order (i.e. the amount of energy that can be input to the storage unit) for any given hour viz. the Energy Capacity of the storage unit, the Maximum Continuous Power Rating of the Unit, and the

Wind Plant Output during the hour in case the storage input is Linked to Wind Plant Output. As discussed in Section 2.4 on storage, the storage unit is limited by its capacity both in terms of the amount of energy that it can store (Energy Capacity) and the maximum rate that it can be charged or discharged (Maximum Continuous Power Rating). Hence for any given hour the storage unit can never be charged at a rate greater than Maximum Continuous Power Rating, this power capacity thus determines the maximum size of the replenishment order that can be placed in any hour. In addition, if the storage unit is already charged to the maximum Energy Capacity at the beginning of the hour then the size of the replenishment order (i.e. input to the storage unit) has to be zero for that hour. If the input to storage is Linked to the Wind Plant Output as discussed in Section 3.1.5, then in addition to the two constraints already mentioned, the input to storage in any given hour (i.e. size of replenishment order) cannot be greater than the wind plant electricity output for that hour.

To summarize, our *input policies* for charging storage are determined by five main factors:

1. The amount of energy stored in the system at the beginning of the hour (Inventory Position). This cannot exceed the Energy Capacity of the storage unit, that limits the maximum amount of energy stored (maximum inventory that the system can hold);
2. The Maximum Continuous Power Rating of the storage unit that limits the amount of energy input in any given hour (Order Size);
3. Hour of the day: charging could be allowed only if the hour is within pre-specified hours to begin and stop charging;
4. Price prevailing in the hour: charging could be allowed only if the price in the hour is below a pre-specified price limit;
5. In case the input to storage is Linked to Wind Plant Output, the input energy in a given hour cannot be more than Wind Plant Output in the hour.

Combinations of these factors are applied for the different input policies that we tried. The specific combinations we used in each policy are described in Section 4.1.

B. Criteria for Output Policies for Discharging Storage

As mentioned previously, Traditional Inventory Control Systems focus primarily on replenishment of inventory under a scenario of probabilistic demand. We used these systems to develop our input (or charging) policies for storage. However, Traditional Inventory Control Systems do not typically include selling policies for product. Thus for our simulation model for a wind plant-plus-storage system, we needed to extend the Traditional Inventory Control System to include selling policies, or output policies for discharging storage in our case. In defining an output policy for discharging storage we considered the following factors:

1. The amount of energy stored in the system at the beginning of the hour (Inventory Position). This cannot fall below the state of minimum amount of energy allowed for the storage unit (defined by the Depth of Discharge discussed in Section 2.4);
2. The Maximum Continuous Power Rating of the storage unit that limits the amount of energy that can be discharged in any given hour;
3. Hour of the day: discharging could be allowed only if the hour is within pre-specified hours to begin and stop discharging;
4. Price prevailing in the hour: discharging could be allowed only if the price in the hour is above a pre-specified price limit.

Different combinations of these four factors were tried to devise different output policies. The specific combinations are described in detail in Section 4.1 when we outline the specifics of the various policies we tried.

3.2.5 Specific Details of Input and Output Policies

By selecting different combinations of criteria for input and output policies described in Section 3.2.4, we evolved four (4) different policies for Daily operations of the wind plant-plus-storage system. In this section we discuss the specific details of the four policies and also the manner in which these policies relate to common concepts and approaches in Traditional Inventory Control Systems discussed in preceding sections. We highlight points of similarity and dissimilarity between the policies for Traditional Inventory Control Systems and the four policies tested through our model.

It should be noted that these four policies are by no means exhaustive. Nor can we say with surety that the policy that gives the best results from amongst our four policies is also the optimal policy for our wind plant-plus-storage system. Our simulation model provides a tool to test out different policies, which if devised intelligently provide significant opportunity to improve revenue. While our four policies do see significant improvement in revenue for our wind plant-plus-storage system (see Results in Section 5), we recommend in Section 5.3 that further research be done in exploring more policies.

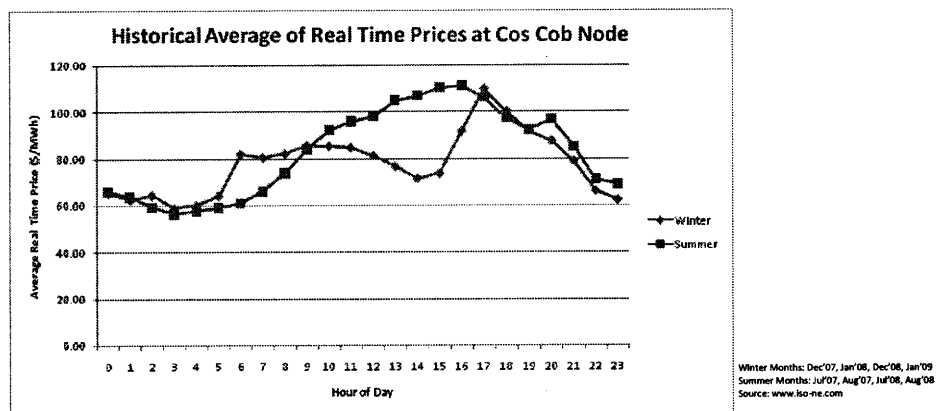
Policy #1: Simple Policy

Policy Objective: Increase daily revenue by simple arbitrage.

Charge-Discharge Strategy: Charge during the historical off-peak hours (night/early morning) and discharge starting at the historical peak hours (late afternoon).

Policy Motivation and Explanation: Based on historical price data, it is possible to identify peak and off-peak hours at the location of the storage unit. Typically, prices are low during the night when the demand is low and are high during early afternoon (for summer) and late afternoon (for winter). This is reflected in the historical hourly average prices shown in the figure below:

Figure 3-2: Historical Average Real-Time Prices Cos Cob, CT



Hence, this policy seeks to set hours for charging based on the historical off-peak hours and discharging during the historical peak hours without taking into account the actual prices prevailing at the hour. Once the historical peak hours begin the storage unit compulsorily sells at the prevailing market price until it reaches the maximum Depth of Discharge so as to not retain any sellable energy (inventory) at the end of the day.

Factors considered for Input Policy: This policy incorporates the input policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Input to storage is allowed only during pre-specified hours (identified as off-peak hours based on historical average prices);
2. **Price:** Actual price prevailing in the hour is NOT considered;
3. **Storage Energy Capacity:** Sets a limit on the maximum amount of energy that can be stored in the system – stopping further charging if the Energy Capacity limit is reached;
4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be input into the system for any given hour;
5. **Wind Plant Output:** Sets limit on charging only in case the input to storage is Linked to Wind Plant Output.

Factors considered for Output Policy: This policy incorporates the output policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Output from storage is allowed only during pre-specified hours (identified as peak hours based on historical average prices);
2. **Price:** Actual price prevailing in the hour is NOT considered;
3. **Depth of Discharge:** Sets a limit on the minimum amount of energy that can be stored in the system – stopping further discharging if the Depth of Discharge limit is reached;
4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be output (discharged) from the system for any given hour.

Comments from a Supply Chain perspective: This policy is based only on historical prices and does not consider actual prices prevailing in the market. The hours for charging and discharging are set based on historical prices to avoid the Cost of Overage (having stored energy remaining at the end of the peak hours that might have to be sold at prices lower than input energy unit cost) and the Cost of Underage (not having enough stored energy to sell during peak hours). Also as discussed earlier, due to the pre-specified hours of charging and the maximum Energy Capacity limit the input policy here is similar to a (R,S) policy for Traditional Inventory Control Systems. However, due to the limit set by the Maximum Continuous Power Rating and the variability in supply introduced by the Wind Plant Output, the simple (R,S) model needs to be extended.

Note: As discussed in our Literature Review (Section 1.4), the Simple Policy described above is similar to the naïve policies used in other existing research studies on the use of energy storage for Time Shifting applications. Many of these other studies use “perfect information” for modeling naïve policies to measure the financial benefits of storage. We purposely tried to replicate the naïve policies used by other studies so we could set a baseline for improvement with our subsequent policies.

Policy #2: Cost-Based Policy

Policy Objective: Increase daily revenue using cost-based dynamic arbitrage

Charge-Discharge Strategy: Charge during historical off-peak hours. Discharge during daytime if prevailing market price is higher (by a specified **Targeted Gross Margin**) than weighted-average amount paid – and then when historical peak hours start, begin compulsory discharge at prevailing market price.

Policy Motivation and Explanation: This policy evolved as a first step to improve the Simple Policy. We wanted to increase the revenue opportunity by allowing a larger window to discharge (sell) as long as we make our Targeted Gross Margin. The input to storage (replenishment) follows the same policy as the Simple Policy, i.e. charge during historical off-peak hours (night). However, for the output from storage (selling) we make the decision more dynamic based on market price. Between the time charging stops in morning to the time the historical peak hours begin in the afternoon, the policy dynamically checks prices at each hour and makes a decision to sell as long as we make a desired margin over the input energy unit variable cost (see section 3.2.2). This desired margin can be set by the business. It is currently set at 35% in our model based on a 10% margin above the Round-Trip Efficiency related loss of 25%. Once the historical peak hours begin, we sell the maximum amount possible irrespective of the actual prevailing price until we reach the Depth of Discharge.

Factors considered for Input Policy: This policy is identical to Simple Policy and incorporates the input policy factors in the following manner (a detailed flow chart can be seen in Appendix 3):

1. **Hour of Day:** Input to storage is allowed only during pre-specified hours (identified as off-peak hours based on historical average prices);
2. **Price:** Actual price prevailing in the hour is NOT considered for input;
3. **Storage Energy Capacity:** sets a limit on the maximum amount of energy that can be stored in the system – stopping further charging if the energy capacity limit is reached;

4. **Maximum Continuous Power Rating:** sets a limit on the maximum amount of energy that can be input into the system for any given hour;
5. **Wind Plant Output:** sets limit on charging only in case the input to storage is Linked to Wind Plant Output.

Factors considered for Output Policy: This policy incorporates the output policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Discharging i.e. selling from storage is possible as soon as the charging (input) hours end. However, until the time historical peak hours begin discharging is based on price. In addition, discharge from the system before the peak hours is allowed only when there is sufficient energy remaining to sell during the peak hours. Once the peak hours begin, there is compulsory discharge;
2. **Price:** Between the hours when charging ends to the beginning of the historical peak hours discharging (selling is possible) only if the market price is greater than the Input Energy Unit Cost plus a desired margin (currently 35%);
3. **Depth of Discharge:** Sets a limit on the minimum amount of energy that can be stored in the system – stopping further discharging if the Depth of Discharge limit is reached;
4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be output (discharged) from the system for any given hour.

Comments from a Supply Chain perspective: The output policy for our Cost-Based Policy is inspired by the Newsvendor model – the policy attempts to reduce the cost of overage (having stored energy remaining at the end of the peak hours that might have to be sold at prices lower than input energy unit cost) by selling before the peak hours begin if there is a good enough price that provides a desired margin. In addition, we ensure that the cost of underage is not increased, by leaving enough energy to sell during peak hours. The input policy is identical to the Simple Policy discussed earlier and can be viewed as a modified (R,S) policy.

Policy #3: Max Peak Policy

Policy Objective: Increase daily revenue by price based dynamic arbitrage

Charge-Discharge Strategy: Charge during historical off-peak hours. Discharge during daytime if prevailing market price is higher the maximum historical average peak price – and then when historical peak hours start, begin compulsory discharge at prevailing market price.

Policy Motivation: This policy attempts to improve upon the Simple and Cost-Based Policies by using a dynamic price-based approach. We increase the revenue opportunity by allowing a larger window to discharge (sell) as long as the price is higher than the highest historical average peak price for a specific peak hour during the day. The input to storage (replenishment) follows the same policy as the Simple Policy, i.e. charge during historical off-peak hours (night). However, for the output from storage (selling) we make the decision more dynamic based on market price. Between the time charging stops in morning to the time the historical peak hours begin in the afternoon, the policy dynamically checks prices at each hour and makes a decision to sell if the price is higher than the highest historical average peak price for a specific peak hour. Hence, we take advantage of opportunities during the day to get prices even higher than the expected price during peak hours. Once the historical peak hours begin, we sell the maximum amount possible irrespective of the actual prevailing price until we reach the Depth of Discharge.

Factors considered for Input Policy: This policy is identical to Simple Policy and incorporates the input policy factors in the following manner (a detailed flow chart can be seen in Appendix 3):

1. **Hour of Day:** Input to storage is allowed only during pre-specified hours (identified as off-peak hours based on historical average prices);
2. **Price:** Actual price prevailing in the hour is NOT considered for input;
3. **Storage Energy Capacity:** sets a limit on the maximum amount of energy that can be stored in the system – stopping further charging if the Energy Capacity limit is reached;

4. **Maximum Continuous Power Rating:** sets a limit on the maximum amount of energy that can be input (charged) into the system for any given hour;
5. **Wind Plant Output:** sets limit on charging only in case the input to storage is Linked to Wind Plant Output.

Factors considered for Output Policy: This policy incorporates the output policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Discharging (selling) from storage is possible as soon as the charging (input) hours end. However, until the time historical peak hours begin, discharging is based on price. In addition, discharge from the system before the peak hours is allowed only when there is sufficient energy remaining to sell during the peak hours. Once the peak hours begin, there is compulsory discharge down to Depth of Discharge;
2. **Price:** Between the hours when charging ends to the beginning of the historical peak hours discharging (selling is possible) only if the market price is greater than the historical maximum average peak price;
3. **Depth of Discharge:** Sets a limit on the minimum amount of energy that can be stored in the system – stopping further discharging if the Depth of Discharge limit is reached;
4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be output (discharged) from the system for any given hour.

Comments from a Supply Chain perspective: The output policy for our Max Peak Policy is also inspired by the Newsvendor model – the policy attempts to reduce the cost of overage (having stored energy remaining at the end of the peak hours that might have to be sold at prices lower than input energy unit cost) by selling before the peak hours begin if there is a price that is even higher than expected price during the peak hours. In addition, we ensure that the cost of underage is not adversely affected, by leaving enough energy to sell during peak hours. The input (charging) policy is identical to the Simple Policy discussed earlier and can be viewed as a modified (R,S) policy.

Policy #4: Rapid Arb Policy

Policy Objective: Increase daily revenue by price based dynamic arbitrage.

Charge-Discharge Strategy: Charge during historical off-peak hours. Discharge during the historical peak hours at prevailing market price and, during the intervening hours dynamically charge or discharge based on price.

Policy Motivation: This policy is intended to improve upon the Cost-Based and Max Peak policies by not only increasing the revenue opportunity with longer discharging hours but also providing additional opportunities to charge up storage if the price is low during the day. This additional opportunity to charge helps to make up for the Standby Losses of electricity while it is stored. Also, this policy reduces the possibility of not having enough energy to sell during the historical peak hours (cost of underage). The input to storage (replenishment) happens during the historical off-peak hours (night) and the compulsory discharging begins once the peak hours begin. However, between the time off-peak hours end in morning to the time the historical peak hours begin in afternoon, the policy dynamically checks prices at each hour. If the price is higher than the highest historical average peak price for a specific peak hour, the model discharges (sells). If the price is lower than the highest historical average peak price for a specific peak hour by a specified percentage, the model charges (buys). This percentage by which the price should be lower than the historical average peak price to trigger buying is an adjustable business decision. (We have currently set our percentage in the model at $35\% = 25\%$ loss for RTE + 10% Targeted Gross Margin) Hence, we take advantage of opportunities during the day to buy if the prices are low and to sell if the prices are high (***rapid arbitrage***). Once the historical peak hours begin, we sell the maximum amount possible irrespective of the actual prevailing price until we reach the Depth of Discharge.

Factors considered for Input (Charging) Policy: This policy incorporates the input policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Input to storage is allowed until the historical peak hours begin in the afternoon. However, during the historical off-peak hours charging happens irrespective of price. Between end of historical off-peak hours ending and historical peak hours beginning, the input decision to storage is price-based;
2. **Price:** Price is dynamically considered between off-peak and peak hours to allow charging only if the price is lesser than the highest historical average peak price for a specific peak hour by a certain percentage (currently set at 35%);
3. **Storage Energy Capacity:** Sets a limit on the maximum amount of energy that can be stored in the system – stopping further charging if the Energy Capacity limit is reached;
4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be input into the system for any given hour;
5. **Wind Plant Output:** sets limit on charging only in case the input to storage is Linked to Wind Plant Output.

Factors considered for Output (Discharging) Policy: This policy incorporates the output policy factors in the following manner (a detailed flow chart for the decision flow can be seen in Appendix 3):

1. **Hour of Day:** Discharging i.e. selling from storage is possible as soon as the historical off-peak hours end. However, until the time historical peak hours begin, discharging is based on price. In addition, discharge from the system before the peak hours is allowed only when there is sufficient energy remaining to sell during the peak hours. Once the peak hours begin, there is compulsory discharge;
2. **Price:** Between the hours when charging ends to the beginning of the historical peak hours discharging (selling is possible) only if the market price is higher than the highest historical average peak price for a specific peak hour;
3. **Depth of Discharge:** Sets a limit on the minimum amount of energy that can be stored in the system – stopping further discharging if the Depth of Discharge limit is reached;

4. **Maximum Continuous Power Rating:** Sets a limit on the maximum amount of energy that can be output (discharged) from the system for any given hour.

Comments from a Supply Chain perspective: As in the Max Peak and Cost-Based policies, this policy continues to reduce the *cost of overage* (having stored energy remaining at the end of the peak hours that might have to be sold at prices lower than input energy unit cost) by selling before the peak hours begin if there is a price that is even higher than expected price during the peak hours.

Moreover, this policy attempts to reduce the cost of underage (not having enough energy to sell during the historical peak hours) by charging during the day if the price is lower than the defined threshold. Thus it compensates for the Standby Losses i.e. makes up partially for the perishable characteristic of stored electricity and improves utilization of the storage unit. The input (charging) policy can be viewed as a modified (R,S) policy though the hours allowed for replenishment would increase. The four policies are summarized and compared in Table 3-1 below:

Table 3-1: Summary Comparison of the Four Operating Policies

Policy	Input (Charging) Policy		Output (Discharge) Policy		Supply Chain Comment
	Hour of Day	Price	Hour of Day	Price	
Simple	<input checked="" type="checkbox"/> Charging allowed only during historical off-peak hours	<input type="checkbox"/> NOT considered	<input checked="" type="checkbox"/> Discharging allowed only after peak hours begin	<input type="checkbox"/> NOT considered	<ul style="list-style-type: none"> Charging and discharging hours can be set based on historical average prices to minimize cost of overage and underage Input policy is like a modified (R,S) policy with shipment capacity constraint and unreliable supply with variable lead time
Cost-based	<input checked="" type="checkbox"/> Charging allowed only during historical off-peak hours	<input type="checkbox"/> NOT considered	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours based on price; Compulsory discharge once peak hours begin	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours only if price higher than average unit input cost by a certain desired margin	<ul style="list-style-type: none"> More discharging hours increase revenue potential and reduce potential cost of overage Input policy is like a modified (R,S) policy with shipment capacity constraint and unreliable supply with variable lead time.
Max Peak	<input checked="" type="checkbox"/> Charging allowed only during historical off-peak hours	<input type="checkbox"/> NOT considered	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours based on price; Compulsory discharge once peak hours begin	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours only if price higher than the highest historical average peak price for a specific peak hour	<ul style="list-style-type: none"> More discharging hours increase revenue potential and reduce potential cost of overage Input policy is like a modified (R,S) policy with shipment capacity constraint and unreliable supply with variable lead time.
Rapid Arb	<input checked="" type="checkbox"/> Charging allowed until historical peak hours begin	<input checked="" type="checkbox"/> Between off-peak and peak hours, charging only if price lower than the highest historical average peak price for a specific peak hour by a certain percentage	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours based on price; Compulsory discharge once peak hours begin	<input checked="" type="checkbox"/> Discharge between off-peak and peak hours only if price higher than the highest historical average peak price for a specific peak hour	<ul style="list-style-type: none"> Applies newsvendor strategies to reduce costs of overage/underage More discharging hours increase revenue potential and reduce potential cost of overage More charging hours aim to improve utilization of storage, compensate for Standby Losses reduce cost of underage. Input policy is like a modified (R,S) policy with shipment capacity constraint and unreliable supply with variable lead time.

Thus with the Network Design Decisions and the daily operating policy decisions identified, we next describe our methodology for calculating incremental revenue and profit.

4 Model Input Configurations and Output

To assess the impact of supply chain management techniques on the profitability wind plant and storage operations, we have built a simulation model with the five main inputs (viz. wind plant electricity output, electricity market prices, storage technology characteristics and supply chain techniques), each with several adjustable parameters, described in Sections 2 and 3. In this section we describe how we used all of these adjustable input parameters to create distinctly meaningful scenarios for our simulation runs. Specifically, we will discuss the simulation Model Input Configurations that we used (Section 4.1) and then depict our model's Dashboard (Section 4.2). This Dashboard allowed us to dynamically adjust the parameters for the different inputs to create many useful system configurations and test multiple scenarios. Finally, we discuss how we calculated the incremental revenue and profit to evaluate these configurations in Section 4.3

4.1 Simulation Model Input Configurations

Given all of the adjustable input parameters we integrated into our model, we have the ability to test results for 121,600 different wind plant-plus-storage system configurations:

Table 4-1: Input Options for Simulation Model

Factor	Possible Value	Number of Values
Wind plant electricity output days	Day 1 to Day 95	95
Seasonality (Section 2.2 & 2.3)	<ul style="list-style-type: none"> • Winter (95 unique days) • Summer (95 unique days) 	2
Storage Technology Type (Section 2.4)	<ul style="list-style-type: none"> • Alpha Battery • Beta Battery 	2
Network Design Decisions (Section 3.1)		
<ul style="list-style-type: none"> • Location of Storage 	<ul style="list-style-type: none"> • Maine (Co-Located with wind plant) • Cos Cob, CT (Located) 	2
<ul style="list-style-type: none"> • Storage Capacity as % of wind plant capacity 	<ul style="list-style-type: none"> • 10% to 100% (in increments of 10%) 	10
<ul style="list-style-type: none"> • Electricity Market to participate in 	<ul style="list-style-type: none"> • Real-Time only • Real-Time and Day-Ahead 	2
<ul style="list-style-type: none"> • Supply input to Storage 	<ul style="list-style-type: none"> • Wind Plant only (Linked) • Wind Plant and / or Electricity Market (Hybrid) 	2
Daily Operating Policies (Section 3.2)	<ul style="list-style-type: none"> • Simple • Cost-Based • Max Peak • Rapid Arb 	4
Total number of possible configurations		$=(95*2*2*2*10*2*2*4)$ $= 121,600$

Based on the convergence of confidence intervals for our results, we chose to run 10,000 simulations per configuration. (For further explanation of our decision to run 10,000 simulations per configuration, see Section 5.1.1) Since running 10,000 simulation runs for all of these 121,600 configurations (total of 1.216 billion runs) was not feasible, we decided to intelligently reduce the number of options to accurately answer our research questions. Our approach for reducing the number of simulation configuration options (our “Short List” of network design options and Daily Operating Policies) is discussed in Section 4.1.1. We follow that with a discussion on shortlisted configurations and lay out the notation that we used to denote the configurations in Section 4.1.2

4.1.1 Process for short-listing input configurations

We shortlisted meaningful scenarios by using criteria such as Seasonality, storage technology type, Network Design Decisions, and Daily Operating Policies. The process of short-listing is described below

Using Seasonality to Short List

First, we decided that we would run simulations for our Short List of network design options and Daily Operating Policies for all the **190 days** over **winter and summer** months and look at the average and variability (as measured by inter-quartile range and standard deviation) across these days. The different days of Wind Plant Output data vary in terms of the total Wind Plant Output during the entire day (“wind rich” days vs. “wind poor” days) as well as the proportion of Wind Plant Output generated during the night (“night rich” vs. “night poor”). Also as discussed earlier in Section 2.2 and Section 2.3 summer and winter represent the extremes in the annual variation for both the Wind Plant Output (based on wind speeds) and the electricity market prices. Hence, by running simulations over all the 190 days (95 in winter and 95 in summer) for the Short List of Network Design Decisions and Daily Operating Policies we could test the robustness of our results across extremes.

Using Storage Technology Type to Shortlist

Second, we decided to test the results for our Short List of Network Design Decisions and inventory management policies for **both Alpha Battery and Beta Battery**. (See Section 2.4.2 for more information about Alpha Battery and Beta Battery.) Since the technical specifications (such as Full-Power Discharge Time, Standby Loss Rate and Round-Trip Efficiency – refer to Section 2.4) for each battery facility are similar, we did not need to repeat the simulation runs separately for each storage technology. We only needed to factor cost differentials between the storage technologies in our Profit & Loss Statement. Our method for calculating financial results is set forth in Section 4.3

Using Network Design Decisions to Shortlist

Third, we decided to establish the impact of each of the five (5) Network Design Decisions (Facility Role, Facility Location, Capacity Allocation, Market Allocation, Supply Allocation – see Section 3.1 for further description) through iterative simulation runs to identify which combinations were superior. We quickly learned trends that helped us to narrow the number of simulations needed. For example, we confirmed that **storage facilities located in Cos Cob, CT had superior financial performance** in than those in Maine

(co-located with wind plant). Also, we learned that charging our storage battery with input from *both* Wind Plant and Electricity Grid was superior to charging with input from *only* Wind Plant due to higher storage utilization. However, we were careful not to create too narrow of a Short List of Network Design Decisions in the absence of substantial simulation. See Section 3.1 for further detail about results for Cos Cob-located versus Co-Located storage.

Using Daily Operating Policies to Shortlist

Finally, we decided to establish the relative effectiveness of our Daily Operating Policies by testing out four different policies (Simple, Cost-Based, Max Peak, Rapid Arb – see Section 3.2 for further description) for two given design configurations. Our goal was to determine the best-performing policy in terms of increasing incremental revenue. We chose the following two configurations to test our policies using Winter Real-Time pricing:

Table 4-2: Configurations Used to Test Operating Policies Using Winter Real-Time Pricing

	Configuration 1				Configuration 2			
Storage Technology	Co-located				Cos Cob CT			
Storage Capacity	50% of wind plant capacity				50% of wind plant capacity			
Electricity Market	Real Time				Real Time			
Supply Input to Storage	From wind plant only				From wind plant only			
Operating Policy	Simple	Cost Based	Max Peak	Rapid Arb	Simple	Cost Based	Max Peak	Rapid Arb

With simulation runs across all 95 days in winter, we established that the ‘Rapid Arb’ policy was distinctly better than the other three policies. Summer results confirmed these results. Hence, we chose to test the other network design decision options with only the Rapid Arb policy. See Section 5 for our results evaluating the four policies.

4.1.2 The Shortlisted Scenarios and Configuration Notation

After starting out with 121,600 possible configurations, we intelligently reduced the number of possible options (for example, siting our storage in Cos Cob; also our use of the Rapid Arb policy). This effort

allowed us to narrow down our scope of work to 5,130 configurations, yet still produce robust results. For each of these configurations, we ran 10,000 simulations for a total of 51.3 million simulations.

Note: 5,130 configurations = 95 seasonal days * 2 seasons * 1 storage unit technical configuration * {4 Daily policies * 1 network design configuration + 1 daily operating policy * 23 network design configurations}

Configuration Notation

To classify and effectively represent the different configuration options that we used in our model, we developed and used the following notation:

Table 4-3: Notation Used for Simulation Configuration Options

Factor	Possible Value	Notation Used
Wind Plant Output days	Day 1 to Day 95	<ul style="list-style-type: none"> Day _ (if results shown only for one day, otherwise “Day” notation not mentioned because results are shown as average across all 95 days of a season) Not mentioned i.e. assumed default if the results are shown as an average / standard deviation across all the 95 days
Seasonality (Section 2.2 & 2.3)	• Winter	Winter
	• Summer	Summer
Storage Technology (Section 2.4)	• Alpha Battery	Alpha
	• Beta Battery	Beta
Network Design Decisions (Section 3.1)		
• Location of Storage	• Maine (co-located with wind plant)	Co-Loc
	• Cos Cob, CT	Cos Cob
• Storage Capacity as % of wind plant capacity	• 50%	50%
	• 35%	35%
	• 20%	20%
• Electricity Market to participate in	• Real-Time only	RT
	• Real-Time and Day-Ahead	DA
• Supply input to Storage	• Wind Plant only	Linked
	• Wind Plant and / or Storage	Hybrid
Daily Operating Policies (Section 3.2)	• Simple	Simple
	• Cost-Based	Cost-Based
	• Max-Peak	Max-Peak
	• Rapid Arb	Rapid Arb

Based on the table above we have used the following notation to describe our various Seasonality, storage, and network design decision configurations:

{Seasonality, Storage Type, Location of Storage, Storage capacity as % of wind plant capacity, Electricity Market to participate in, Supply Input to Storage, Daily Operating Policy}

For example, to describe average results for a simulation configuration for the summer season, using Alpha Battery, with the Storage Unit located in Maine with the wind plant, storage unit capacity of 50% of wind plant installed capacity participating only in the Real-Time Market with input to the wind plant coming only from the wind plant using the Simple Policy we use the following notation:

{Summer, Alpha, Co-Loc, 50%, RT, Linked, Simple}

Another example to describe average results for a simulation configuration for the winter season, using Beta Battery located in Cos Cob CT, storage unit capacity of 50% of wind plant installed capacity participating only in the Real-Time Market with input to the storage unit coming from the electricity market but not confined only to Wind Plant Output using the Rapid Arb Policy we use the following notation:

{Winter, Beta, Cos Cob, 50%, RT, Hybrid, Rapid Arb}

The table below is a snapshot of how we structured our configurations in our model for simulation runs.

Table 4-4: Sample of Model Configurations

LOCATION	Co-Located	Co-Located	Co-Located	Co-Located	CosCob	CosCob	CosCob	CosCob
STORAGE CAPACITY as % of Wind Capacity	50%	50%	50%	50%	50%	50%	50%	50%
MARKET	Real Time	Real Time	Real Time	Real Time	Real Time	Real Time	Real Time	Real Time
SUPPLY LINKAGE	Linked	Linked	Hybrid	Hybrid	Linked	Linked	Hybrid	Hybrid
Day-to-Day Operating Policy	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb
Battery	ALPHA	BETA	ALPHA	BETA	ALPHA	BETA	ALPHA	BETA

To see all 54 shortlisted configurations that we simulated results for, see Appendix 4.

4.2 Model Dashboard: Selecting Input Parameters

We have built into our model the capability to select any of the shortlisted input configurations through a Dashboard. The details of the Dashboard for the various inputs are discussed in this section.

4.2.1 Wind Plant Section of Dashboard

As explained in Section 2.2, we have synthesized output for a 120 MW wind plant located in Presque Isle, Maine. Our plant is located in an area of Class 3 wind speeds, and the plant features 80 GE 1.5 MW turbines at a Hub Height of 80 meters. Our electrical output by turbine is 60% correlated across all 80 turbines. We have used output from this wind plant profile in all of our simulation runs.

However, we have the ability to adjust our wind plant's profile, if needed, in our model. The wind plant characteristics that we can change are listed below:

Table 4-5: Wind Plant Parameters on Dashboard

Parameter	Range of settings possible in our model Dashboard	Selected value for our model
Season	Winter (95 days) Summer (95 days)	Both winter and summer
Size of the Wind Plant – Installed Capacity	40 MW to 300 MW	120 MW
Wind Turbine Rating and Model	1.5 / 1.8 / 2.1 / 2.3 / 2.5 / 3.0 MW	1.5 MW
Turbine Hub Height	50 / 60 / 70 / 80 / 90 / 100 meters	80 meters
Coefficient used to extrapolate for Hub Height (Power Law)	Any value can be input (typical value 1/7)	0.32 (suitable for Presque Isle)
Wind Class Resource at location	1 / 2 / 3 / 4 / 5 / 6 / 7	3
Spatial correlation factor for wind turbine output in the wind plant	Any value <1	0.60

We can adjust any of the above parameters on our model's Dashboard. In fact, our model has the ability to synthesize power output for *any* wind plant profile as long as we modify the parameters on the Dashboard suitably. A screenshot of the Wind Plant section of our Dashboard is provided below:

Figure 4-1: Dashboard Screenshot – Wind Plant Section

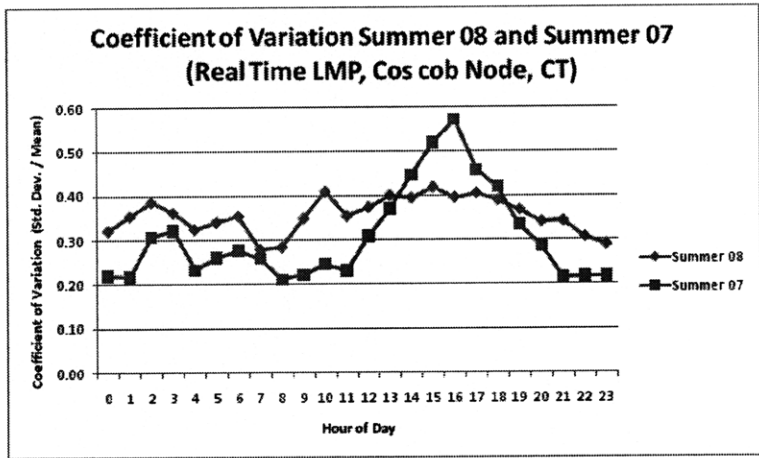
1	WIND		MARKET		STORAGE	
2	Choose Wind Turbine Rating (MW)	1.5	Market Volatility	Regular	Storage Type chosen	BETA BATTERY
3	Choose Hub Height (m)	80	Market Volatility Multiplier	1	Storage Capacity as % of wind Plant Capacity	50%
4	Coefficient to use for extrapolation of hub height (Power Law) <small>Source: Final Report for Prudence Isle (Pg 2), REEL website. "The average wind shear power-law factor is 0.32, and it is calculated from data from the 39 m and 30 m anemometers"</small>	0.32	Location of storage	Cambridge, MA	Maximum Feasible Storage Capacity Power Output (MW)	300
5	Wind Class Resource at wind plant location	3	Does State Production Incentive Apply	Y	Storage Capacity Max Power Output (MW)	60
6	Correlation Factor of wind turbine output (var = 30.9% to 90.3%, Wan)	60%	60.6 Minimum Price ever possible (\$/MWh)	0.00	Full Power Discharge Time per cycle (Hrs)	8
7	Size of the power plant	120	Targeted Gross Margin	10%	AC Round Trip Efficiency	75%
8	Number of Turbines in the Power Plant	80	Deviation charge for not meeting commitment in DA market (\$/MWh)	0.50	Full Power Charge Time per cycle (Hrs)	8.7
9	Correction Factor for deciding maximum power output range when the power output based on actual wind speed data is zero: Percentage of rated capacity that can be produced	0.5%			Energy Output Capacity (MWh)	300
10						

Refer to Section 2.2 for more information about the Wind Plant inputs used in our simulation model.

4.2.2 Market Pricing Section of Dashboard

Our decision to dedicate a section of our Dashboard to market pricing was borne out of observations made during our research into the New England ISO market. During the course of our research into the New England ISO's wholesale electricity market, we noticed several trends. One trend is that market volatility can increase and decrease from year to year, season to season and even month to month. For example, the graph below shows the difference in Coefficient of Variations for Summer 2008 pricing versus Summer 2007 pricing:

Figure 4-2: Coefficient of Variation of Prices – Summer '08 and Summer '07



Summer'07: Jul & Aug 2007
 Summer'08: Jul & Aug 2008
 Source: www.iso-ne.com

The causes of these differences in electricity price variability could be commodity prices, weather or outages. Knowing that such variability in volatility could have dramatic impacts on our results, we decided to create a Market Pricing section within our Dashboard so we could test extreme market pricing scenarios. In addition to adding a Market Volatility parameter, we also added other market-related parameters such as Location of Storage and Day-Ahead Market Deviation Penalty. A screenshot of the Market section of our Dashboard appears below:

Figure 4-3: Dashboard Screenshot – Market Pricing Section

WIND		MARKET		STORAGE	
Choose Wind Turbine Rating (MW)	1.5	Market Volatility	Regular	Storage Type chosen	BETA BATTERY
Choose Hub Height (m)	80	Market Volatility Multiplier	1	Storage Capacity as % of wind Plant Capacity	50%
Coefficient to use for extrapolation of hub height (Power Law) [Source: Final Report for Project Ite (Pg 8), RERL website: "The average wind shear power-law factor is 0.32, and is calculated from data from the 39 m and 30 m anemometers"]	0.32	Location of storage	Cambridge, MA	Maximum Feasible Storage Capacity Power Output (MW)	100
Wind Class Resource at wind plant location	3	Does State Production Incentive Apply	Y	Storage Capacity Max Power Output (MW)	50
Correlation Factor of wind turbine output (+ or - 30.5% to 50.3%, Wan)	60%	60.6 Minimum Price ever possible (\$/MWh)	0.00	Full Power Discharge Time per cycle (Hrs)	5
Size of the power plant	120	Targeted Gross Margin	10%	AC Round Trip Efficiency	75%
Number of Turbines in the Power Plant	30	Deviation charge for not meeting commitment in DA market (\$/MWh)	0.50	Full Power Charge Time per cycle (Hrs)	6.7
Correction Factor for deciding maximum power output range when the power output based on actual wind speed data is zero: Percentage of rated capacity that can be produced	0.5%			Energy Output Capacity (MWh)	300

The table below describes other parameters we added to the Market section of our Dashboard:

Table 4-6: Market Pricing Parameters on Dashboard

Parameter	Range of settings possible in our model Dashboard	Selected value for our model
Market Volatility	<ul style="list-style-type: none"> • Low • Regular • High 	Regular
Market Volatility Multiplier	If "Low" = 0.6 If "Regular" = 1 If "High" = 1.4	1
Location of Storage	<ul style="list-style-type: none"> • Presque Isle, Maine • CosCob, Connecticut • Cambridge, Massachusetts • Providence, Rhode Island 	<ul style="list-style-type: none"> • In our Co-Located scenarios, we choose Presque Isle, Maine • In our Located scenarios, we chose CosCob, CT
Does State Production Incentive Apply?	Yes or No	No
Minimum Price ever possible (\$/MWh)	Any value \geq \$0.00 <i>Note: This value is set by historical pricing in the New England ISO, and is subject to change</i>	\$0.00
Targeted Gross Margin	Any value \geq 0%	10%
Day-Ahead (DA) Market Deviation Penalty (in \$/MWh)	Any value \geq \$0.00 <i>Note: This value is set by the New England ISO, and is subject to change</i>	\$0.50

Below are further explanations of the parameters in the above table:

- Market Volatility: As shown in the screenshot above we can adjust Market Volatility between Low, Regular and High. This parameter allows us to change market conditions to test extremes. By choosing Regular, we use the existing standard deviations for each of the 24 hours as set by the lognormal distribution in Crystal Ball. However, if we change the market volatility to Low or High, we adjust the standard deviation used by Crystal Ball to create greater price fluctuations.
- Market Volatility Multiplier: When we change the Market Volatility described above, the existing standard deviations for each of the 24 hours (as set by the lognormal distribution in Crystal Ball) is multiplied by the Market Volatility Multiplier set forth in the Table below:

Table 4-7: Choice of Market Volatility Multiplier on Dashboard

Market Volatility	Multiplier
Low	0.6
Regular	1
High	1.4

- Location of Storage:** Another parameter we can change in the Dashboard is the Location of Storage. As mentioned above in Section 2.3, we identified three locations in New England – CosCob CT, Cambridge MA, Providence RI – that experience consistently high market prices and high price variability. We chose to locate our storage unit in CosCob CT because the pricing scenario was most favorable. However, we wanted to maintain flexibility to test performance in the other areas as well. Therefore, we built our model’s Dashboard to allow us to choose the location of the storage unit:

Table 4-8: Choice of Location of Storage on Dashboard

Option	Location of Wind Plant	Location of Storage
1	Presque Isle, ME	Presque Isle, ME
2	Presque Isle, ME	CosCob, CT
3	Presque Isle, ME	Cambridge, MA
4	Presque Isle, ME	Providence, RI

Note: Option 1 in the table above is a scenario where the storage units are co-located next to our Presque Isle Wind Plant. Options 2 through 4 are scenarios where the storage units are located in Connecticut, Massachusetts or Rhode Island, away from the Maine wind plant.

- Does State Production Incentive Apply?:** While the main component of the ISO-NE electricity market is pricing, another important component of the market is the State Production Incentive. State Production Incentives are paid by individual state governments to renewable electricity Generators. These incentives are paid at different rates per KWh produced on a state-by-state basis, as well as on a technology-by-technology basis (Interstate Renewable Energy Council,

2009). Because of the significant financial impacts of these incentives for renewable power Generators, we have included them in our model as an input to consider. On our Dashboard, we can turn these incentives “on” an “off.” We have turned them “off” for our results.

- Targeted Gross Margin: This metric can be set based on margin goals of a wind plant operator. We included this metric in the Dashboard as a way for wind plant operators to increase/decrease their margin goals relative to the electricity market’s volatility. For example, if the market is volatile then a wind plant operator can choose to increase his Targeted Gross Margin. This metric then impacts our Cost-Based and Rapid Arb operating policies for buying/selling electricity based on the prevailing market price relative to the Targeted Gross Margin. We have set our Targeted Gross Margin to “10%” for our results.
- Day-Ahead (DA) Market Deviation Penalty: In DA market, a Generator is penalized if it does not fulfill its commitment. For example, if a Generator says it will provide two hours of power at 60 MW (120 MWh) the follow day, and then only provides 100 MWh, then that Generator pays a Deviation Charge (per MWh) he is short. We have set this value at \$0.50 per MWh based on interviews with the New England ISO (Peet, 2009).

Refer to Section 2.3 for more information about the Market Pricing inputs used in our simulation model.

4.2.3 Storage Section of Dashboard

We explored many different types of energy storage for possible inclusion in our model. After whittling down our list of possibilities to utility-scale battery storage (for a description of our storage selection criteria, see Section 2.4), we realized that storage technologies had widely-varying technical profiles – even for products within the same technology family. Therefore we decided to use actual ZnBr and NaS battery products (i.e. products currently available for purchase) in our model and synthesized two battery facilities, Alpha Battery and Beta Battery. (See Section 2.4.2 for more information about Alpha Battery and Beta Battery.)

Since we wanted to be able to switch between storage technologies during our simulation runs, this led us to add a Storage section to our Dashboard. A screenshot of this Dashboard section appears below:

Figure 4-4: Dashboard Screenshot – Storage Section

1					
2	WIND		MARKET		STORAGE
3	Choose Wind Turbine Rating (MW)	1.5	Market Volatility	Regular	Storage Type chosen
4	Choose Hub Height (m)	80	Market Volatility Multiplier	1	BETA BATTERY
5	Coefficient to use for extrapolation of hub height (Power Law) [Source: Final Report for Presque Isle (Pg 8), RERL website: "The average wind shear power-law factor is 0.32, and is calculated from data from the 39 m and 30 m anemometers"]	0.32	Location of storage	Cambridge, MA	Storage Capacity as % of wind Plant Capacity
6	Wind Class Resource at wind plant location	3	Does State Production Incentive Apply	Y	Maximum Feasible Storage Capacity Power Output (MW)
7	Correlation Factor of wind turbine output (+ or - 30.5% to 30.3%, Wan)	60%	60.6 Minimum Price ever possible (\$/MWh)	0.00	Storage Capacity Max Power Output (MW)
8	Size of the power plant	120	Targeted Gross Margin	10%	Full Power Discharge Time per cycle (hrs)
9	Number of Turbines in the Power Plant	80	Deviation charge for not meeting commitment in DA market (\$/MWh)	0.50	AC Round Trip Efficiency
10	Correction Factor for deciding maximum power output range when the power output based on actual wind speed data is zero: Percentage of rated capacity that can be produced	0.5%			Full Power Charge Time per cycle (hrs)
					Energy Output Capacity (MWh)

The Storage section of our Dashboard allows us to make two (2) important selections for our simulation runs:

- Storage Type Chosen: This parameter sets the storage type we want to utilize for a given simulation run. Currently, we have two storage technologies available for selection, Alpha Battery and Beta Battery. When a storage type is chosen here, all of the specific technical parameters (Round-Trip Efficiency, Standby Loss per hour, etc.) and cost parameters of that storage type are pre-populated into our model’s simulation calculations.

Note: In the future we can add more storage type choices to the model.

- Storage Capacity as a % of Wind Plant Capacity: This parameter sets the size of our battery facility in direct proportion to the size of our wind plant. For example, if our wind plant is 120 MW and we choose a “Storage Capacity as a % of Wind Plant Capacity” value of 50%, then our

storage facility will be sized at 60 MW. Storage size relative to wind plant size is an important metric to consider when optimizing the combined operation of a wind plant and storage facility. (For further discussion on storage facility size, see Section 3.1.3.)

For more information about the Storage inputs used in our simulation model, see Section 3.4.

4.2.4 Operating Policies Section of Dashboard

Since the Operating Policies section of the Dashboard was at the crux of our research topic (i.e. whether or not supply chain techniques could impact profitability of a wind plant-plus-storage system), this section became the most iterative part of our entire model. This Dashboard section started with one policy – our Simple Policy – and soon expanded to six additional policies before we finally focused on four core policies Simple, Cost-Based, Max Peak and Rapid Arb. A screenshot of the Dashboard’s Operating Policies section appears is provided in Figure 4-5 below:

Figure 4-5: Dashboard Screenshot – Operating Policies Section

DAY-AHEAD, COLOCATED				DAY-AHEAD, COSCOB			
Simple	Cost-Based		Max Peak	Rapid Arb		Simple	Cost-Based
DA 2-Day Colocated Inventory Policy #1 (Simple Policy)	DA 2-Day Co-located Inventory Policy#2 (Price Dynamic - Opportunity Cost Based)		DA 2-Day Co-located Inventory Policy#5 (Price Dynamic - Max Peak)	DA 2-Day Co-located Inventory Policy#6 (Price Dynamic - Rapid Arb)		DA 2-Day Co-located Inventory Policy #1 (Simple Policy)	DA 2-Day Co-located Inventory Policy #2 (Price Dynamic - Opportunity Cost Based)
Hour for start charging	0.0	Hour for start charging	0.0	Hour for start charging	0.0	Hour for start charging	0.0
Hour for stop charging	8.0	Hour for stop charging	8.0	Hour for stop charging	8.0	Hour for stop charging	8.0
Hour to start discharging	17.0	Hour to start discharging	8.0	Hour to start discharging	8.0	Hour to start discharging	17.0
Hour to stop discharging	24.0	Day Ahead Commitment Start (Corresponds to Peak hours begin)	17.0	Day Ahead Commitment Start (Corresponds to Peak hours begin)	17.0	Hour to stop discharging	24.0
Day Ahead Commitment Start	17.0	Day Ahead Commitment End (Corresponds to Peak hours end)	20.0	Day Ahead Commitment End (Corresponds to Peak hours end)	20.0	Day Ahead Commitment Start	17.0
Day Ahead Commitment End	20.0	Required Sell-off period begin	20.0	Required Sell-off period begin	20.0	Day Ahead Commitment End	20.0
Amount of Energy committed in the Day ahead Market for each hour committed (MWh / Hr)	60.0	% by which the selling price should be more than the weighted average of revenue opportunity foregone by not selling in the night (i.e. can be set to recapture losses due to Round Trip Efficiency)	35.0%	% by which the selling price in the hour should be below the historical Max. peak period average price	0.0%	Amount of Energy committed in the Day ahead Market for each hour committed (MWh / Hr)	60.0

For each policy, we had to conceptualize both input (charge) and output (charge) strategies, and then build functionality in Crystal Ball so our model could execute those strategies in dynamic pricing and Wind Plant Output environments. Technical capabilities of our storage, as well as historical pricing trends also figured prominently into our operating policy creation. For each completed policy we then ran

simulation runs for various configurations (storage located in Maine or Connecticut, Real-Time or Day-Ahead market, winter or summer, Linked or Hybrid, etc.) to gauge the policy’s impact on the incremental profitability that energy storage units provide to a wind plant. Out of this process, we were able to accumulate results that proved that supply chain techniques do, in fact, impact wind plant-plus-storage system operations. Those results are set forth in Section 5.

4.3 Incremental Revenue and Profit

Having explained each of the five (5) *inputs* for our simulation model, we will now explain the *outputs* of our model, namely the **Incremental Revenue** and Incremental Gross Profit calculations. We begin in Section 4.3.1 by describing our model’s incremental revenue and gross profit calculations. In Section 4.3.2 we explain the different components of our Profit & Loss Statement.

4.3.1 Incremental Revenue and Incremental Gross Profit

Having thus classified and shortlisted the various input options to our model, we now describe the process by which we calculate the incremental revenue and profit. In each case the incremental revenue was calculated over the Base Case defined in Section 4.3. (The Base Case being our wind plant in Maine with no access to storage and selling electricity directly into the Real-Time electricity market at the prevailing market price.)

- 1) Revenue for our **Base Case** can be expressed as (This is denoted by R_{BC})

$$R_{BC} = \sum_{H=0}^{H=23} P_{HRT} * WPO_H$$

Where R_{BC} is the Revenue per day in the Base Case; H is the hour of the day; P_{HRT} is the Real-Time Market price prevailing in the hour of the day and; WPO_H is the Electricity output of the wind plant in hour H.

- 2) Incremental revenue for the wind plant with storage for any of the shortlisted input configurations can be calculated as follows. (This is denoted by R_{WP+St}):

Case 1: Storage co-located with wind plant in Maine and Real-Time Market only

$$R_{WP+St} = \sum_{H=0}^{H=23} (WPO_H - ITS_H + OFS_H) * P_{HRTLakewood}$$

Case 2: Storage located in Cos Cob and Real-Time Market only

$$R_{WP+St} = \sum_{H=0}^{H=23} (WPO_H * P_{HRTLakewood} + OFS_H * P_{HRTCosCob})$$

Case 3: Storage co-located with wind plant in Maine and Real-Time and Day-Ahead Market*

$$\begin{aligned} R_{WP+St} &= \sum_{H=0}^{H=H_{Commit\ Begin}} (WPO_H - ITS_H + OFS_H) * P_{HRTLakewood} \\ &+ \sum_{H=H_{Commit\ End}}^{H=23} (WPO_H - ITS_H + OFS_H) * P_{HRTLakewood} \\ &+ \sum_{H=H_{Commit\ End}}^{H=H_{Commit\ Begin}} \{ (WPO_H - ITS_H + OFS_H - E_{Commit}) * P_{HRTLakewood} + E_{Commit} * P_{HDALakewood} \} \end{aligned}$$

Case 4: Storage located in Cos Cob and Real-Time and Day-Ahead Market*

$$\begin{aligned} R_{WP+St} &= \sum_{H=0}^{H=23} (WPO_H) * P_{HRTLakewood} + \sum_{H=0}^{H=H_{Commit\ Begin}} (OFS_H) * P_{HRTCosCob} \\ &+ \sum_{H=H_{Commit\ End}}^{H=23} (OFS_H) * P_{HRTCosCob} + \sum_{H=H_{Commit\ End}}^{H=H_{Commit\ Begin}} E_{Commit} * P_{HDALakewood} \end{aligned}$$

Where ITS_H is Electrical Energy Input to Storage in hour H; OFS_H is Electrical Energy Output from Storage in hour H; $P_{HRTLakewood}$ is the price in Real-Time market at Lakewood node; $P_{HRTCosCob}$ is the price in Real-Time market at Cos Cob node; E_{Commit} is the amount of electrical energy per hour committed to the Day-Ahead market; $P_{HDALakewood}$ is the price in Day-Ahead market at Lakewood node; $P_{HDACosCob}$ is the price in Day-Ahead market at CosCob node.

Note: These calculations are for incremental revenue earned from the sale of energy by the wind plant/storage facility. The additional incremental revenue from Installed Capacity Payments is not part of these calculations. See Section 5.2 for calculations of Installed Capacity Payments.

- 3) In addition, we calculated for each run the following *Incremental Costs of Energy* incurred by the wind plant-plus-storage unit. (These are denoted by C_{WP+St}):
- a. Opportunity Cost of not selling the wind plant electricity output to the Electricity Grid when the storage is being charged from the Wind Plant Output
 - b. Cost of buying the electricity from the electricity market for charging the storage when the storage unit is located in Cos Cob and also when we operate under the Hybrid model even when we are co-located
 - c. Losses incurred due to energy lost due to Standby Losses of the storage unit
 - d. Penalty cost for not being able to meet the commitment in the Day-Ahead market. This has two components: 1) the difference between the Real-Time Price and the Day-Ahead price times the amount of electrical energy deficit to meet commitment; 2) a fixed penalty cost for the amount of electrical energy deficit to meet commitment.

From the above revenue and cost calculations we are able to determine the Incremental Gross Profit earned by the wind plant-plus-storage facility for each of the shortlisted input option under different simulated pricing scenarios. The Incremental Gross Profit calculation is as follows:

$$\begin{aligned}
 \text{Incremental Gross Profit (IGP)} &= \text{Revenue for Wind plant-plus-storage} - \text{Revenue in Base Case} - \\
 &\quad \text{Incremental Costs of Energy for Wind plant-plus-storage} \\
 &= R_{WP+St} - R_{BC} - C_{WP+St}
 \end{aligned}$$

The Incremental Gross Profit calculations revealed which of the several model input options are potentially most profitable.

4.3.2 Profit and Loss Statement

After calculating the Incremental Gross Profit earned by the wind plant-plus-storage unit, we calculated Incremental Operating Profit and Pre-Tax Profit by including the cost of storage. To do this we created a Profit & Loss Statement to calculate the operating profit and Pre-Tax Profit. Our goal was twofold. First, we wanted to find which configuration was most profitable from an operating perspective when compared to the operating costs of various storage technologies. Second, we wanted to see if any configuration could generate a Pre-Tax Profit when capital costs as well as other possible income streams such as Installed Capacity Payments by the New England Independent System Operator are included. A screen shot of our Profit & Loss Statement is provided in Figure 4-6 below.

Figure 4-6: Screenshot of Profit & Loss Statement

PROFIT AND LOSS STATEMENT		Scenario	1	2	3	4	5	6	7	8
<i>All numbers are in \$/Day</i>		LOCATION	Co-Located	Co-Located	Co-Located	Co-Located	CosCob	CosCob	CosCob	CosCob
STORAGE CAPACITY as % of Wind Capacity			50%	50%	50%	50%	50%	50%	50%	50%
MARKET			Real Time	Real Time	Real Time	Real Time	Real Time	Real Time	Real Time	Real Time
SUPPLY LINKAGE			Linked	Linked	Linked	Linked	Linked	Linked	Linked	Linked
Day-to-Day Operating Policy			Simple	Cost-Based	Max Peak	RapidArb	Simple	Cost-Based	Max Peak	RapidArb
Battery			ALPHA	ALPHA	ALPHA	ALPHA	ALPHA	ALPHA	ALPHA	ALPHA
Item		Source								
Incremental Revenue [A]										
Incremental Cost of Electricity [B]										
Incremental Gross Profit [C = A - B]		From Simulation Results								
Operating Cost of Storage [D]		From Storage Technologies .xls								
Incremental Operating Profit [E = C - D]										
Depreciation (Capital Cost of Storage) [F]		From Storage Technologies .xls								
Other Income										
Incremental Fixed Capacity Payments		Not Considered in our calculation								
State or Federal Green Incentives		Not Considered in our calculation								
Total Other Income [G]										
Incremental Profit Before Tax [H = E - F + G]										

Template Only – Numbers shown in Results (Section 5)

Each of the line items in the Profit & Loss Statement is listed below:

Incremental Revenue [A] – Additional revenue received from the sale of goods to customers. In this case, revenue is earned by selling electricity to the Electricity Grid either from our wind plant, or from a storage unit. As discussed in Section 4.3.1 we consider Incremental Revenue only, defined as *Revenue for Wind plant-plus-storage – Revenue in Base Case* = $R_{WP+St} - R_{BC}$

Incremental Cost of Electricity [B] – This is the cost of either buying electricity off the Electricity Grid to charge the storage battery, or the opportunity cost of not selling wind plant electricity in order to charge storage unit. This also includes the costs of electricity lost due to inefficiency and the penalty of not meeting commitment in the Day-Ahead Market. As discussed in Section 4.3.1 this is the *Incremental Costs of Energy* (C_{WP+St})

Incremental Gross Profit [C=A-B] – As discussed in Section 4.3.1, we are looking at only Incremental Gross Profit as the difference between incremental revenue and the incremental cost.

Operating cost of storage [D] – The cost per day to operate and maintain our selected storage units. (We **do not** factor wind plant operating costs into our model's Profit & Loss Statement because we are only looking at *incremental* revenue and costs created by the addition of energy storage to a wind plant's existing operations.)

Incremental Operating Profit [E=C-D] – is a measure of incremental profit generated from operations.
Operating profit = gross profit – operating expenses.

Depreciation [F] – A noncash accounting expense that reduces the value of an asset over time as a result of wear and tear, age, or obsolescence. We calculate our storage capital costs per day by using straight-line depreciation over the life time of the storage unit. (We **do not** factor wind plant depreciation into our model's Profit & Loss Statement because we are only looking at *incremental* costs created by the addition of energy storage to a wind plant's existing operations.)

Other income [G] – There can be other income streams earned by wind plants and storage units in addition to revenue earned from direct sale of electricity in Day-Ahead and/or Real-Time markets. These possible income streams include:

Incremental Installed Capacity Payments – Installed Capacity Payments are made by the New England Independent Service Operator to electricity Generators based on their consistent

generating capacity (or “firm” generating capacity). These payments are a means to ensuring adequacy of installed electricity generation capacity in the New England region to meet current and future requirements. Our discussions with the New England ISO personnel suggest that rules for fixed capacity payment to storage units are still not defined. However, the rules for storage units when they do get defined should be quite similar to those for Pumped Hydroelectric storage units. However, due to the uncertainty involved we have not included these in our calculations. (See Management Insights in Section 5.2 for further discussion of Incremental Installed Capacity Payments.)

Incremental Renewable Energy Credits (REC) – RECs are certificates that are traded. Typically, RECs are purchased from renewable electricity Generators by non-renewable electricity Generators who want to offset the carbon created by their fossil fuel-generated power. REC’s are essentially a tax paid by non-renewable electricity Generators to subsidize renewable generation (Peet, Renewable Portfolio Standards Paper, 2009) and (DOE's Energy Efficiency & Renewable Energy Dept., 2009). It is important to understand that the energy associated with a REC is sold separately and is used by another party. The consumer of a REC receives only a certificate. However, the rules on whether and how RECs will be applied to storage units are still evolving at the time of this research. Hence, we have not included these in our calculations

Incremental state production incentives – Incentives paid by individual state governments to renewable electricity Generators. These incentives are paid at different rates per KWh produced on a state-by-state basis, as well as on a technology-by-technology basis (Interstate Renewable Energy Council, 2009). Once again it is still not well established whether, when and how will these incentives be applied to storage units. Hence, we have excluded state production incentives from our analysis.

Incremental federal production incentives – Incentives paid by the United States government to renewable electricity Generators. These incentives are paid at different rates on a technology-by-technology basis for each KWh produced (Interstate Renewable Energy Council, 2009). We have also excluded federal production incentives from our analysis as their applicability to storage is still not established.

As discussed above, we have not included any of these additional revenue streams (Other Income) into our calculation.

Incremental Pre-Tax Profit [H=E-F+G]: Finally, we calculate the incremental Pre-Tax Profit by subtracting the depreciation (capital costs of storage) from the operating profit. We have not currently included any of the other income sources into our calculation. Nonetheless we do mention them here and keep a provision for including them in our calculation because they might become extremely important in making a compelling case of storage in the future.

Thus we were able to successfully set up our model and use it to run simulations to calculate incremental revenue and profits for the short-listed input configurations. The results of these simulation runs are discussed in the next section.

5 Simulation Results and Conclusion

Using our simulation model, we have run our 10,000 pricing simulations for each of our 5,130 configurations. We have tested various supply chain decisions for network design and daily operating procedures. For each scenario, we have calculated incremental gross, operating and Pre-Tax Profits. In this Section 5, we share our results.

In Section 5.1 we discuss the simulation runs of our model and provide profitability results to evaluate our various supply chain decisions. We follow that in Section 5.2 with important management insights developed from our analysis and results. Finally, in Section 5.3 we discuss several avenues of future research, many of which can be conducted with our model in its current form.

Note: At this point we would like to highlight that the benefit estimates that we provide in this section are based on the most accurate and up-to-date information available at the time of this research. We have also explicitly stated the assumptions that go into our calculations. The estimates of revenue and profits will vary significantly based on the specific operating conditions, rules and regulations, methodology used for valuation and market conditions. Nonetheless, we believe that our approach provides a fairly robust estimate of the benefit in the given set of conditions and is also valid if another set of conditions is used.

5.1 Simulation Results for Incremental Revenue and Profit

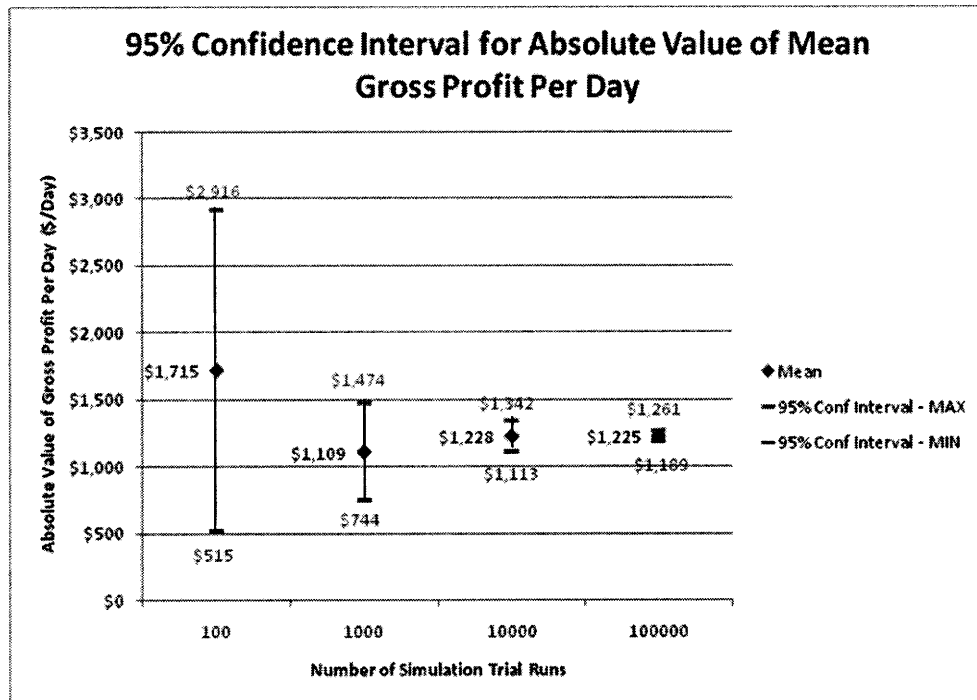
In this section we discuss the results of our simulation runs and the various insights that these results provide from a supply chain perspective. In Sections 5.1.1 we discuss our approach to determine the number of simulation runs (i.e. 10,000). Then we discuss the results of our simulation runs and answer the Network Design Decisions (raised Section 3.1) and the Daily operating policy (raised in Section 3.2) questions for both summer and winter season in Section 5.1.2. In Section 5.1.3 we extend the results of Gross Profit obtained from our simulation model to include the operating and capital costs of storage to

calculate the Operating Profit (defined as Gross Profit – Operating Costs of Storage) and the Pre-Tax Profit (defined as Operating Profit - Depreciation of Capital Cost).

5.1.1 Deciding the Number of Simulation Runs

To decide the number of simulation runs required for our results, we used the extent of reduction in the range of the 95% confidence interval for the Expected Gross Profit per day with increasing number of simulation runs. We used the following configuration to calculate the Gross Profit with different number of trial runs for the following configuration *{Day95, Winter, Alpha, Co-loc, 50%, RT, Linked, Simple}* (for explanation of the notation please refer to Section 4.1.2) We calculated the 95% confidence interval with 100; 1000; 10,000 and 100,000 simulations trial runs. The absolute value of the Gross Profit with the different number of trial runs is plotted in Figure 5-1 below.

Figure 5-1: 95% Confidence Interval with Different Number of Simulation Runs
{Day95, Winter, Alpha, Co-loc, 50%, RT, Linked, Simple}



As we can see from the figure above, the 95% confidence interval converges significantly as we move from 100 to 1000 to 10,000 runs. However, the improvement obtained from 10,000 to 100,000 runs is

only marginal while the computational effort required is significantly more (10 times). So we decided to run 10,000 simulation runs for all the different configuration settings.

5.1.2 Evaluating Network Design Decisions and Daily Operating Policies

Having decided the number of simulation runs and the various input configurations for our model we then ran 10,000 market price simulation runs for each scenario with the view to answer the following questions:

Daily Operating Policies

1. Which is the most profitable Daily operating policy?

Network Design Decisions

2. ***Location***: Which is the better location to locate the storage unit (Lakewood or Cos Cob)?
3. ***Size of Storage***: What is the ideal size of storage as a % of the wind plant capacity?
4. ***Electricity Market***: Given the increased predictability of output with storage, is it more profitable to participate in the Day-Ahead or in the Real-Time market?
5. ***Storage Input Supply Linkage***: Should the input of electrical energy to storage be linked only to Wind Plant Output (our Linked scenario) or should we buy from the market when wind plant has insufficient output (our Hybrid scenario)?

Seasonality and Pre-Tax Profit

6. ***Seasonality***: How does the Gross Profit vary between summer and winter months?
7. ***Storage Technology***: How do Operating Profit and Pre-Tax Profit Tax vary by Type of Storage technology chosen?

To answer Questions 1 to 6 above we have used the Incremental Gross Profit per day as the basis for comparison. The answers to Questions 1 to 6 above are discussed in this section. For answering question 7, we needed to calculate the Incremental Operating Profit (defined as Incremental Gross Profit – storage operating costs) and incremental Pre-Tax Profit (defined as Operating Profit - Depreciation of Capital Cost). The answer to Question 7 is discussed in Section 5.1.3.

Before we begin to answer these questions, it will be useful to revisit our Base Case scenario where our wind plant in Maine is generating electrical power and selling directly to the Real-Time electricity market at the prevailing market price. We simulated the Base Case for 10,000 pricing simulation runs for all the 95 winter days and 95 summer days. The revenue for the wind plant in the Base Case across all 95 summer days is plotted in Figure 5-2 for winter and Figure 5-3. From these graphs it is evident that as the amount of electricity output from the wind plant (depending on the speed and duration of wind blowing during a day) increases (along the horizontal axis) both the expected daily revenue of the wind plant and the range of variation of the daily revenue increase significantly. The expected revenue for the wind plant operator in Base Case across all the 95 winter days and different pricing scenarios is **\$78,975 per day** in winter. For *summer* due to the lower Capacity Factor the expected Base Case revenue is **\$61,548/day**. There is a significant range of variation for the daily revenue across days of Wind Plant Output and pricing scenarios.

Figure 5-2: Inter-quartile Range of the Daily Wind Plant Revenue in the Base Case (Winter)

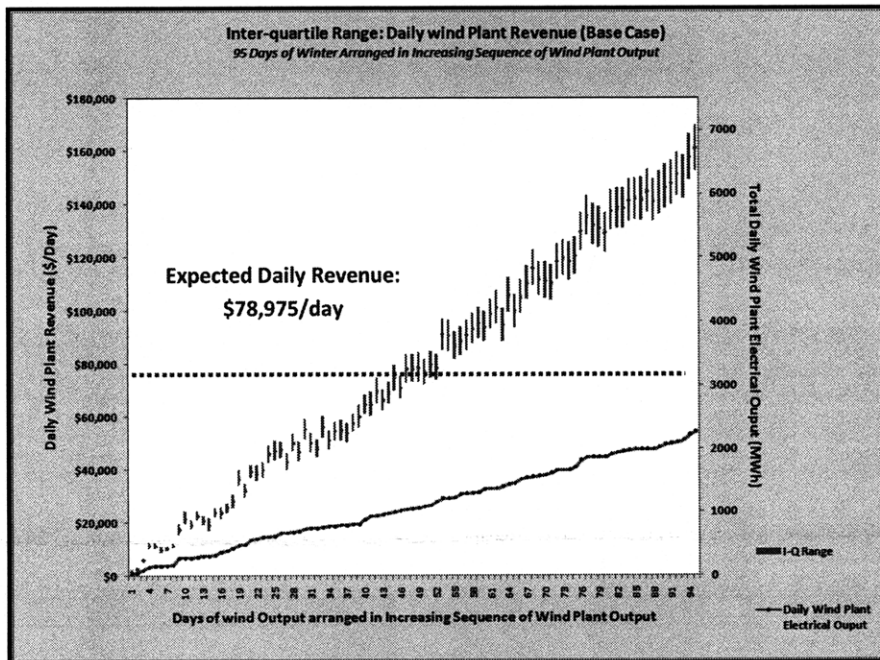
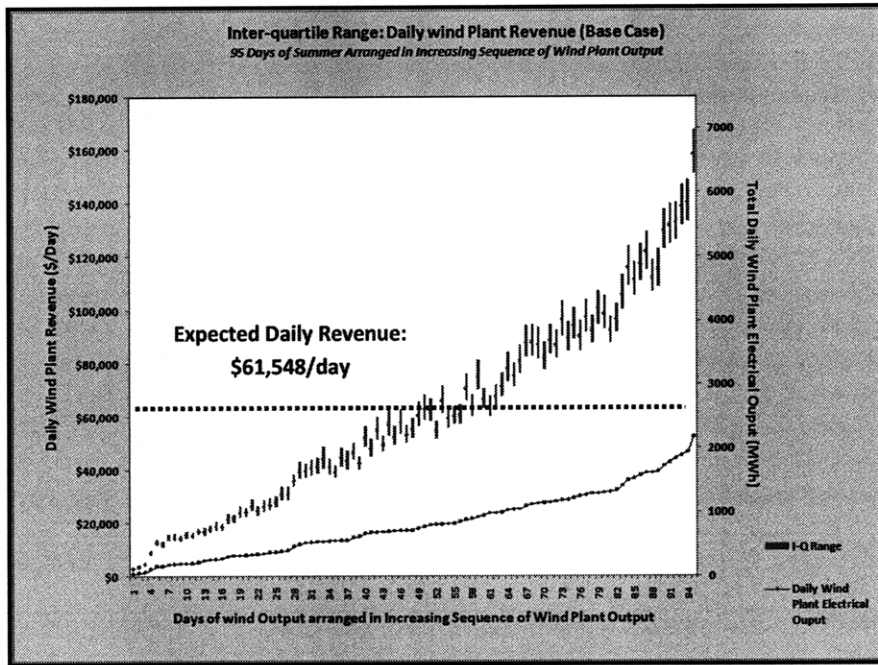


Figure 5-3: Inter-quartile Range of the Daily Wind Plant Revenue in the Base Case (Summer)



In this context of the Base Case, we now discuss the results that help us to answers to questions 1 to 6 raised earlier.

5.1.2.1 Daily Operating Policy: Which is the most profitable daily operating policy?

As discussed in Section 3.2, we evolved four operating policies (these being Simple, Cost-Based, Max Peak and Rapid Arb) by incorporating learning from the Newsvendor model and inventory management policies in supply chain management. To test the different policies we used the following Wind configuration {Winter& Summer, Alpha or Beta, Co-loc, 50%, RT, Linked}. As discussed in Section 2.4 we have selected the storage technologies to have the same technical specification so the choice of storage technology does not impact the calculation of Gross Profit. Also as discussed in Section 4.1, we calculate the Incremental Gross Profit for all the available 190 days of Wind Plant Output both in the winter and in the summer seasons. The results are presented in Figure 5-4 and Figure 5-5.

Figure 5-4: Mean Incremental Daily Gross Profit with different Daily Operating Policies (Winter)

{Winter, Alpha or Beta, Co-loc, 50%, RT, Linked}.

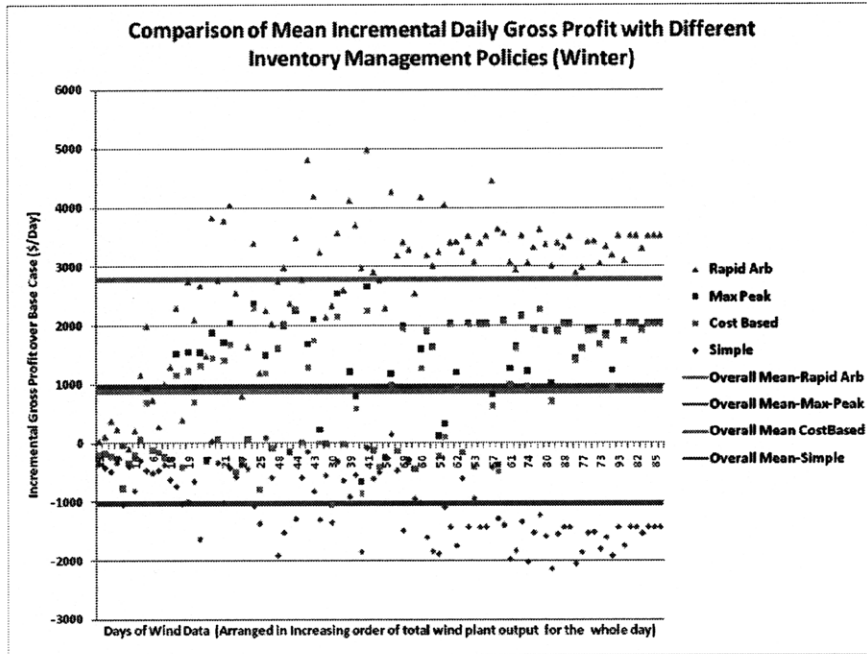
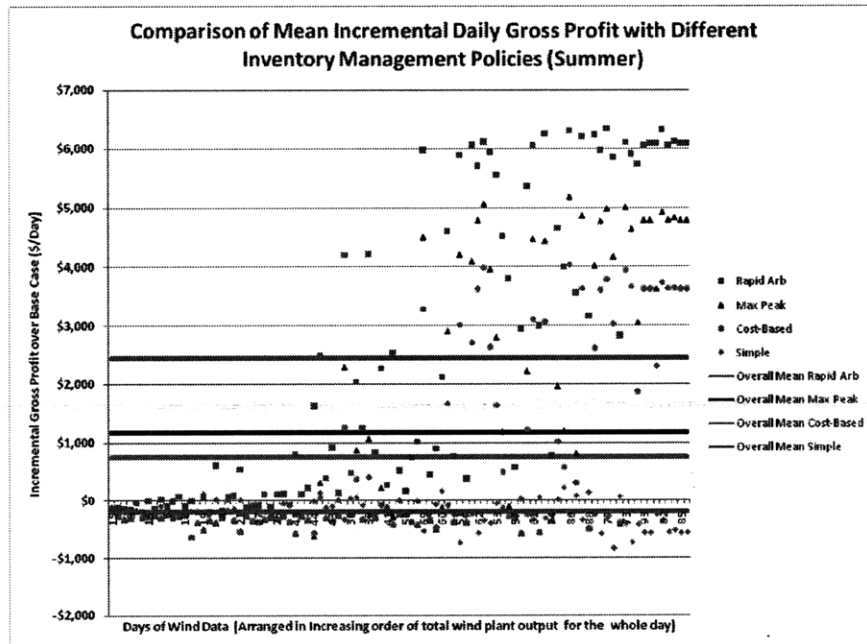


Figure 5-5: Mean Incremental Daily Gross Profit with different Daily Operating Policies (Summer)

{Summer, Alpha or Beta, Co-loc, 50%, RT, Linked}.



In the figure the horizontal axis represents the different days of Wind Plant Output data in winter. The days are arranged in increasing order of total Wind Plant Output for the whole day. On the vertical axis, we plot the Mean of the Daily Gross Profit across all the 10,000 pricing simulations. The Mean Daily Gross Profit is plotted for each day as well as the mean across all the 95 days is plotted.

From these results we can draw the following conclusions:

1. For each Wind Plant Output day, the Gross profit per day increases significantly as we move from the Simple policy to the Cost-Based policy to the Max Peak policy to the Rapid Arb policy. Hence the Rapid Arb policy outperforms all the other policies irrespective of the total Wind Plant Output (wind resource richness) for the day.
2. As we go from a day with low Wind Plant Output to high Wind Plant Output, the magnitude of improvement obtained by moving from Simple to Rapid Arb policy also increases.
3. The mean of the daily gross profit across all the 95 winter days for the different policies is tabulated below:

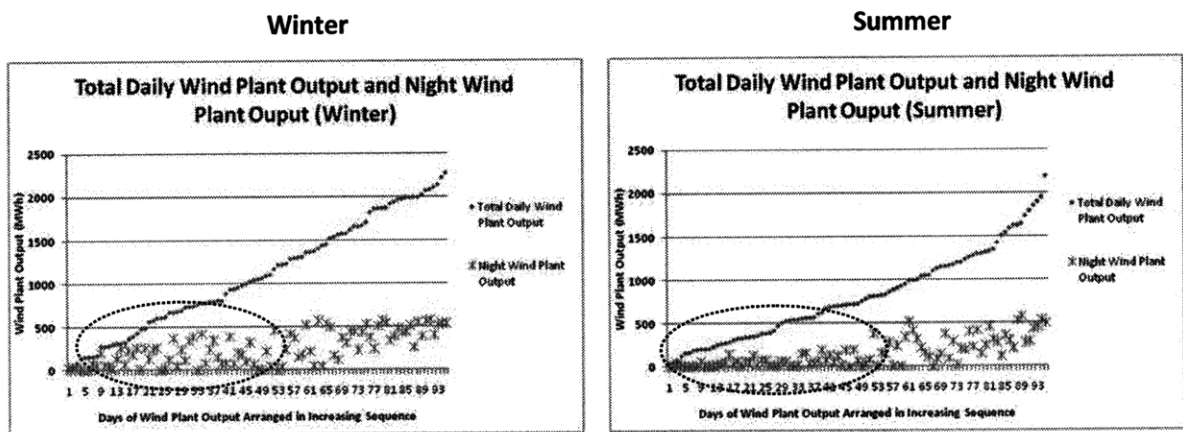
Table 5-1: Comparison on Mean Incremental Daily Gross Profit for different Daily Operating Policies
{Winter and Summer, Alpha or Beta, Co-loc, 50%, RT, Linked}.

Daily Operating Policy	WINTER Mean Daily Incremental Gross Profit with storage across all 95 days (\$/Day)	SUMMER Mean Daily Incremental Gross Profit with storage across all 95 days (\$/Day)
Simple	(\$1036)	(\$206)
Cost-Based	\$872	\$757
Max Peak	\$965	\$1,169
Rapid Arb	\$2,775	\$2,444

We obtain similar results for *summer*. However, as the Wind Plant Output is lower in summer, the Mean Incremental Daily Gross Profit increases from (\$206) for Simple Policy to +\$2,444 with Rapid Arb policy in summer. Moreover, it is to be noted that the summer months see a much greater fluctuation in the Incremental Mean Daily Gross Profit. On days with high Wind Plant Output, the daily Incremental Gross Profit is much larger due to higher prices during summer.

However, when the Wind Plant Output is low there is a much lower value of daily Incremental Gross Profit. To understand this fluctuation we compare below in Figure 5-6 the total daily Wind Plant Output and the night Wind Plant Output for summer and winter months. From this graph it is evident that for summer, most days with low total daily Wind Plant Output have a much lower night time output, while this is not necessarily the case in winter. This difference between the night time Wind Plant Outputs explains the higher variability in the summer results.

Figure 5-6: Total Daily Wind Plant Output and Night Time Output



On the whole though, we can say that the Rapid Arb policy gives the most significant improvement in Incremental Gross Profits for each of the 95 winter days and 95 summer days.

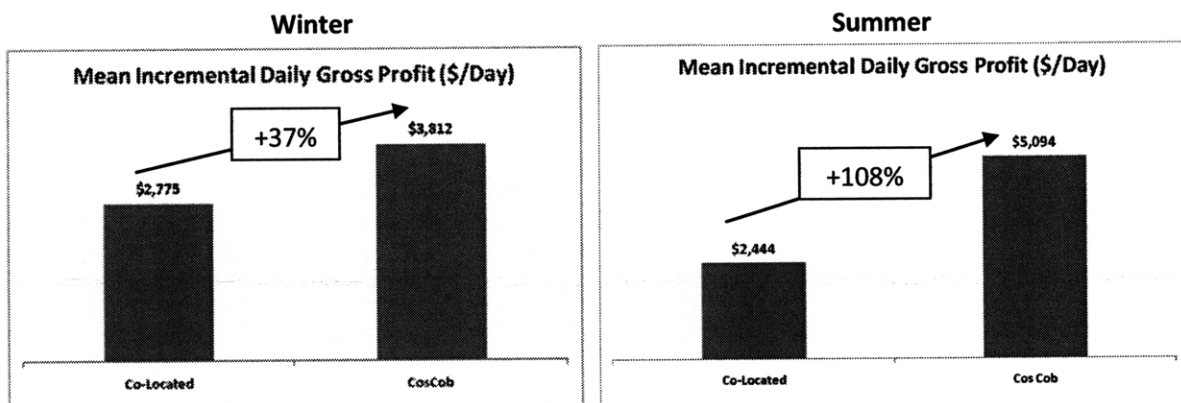
4. To show that there is a statistically significant difference between the Incremental Daily Gross Profit results for the four policies we conducted a One-way ANOVA test on the results for both a Low Wind Plant Output day and a High Wind Plant Output day. The results of the ANOVA test are given in Appendix 5. From these results (based on the extremely low p-value $\ll 0.01$ of the ANOVA test and the results of the Tukey's Test) it is evident that the Incremental Daily Gross Profit obtained with the Rapid Arb policy is significantly higher from those of the other three policies. Also the Incremental Daily Gross Profit obtained with the Simple policy is significantly lower than those of the other three policies. There is no statistically significant difference between

the results obtained with the Cost-Based and the Max Peak policies. Hence, we can conclusively say that of the four policies tested, the Rapid Arb policy produces the highest Incremental Daily Gross Profit irrespective of the pricing scenario and variation in Wind Plant Output.

5.1.2.2 Location: Which is the better location for the storage unit (Presque Isle, Maine or Cos Cob, Connecticut)?

As explained in Section 3.1.2, we have considered two scenarios for locating our wind plant’s proposed storage unit: Presque Isle, ME or Cos Cob, CT. We hypothesized that since the Cos Cob Node has higher average prices than Maine does (due to higher population density and higher demand), then a wind plant-plus-storage facility could earn greater incremental profits. Using the Rapid Arb policy, we first tested the results for the following configurations {Winter, Alpha or Beta, Co-loc / Cos Cob, 50%, RT, Linked, Rapid Arb} and {Winter, Alpha or Beta, Co-loc / Cos Cob, 50%, RT, Linked, Rapid Arb}. We calculated the mean Incremental Gross Profit per day across the 10,000 price simulation runs for all 190 days in winter and summer, as shown in Figure 5-7. We found the mean incremental daily gross profit to be nearly a 37% increase from \$2,775/day (Co-located) to \$3,812/day (Cos Cob) in winter.

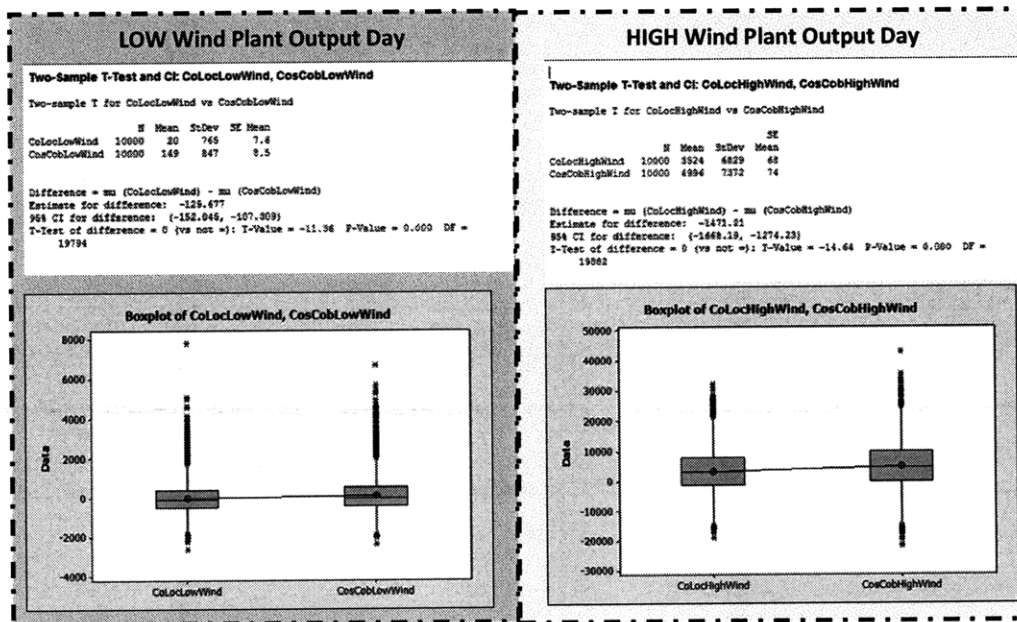
Figure 5-7: Mean Incremental Gross Profit per Day – Co located vs. Cos Cob
{Winter, Alpha or Beta, 50%, RT, Linked, Rapid Arb}



We obtain a higher magnitude of improvement for summer. The mean incremental daily gross profit for the configuration {Summer, Alpha or Beta, 50%, RT, Linked, Rapid Arb} increases from \$2,444 for Co-located to \$5,094/day for Cos Cob. This is due to the difference between summer and winter prices for Cos Cob being much higher than at Lakewood. To test the sensitivity of these results we also calculated the difference in incremental daily gross profit for other configurations of storage capacity, electricity markets and storage input supply linkage. In all cases we found that the incremental daily gross revenue was higher for Cos Cob than for the Co-located case.

In addition we examined the difference in Incremental Daily Gross Profit, across different days of Wind Plant Output and also the range for different pricing scenarios. To assess the impact of total Wind Plant Output, we compared the incremental daily gross profit between Co-located and Cos Cob for low and high Wind Plant Output days. The incremental daily gross profit between co-located and Cos Cob was compared using the 2-sample t-test for low and high Wind Plant Output days. The results of the 2-sample t-test and the box plots are shown in Figure 5-8 below:

Figure 5-8: 2-sample t-test and Box Plot Incremental Daily Gross Profit – Co located vs. Cos Cob
{Winter, Alpha or Beta, 50%, RT, Linked, Rapid Arb}



From these results it is evident that there is a statistically significant difference (p-value $\ll 0.01$) between the incremental daily gross profits for co-located and for Cos Cob cases for both low and high Wind Plant Output days. From the box plots we can also see that there is quite a large spread in the Incremental Gross Profit for different simulated pricing scenarios. For the low wind output days the incremental daily gross profit ranges from approximately -\$3000/day to as high as +\$8000 / day. For the high wind day, the spread is much larger, from approximately -\$25,000/day to +\$40,000/day. **Hence, we can conclusively say that it is more profitable to place the storage unit in Cos Cob.**

Note: That said, from the perspective of a wind plant operator located in Maine it might not always be possible – or preferable – to locate the storage unit in Cos Cob, or any other location that is far away from the wind plant. Reasons for this could include land availability, differing state production tax incentives, need for *Transmission Curtailment* (see Section 5.3 – Further Research), among others.

5.1.2.3 Storage Capacity: What is the best storage capacity as a % of the wind plant capacity?

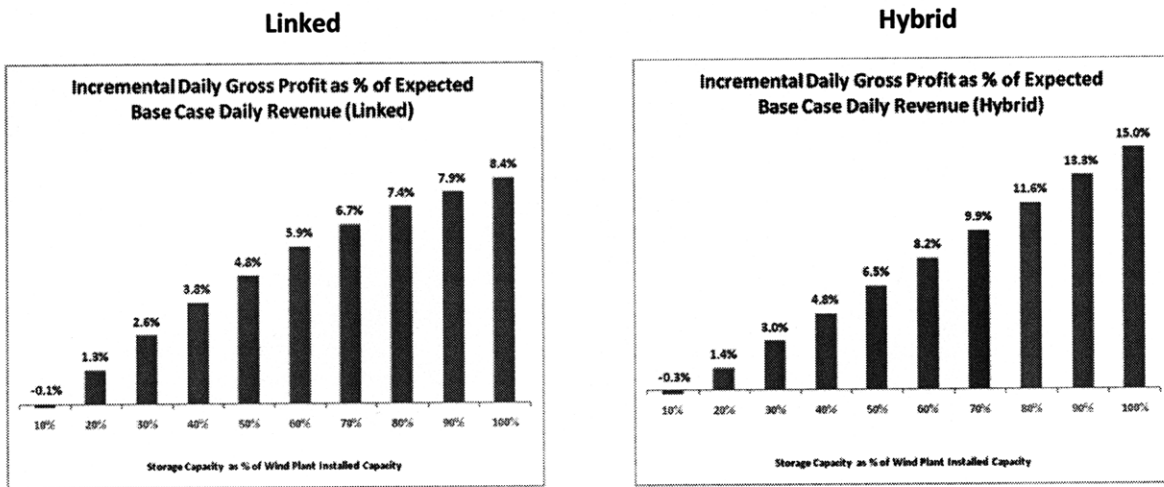
So far, we have established that using the Rapid Arb policy and locating storage in Cos Cob gives the best results. Next up, we determine the optimal storage capacity as a % of the wind plant capacity. The process of optimally sizing storage is dependent on whether the storage is Linked to the wind plant (i.e. input into storage is dependent on Wind Plant Output), or operated in a Hybrid mode (i.e. input into storage can be from *both* Wind Plant Output and Electricity Grid).

To determine the optimal size of the storage unit we tested our model for different storage capacities for the following configuration {*Winter, Alpha or Beta, Cos Cob, RT, Linked and Hybrid, Rapid Arb*}. We ran simulations on our model with these configurations for storage capacity ranging from 10% of wind plant installed capacity (12MW) to 100% of wind plant installed capacity (120MW). We conducted 10,000 pricing simulation trials across all 95 winter days of Wind Plant Output and calculated the Incremental Daily Gross Profit. This profit is then expressed as a % of the expected daily wind plant

revenue in the Base Case (i.e. \$78,975/day). (For summer the % of incremental daily gross profit is much higher than in winter because the Base Case daily revenue for the wind plant (\$ 61,424/day) is lower and the incremental daily gross profit is higher due to the higher price differential at Cos Cob.) The winter results are plotted below in Figure 5-9.

Figure 5-9: Incremental Gross Profit / Expected Base Case Revenue for Different Storage Capacities

{Winter, Alpha or Beta, Cos Cob, RT, Linked and Hybrid, Rapid Arb}



From the “Hybrid” figure above it is evident that as we increase the storage capacity the Incremental Gross Profit increases at nearly a fixed rate. Thus the optimal size of storage should be sized accordingly based on technology capabilities, capital availability, and land availability, among other factors.

Note: The linear increase in gross profit as storage size is increased under the Hybrid scenario is to be expected as the storage unit is being fully charged up to capacity irrespective of Wind Plant Output. The only limit on profit increase is in terms of the number of hours in a day, and the maximum possible continuous power rating of a storage unit.

However, as shown in the “Linked” figure above, for each 10% increase in storage capacity (i.e. steps of 12MW) the increase in Incremental Gross Profit is much higher at lower capacities than at higher

capacities. For example, when we increase the storage capacity from 20% to 30% of wind plant capacity the Incremental Gross Profit jumps from 1.3% to 2.6% of Base Case revenue (i.e. increase of 1.3%). However, when we increase the storage capacity from 80% to 90% of wind plant capacity the Incremental Gross Profit rises only from 7.4% to 7.9% of Base Case revenue (i.e. increase of only 0.5%) This is consistent with the results obtained by other authors (García-González, Muela, Santos, & González, 2008). The decision on the size of the storage facility will depend on the *Capital Cost of Storage* for different sizes and the associated *return on investment* analysis. There can be two scenarios depending on how the Capital Cost of Storage varies with the capacity of the storage unit.

If the cost per module or cost per unit of storage is fixed then the additional cost of adding more capacity is the same for each increment. However, as we saw earlier the increment in the benefits at higher capacities is much lower than the increment in benefits at lower capacities. Hence, if the storage capital cost increases linearly then it is definitely not advantageous to add storage capacity beyond a certain point as the improvement in benefits reduces for the same increase in capacity at higher capacities. As mentioned in Section 3.1.3, studies in Japan have suggested size of storage at 20% of wind plant capacity (Kamath, 2009). Our results also support this result if the input to storage is Linked to the Wind Plant Output.

However, as the capacity of the storage unit increases if it is possible to get discount for buying a larger number of modules (i.e. the cost of adding more capacity is lower at higher levels of capacity) then it might be better to install a higher size facility. Our discussion with the storage companies indicated that such a discount is definitely available so we for the purpose of our model we have assumed *storage capacity at 50% of the wind plant installed capacity*.

5.1.2.4 Electricity Market: Is it more profitable to participate in the Day-Ahead or in the Real-Time market?

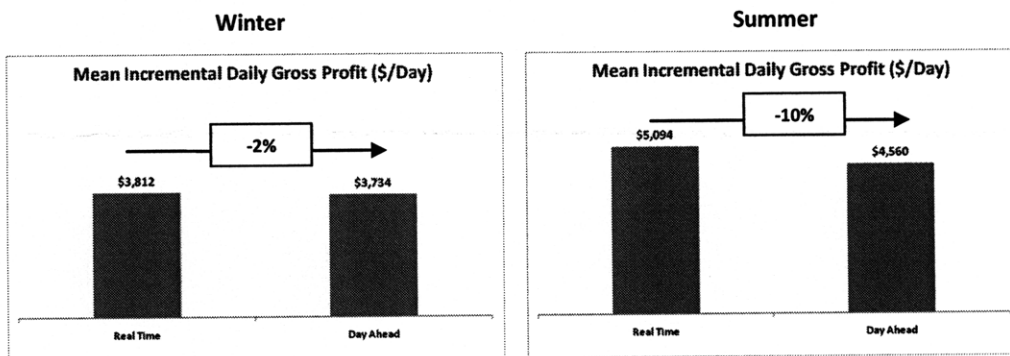
As explained in Section 3.3, wind plant operators in New England are classified as intermittent resources and only participate in the Real-Time market. However, with access to storage, the combined output from

the wind plant and storage unit can become more predictable allowing participation in the Day-Ahead market. Prices in the Day-Ahead market are on average higher than the prices in the Real-Time market. Hence our hypothesis was that it might be more profitable to participate in the Day-Ahead market with our wind plant-plus-storage facility.

Note: Our model factors in both penalties for failing to fulfill on Day-Ahead commitments. For example, if our storage unit does not have enough energy to meet the commitment during the peak hours, then we have to buy from the Real-Time market to fulfill our commitment. If the Real-Time price is high, we produce a net loss on the transaction. Also, our model forces us to pay a \$0.50-per-MWh short penalty.

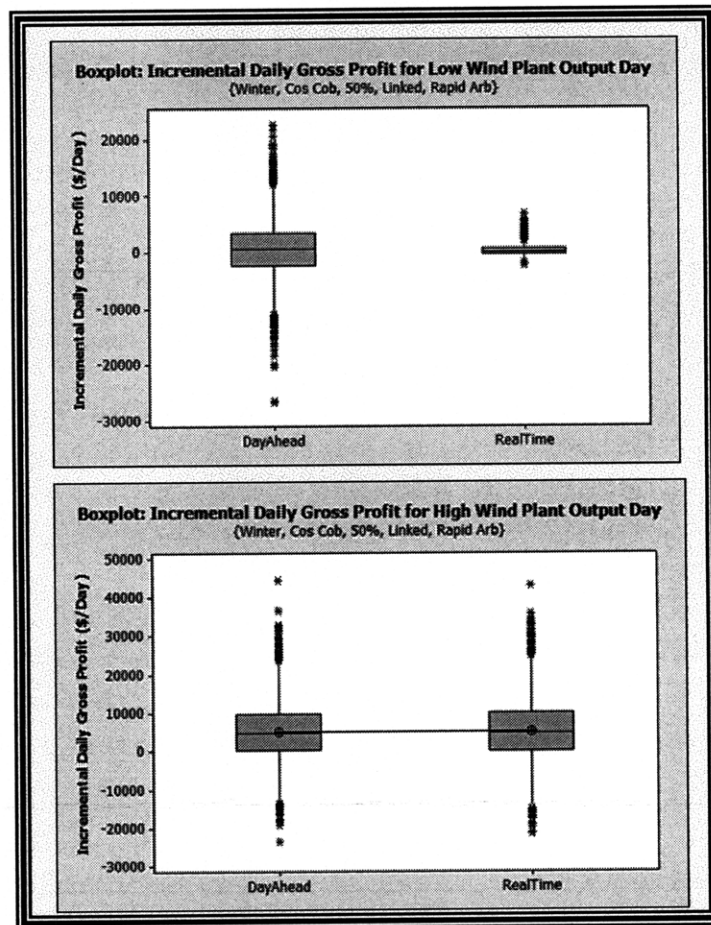
To test our hypothesis we ran simulations to compare incremental daily gross profit for our wind plant-plus-storage facility for each market. (To ensure that our bids in the Day-Ahead market get accepted in Peak Hours, we offer to sell at an exorbitantly high price (>\$500/MWh) for the non-peak hours and at an extremely low price (<\$5/MWh) for the Peak hour. This way we always get to supply in the Peak hours at the prevailing Day-Ahead market price.) We did 10,000 price simulations for all 190 days in winter and summer. The mean value of the Incremental Gross Profit for the two markets is shown in Figure 5-10 below for the following configuration {*Winter, Alpha or Beta, Cos Cob, 50%, Linked, Rapid Arb*}. We also ran similar simulations for the co-located scenario and for summer, the results were very similar.

Figure 5-10: Mean Incremental Gross Profit per Day – Real-Time vs. Day-Ahead
{Winter & Summer, Alpha or Beta, Cos Cob, 50%, Linked, Rapid Arb}



Much to our surprise, our results show that on average the Incremental Gross Profit earned by our wind plant-plus-storage facility participating in the Day-Ahead market is slightly lower than that in the Real-Time market. Hence, *there is no improvement in incremental daily gross profit by participating in the Day-Ahead market*. Similar results were obtained for the co-located scenario and for the summer season. These results were contrary to our expectations. So we tried to understand why this might be happening. We compared the incremental daily gross profit numbers for Real-Time and Day-Ahead markets for both low Wind Plant Output and high Wind Plant Output days. The results are shown in the figure below:

Figure 5-11: Box Plot - Day-Ahead & Real-Time Market
{Winter, Alpha or Beta, Cos Cob, 50%, Linked, Rapid Arb}



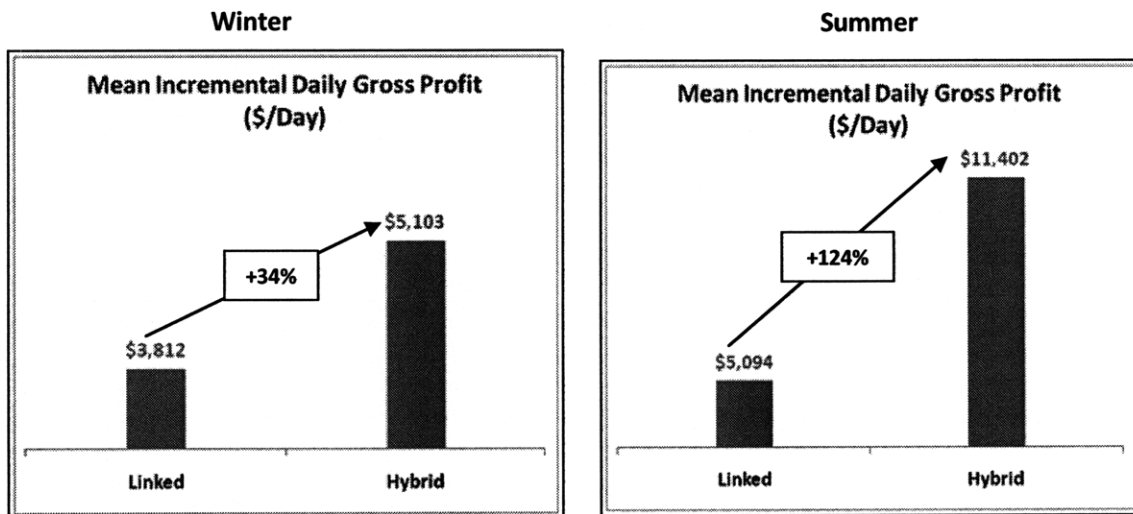
From these figures it is evident that for high Wind Plant Output days the incremental daily gross profit results for the Day-Ahead and Real-Time markets are almost identical. However, for the low Wind Plant Output days the variability of incremental daily gross profit for the Day-Ahead market is much higher than the variability for the Real-Time market. This can be explained as follows. For days with low Wind Plant Output the storage unit is not adequately charged up, so there is not enough electrical energy available to meet the commitment made in the Day-Ahead market for the historical peak hours. So, we need to buy in the Real-Time market and sell in the Day-Ahead market to meet the commitment. This increases the overall amount of electrical energy traded, but it can result in a profit (if the Real-Time price of buying is lower than the Day-Ahead price of selling) or a loss (if the Real-Time price of buying is higher than the Day-Ahead price of selling). Hence, participating in the Day-Ahead market on a low Wind Plant Output day can be extremely risky but can also result in significantly higher profits if the prices are favorable.

However, this analysis at the level of the Incremental Gross Profit per day does not represent the complete picture. While there is no benefit in the Incremental Gross Profit per day for participating in the Day-Ahead market over the Real-Time market purely on wholesale energy sales, there could be a significant difference in the Pre-Tax Profit if we incorporate the monthly Installed Capacity Payments by the New England Independent Service Operator. Currently, the rules for payment of Installed Capacity Payments to energy storage units are not well established. Hence, we have not incorporated them into our model. However, in case the payment of Installed Capacity Payments to storage will be contingent on storage committing energy output in the Day-Ahead market, then these Payments could make the Pre-Tax Profit of the Day-Ahead scenario much more attractive (see Section 4.2 and Appendix 6 for more details).

5.1.2.5 Storage Input Supply Linkage: Should the input of electrical energy to storage be Linked only to Wind Plant Output or should we buy from the market when wind plant has insufficient output?

While we began examining the issue of combining storage units with wind plants to improve the profitability of wind plant operators, during the course of our analysis we realized that it may be prudent to not confine the input to storage to just the Wind Plant Output (the Linked scenario). In fact, having installed a certain Capacity of Storage it might be more profitable to buy electrical energy from the Real-Time market to charge up the storage in case the wind plant is not generating enough electrical energy when the prices are low. So we considered our Hybrid option, where the input of electrical energy to the storage unit is not confined to Wind Plant Output but can also be bought from the electricity market. We evaluated the Hybrid and the Linked scenario by running 10,000 pricing simulations for all the 190 days of winter and summer for the following configuration {Alpha or Beta, Cos Cob, 50%, Real-Time, Rapid Arb}. The mean of the incremental daily gross profit for the Linked and Hybrid scenarios is shown in the figure below

Figure 5-12: Mean Incremental Gross Profit per Day – Linked vs. Hybrid
{Winter and summer, Alpha or Beta, Cos Cob, 50%, Real-Time, Rapid Arb}

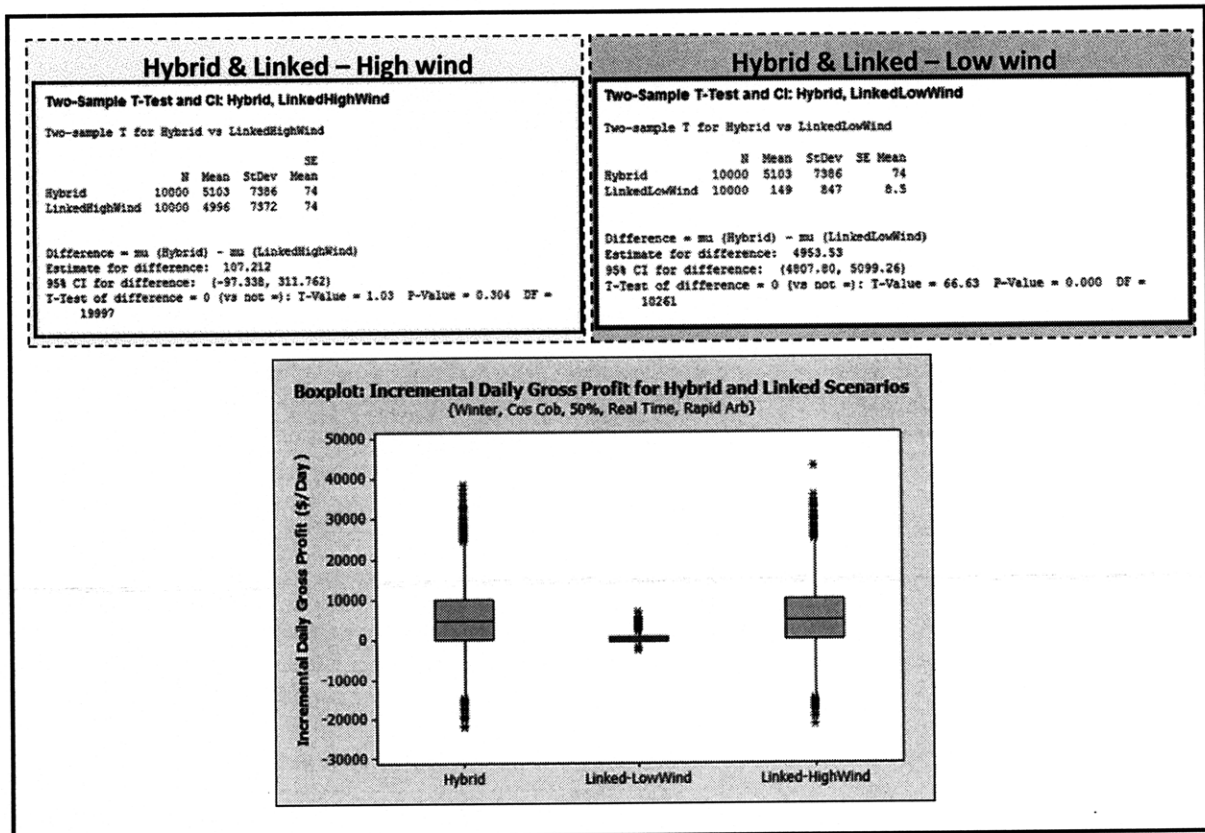


From these results it is evident that for a certain size of storage unit it is more profitable to operate the wind plant and storage unit in a Hybrid fashion so that whenever the output from the wind plant is not sufficient to fully charge the storage unit when prices are low, we buy from the electricity market. This

improves the utilization of the storage unit and helps improve the Incremental Gross Profit earned per day. Especially, for the summer season when the difference in prices between peak and off-peak hour prices is much larger, we can significantly improve the incremental daily gross profit by operating under a Hybrid regime.

The incremental daily gross profit under the Hybrid scenario is not dependent on the daily Wind Plant Output and has the same expected value across all 190 days (winter and summer) of Wind Plant Output. So to get a better insight into this improvement we compared the incremental daily gross profit for the Hybrid scenario with the incremental daily gross profit for a day with low Wind Plant Output and a day with high Wind Plant Output. The results of the comparison (2-sample t-tests and box plots) are shown in the figure below:

Figure 5-13: 2-sample t-test and Box Plot Incremental Daily Gross Profit – Hybrid vs. Linked
{Winter, Alpha or Beta, Cos Cob, 50%, RT, Rapid Arb}



From these tests we can see that there is no significant difference for the incremental daily gross profit for the Hybrid scenario and the Linked scenario for a day with high Wind Plant Output (p-value = 0.304 for the two sample t-test). However, there is a statistically significant difference between the Hybrid scenario and the Linked scenario for a day with low Wind Plant Output (p-value<0.0001 for two sample t-test)

Based on these results we can conclude that for days with high Wind Plant Output the storage unit achieves a high utilization and hence we are able to generate Incremental Gross Profits similar to Hybrid operation. However, for a day with low Wind Plant Output we can significantly improve the incremental daily gross profit by operating the storage unit in a Hybrid manner. On the whole the Hybrid unit gives significantly superior results to the Linked policy.

5.1.2.6 Seasonality: How does the Gross Profit vary between summer and winter months?

Based on our analysis of the different network design and operating policy decisions thus far, we have been able to conclude that it is most profitable to operate with the following configuration *{Cos-Cob, 50%, RT, Hybrid, Rapid Arb}*. However as explained in Section 2.2 and section 2.3 the wind speeds (thus the Wind Plant Output) in summer are the lowest while the electricity prices are the highest in the summer. So to assess the impact of Seasonality on incremental daily gross profit we ran price simulations under different policies and configurations for winter as well as summer months. This gives us results under two extreme conditions to help understand the range of variation throughout the year. We have been mentioning results for both winter and summer months while answering the questions in the previous sections. Here we provide the salient points of similarity and difference between summer and winter months:

To begin with, we can safely conclude from the results that our chosen solution for location, storage capacity, electricity markets, storage input supply linkage and Daily operating policy are consistent for both summer and winter seasons. Thus, these recommendations are valid throughout the year. In addition, there are some areas where the prices in summer further accentuate our results:

- The difference between peak and off-peak electricity prices for summer and winter is much higher for a node with high demand like Cos Cob CT, as compared to a node with low demand like Lakewood ME. Hence, the benefit (in terms of incremental daily gross profit) of locating the storage unit in Cos Cob gets further accentuated during summer despite the drop in the wind plant electricity output during summer.
- In addition, the case for operating under a Hybrid model becomes even stronger during the summer months. The Wind Plant Output drops, the price differential increases. Hence, to fully utilize the improved arbitrage opportunity (as represented by the higher price differential) the storage facility should operate under a Hybrid policy and charge up to full capacity by buying from the electricity market.

On the whole, we can say that our results and findings are valid for both the summer and winter season.

Thus our recommendations can be used throughout the year.

5.1.3 Incremental Operating Profit and Pre-Tax Profit

In this section we discuss the results for incremental Operating Profit and Pre-Tax Profit that we obtained by incorporating the storage costs into our model. As explained in section 4.3, for the purpose of our model, we have defined Incremental Operating Profit = Incremental Gross Profit – Operation and Maintenance costs of Storage; and Incremental Pre-Tax Profit = Incremental Operating Profit – Depreciation of Capital costs of Storage. We begin by discussing our results for *Incremental Daily Operating Profit*, then we include the depreciation of the capital costs of storage to calculate the Pre-Tax Profit. Finally, we conclude this section by calculating the *target cost estimates* for storage systems for the wind plant-plus-storage system to generate Pre-Tax Profit.

Note: We wish to highlight that the cost estimates used in our calculations are based on our discussions with the storage industry experts and storage manufacturing companies for our context. The costs could vary significantly depending on the specific operating conditions,

technical parameters of the storage unit and other extraneous factors such as prices of input raw materials to storage etc. While we have tried to achieve as much accuracy as possible in these estimates, these estimates are still at best 'estimates'. The true costs can only be established through detailed design calculations, which was beyond the scope of this work. Our purpose in including the cost and profit calculation here is to develop range estimates of the target cost of storage for it to become economically viable given the improvement in daily gross profit for the wind plant-plus-storage unit using supply chain management techniques.

Incremental Daily Operating Profit

Based on our results for incremental daily gross profit, we calculated the incremental daily operating profit for the wind plant-plus-storage unit by subtracting the operation and maintenance cost of the storage facility from the Incremental Gross Profit. As discussed in Section 2.4.2 on Storage, the operating Cost-per-Cycle is \$2,466/cycle for Alpha battery and \$ 5,918 / cycle for a storage unit of 60MW installed capacity (50% of wind plant capacity). The incremental daily operating profit for different Model Input Configurations is discussed in this section.

We have established in Section 5.1.2 that the Rapid Arb Daily operating policy gives the best results. Also if we do not consider incremental fixed capacity payments the Real-Time market seems to be more profitable and the best storage capacity is at 50% of wind plant installed capacity. We present in Table 5-2 below the operating profit for other input configurations for {Real-Time, 50%, Rapid Arb} that we tested in our simulation model for both winter and summer months.

Table 5-2: Daily Incremental Operating Profit

LOCATION	Co- Located	Co- Located	Co- Located	Co- Located	CosCob	CosCob	CosCob	CosCob
STORAGE CAPACITY as % of Wind Capacity	50%	50%	50%	50%	50%	50%	50%	50%
MARKET	Real-Time	Real-Time	Real-Time	Real-Time	Real-Time	Real-Time	Real-Time	Real-Time
SUPPLY LINKAGE	Linked	Linked	Hybrid	Hybrid	Linked	Linked	Hybrid	Hybrid
Daily Operating Policy	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb
Battery	ALPHA	BETA	ALPHA	BETA	ALPHA	BETA	ALPHA	BETA
WINTER								
Incremental Gross Profit per day [C]	\$2,775	\$2,775	\$3,541	\$3,541	\$3,812	\$3,812	\$5,103	\$5,103
Operating Cost of Storage per Cycle [D]	\$2,466	\$5,918	\$2,466	\$5,918	\$2,466	\$5,918	\$2,466	\$5,918
Incremental Operating Profit per day [E = C - D]	\$309	(\$3,143)	\$1,075	(\$2,377)	\$1,346	(\$2,106)	\$2,637	(\$815)
SUMMER								
Incremental Gross Profit per day [C]	\$2,444	\$2,444	\$6,075	\$6,075	\$5,094	\$5,094	\$11,402	\$11,402
Operating Cost of Storage per Cycle [D]	\$2,466	\$5,918	\$2,466	\$5,918	\$2,466	\$5,918	\$2,466	\$5,918
Incremental Operating Profit per day [E = C - D]	(\$22)	(\$3,474)	\$3,609	\$157	\$2,628	(\$824)	\$8,936	\$5,484

From these operating profit calculations we can infer the following:

1. With the Alpha Battery, it is possible to generate an operating profit throughout the year (i.e. in both winter and summer seasons) under a Hybrid scenario for both the storage unit co-located with the wind plant in Maine and for the storage unit located in Cos Cob. However, the operating profit is higher when the storage unit is located in Cos Cob.
2. Given the higher operating costs of Beta Battery, it is not possible to generate an operating profit throughout the year (i.e. in both winter and summer seasons) with any of our Network Design Decisions and Daily Operating Policies. However, it seems that if we operate the storage unit under a Hybrid supply scenario in Cos Cob, it might be possible to generate an operating profit for most parts of the year and overall profit for the year given that the incremental daily operating profit for summer is \$5484 / day while the incremental daily operating loss for winter is only - \$815/day.
3. As seen in Section 5.1.2, the most profitable (from an operating profit point of view) network design and operating policy for our storage unit is defined by the following configuration {Alpha,

Cos-Cob, 50%, Real-Time, Hybrid, Rapid Arb}. However, given the high capital cost of Alpha Battery this might not be the most profitable option from the point of view of Pre-Tax Profit, which is discussed next.

Pre-Tax Profit

To calculate the Pre-Tax Profit we need to incorporate the capital cost of the storage unit. For the sake of simplicity, we have assumed straight line depreciation where the capital investment in the storage unit is depreciated in a linear manner over the entire Cycle Life. This gives us the capital Cost-per-Cycle of the storage unit. As discussed in Section 2.4 on Storage Technologies, the capital costs per cycle for storage units of 60MW installed capacity (50% of wind plant installed capacity) are \$ 25,263 / cycle for Alpha battery and \$ 5,479 / cycle for Beta Battery. This large range is because the Replacement Interval of Beta Battery (30 years) is twice that of Alpha Battery (15 years).

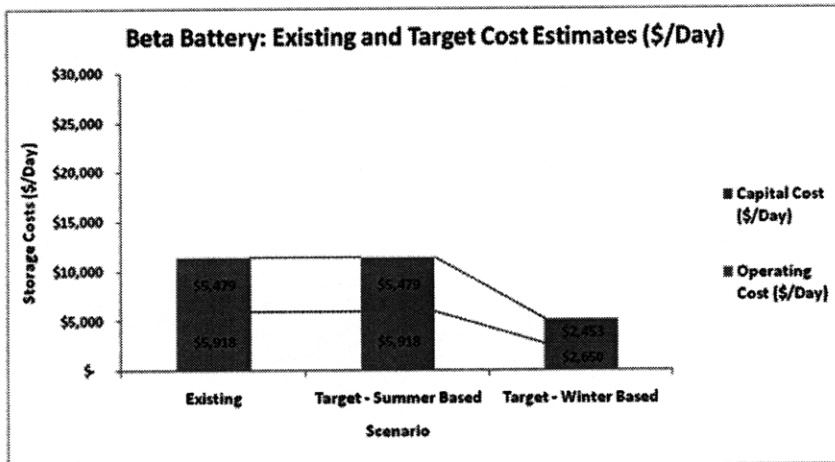
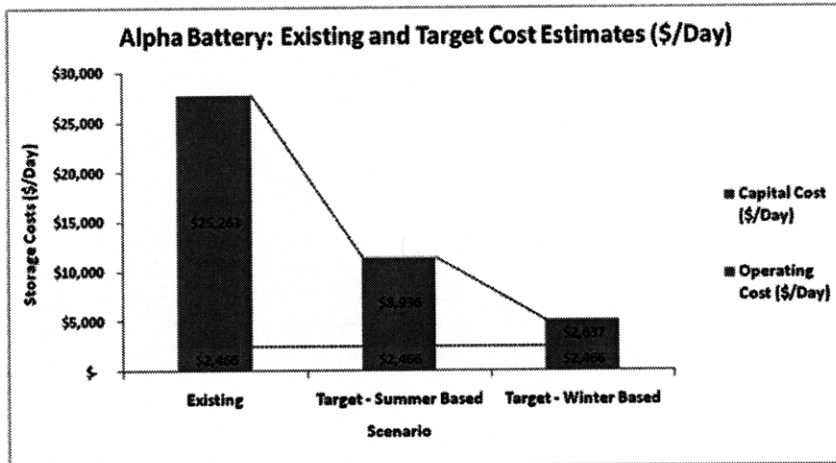
Based on these extremely high capital costs and the daily Incremental Operating Profit we see that it is not possible to earn a Pre-Tax Profit under the best design configuration and operating policy currently available for either Alpha or Beta Battery through wholesale electricity revenue alone. (However, with Installed Capacity Payments, Pre-Tax Profit can be achieved. (see Section 5.2)

Given that we can earn a daily Incremental Operating Profit ranging from \$ 2,637 / day (winter) to \$ 8,936 / day (summer) for the configuration *{Alpha, Cos-Cob, 50%, Real-Time, Hybrid, Rapid Arb}* we can calculate the time required to recover the capital investment (simple payback period). A simple calculation ignoring the time value of money shows that the investment in Alpha battery can be recovered in approximately 65 years. Hence, it is evident that given the high costs of storage it is not economically viable under these design conditions and Daily Operating Policies to invest in storage.

Estimates of Target Costs

Based on the calculation of incremental daily operating profit and incremental daily Pre-Tax Profit, we concluded that given the current high costs of storage it will not be possible to have year-round profitable operations without perhaps including benefits of Installed Capacity Payments for storage and/or federal or state green incentives. However, it would be insightful to back-calculate the extent to which the costs of these storage units would need to come down for the wind plant-plus-storage unit to become profitable overall. To develop a range for these estimates, we have used both the summer and winter numbers for the scenario that generated the maximum mean Incremental Gross Profit for both summer and winter viz. *{Alpha, Cos-Cob, 50%, Real-Time, Hybrid, Rapid Arb}*. This way we can develop a range of estimates even for the best case scenario for storage costs. As discussed earlier, the operating and capital costs for the two batteries that we have used vary widely. For Alpha battery the operating costs are fairly low at \$2,466/cycle but the depreciation of capital costs is high at \$25,263 / cycle. For Beta Battery, both the operating and capital costs are comparable at \$5,918/cycle and \$5,479/cycle but both of them higher than our best case benefits per day. Hence for the purpose of calculating the target cost estimates we have assumed that for Alpha battery all the reduction should come from capital costs, whereas for Beta Battery the reduction will come proportionately from both operating and capital costs. The results of the target costs estimates is shown in Figure 5-14 below

Figure 5-14: Existing and Target Cost Estimates for Storage



Based on these target costs estimates in the best case scenario, we can conclude that the costs of *Alpha battery* need to come down to between approximately \$2,600/day to \$9,000/day. To achieve this reduction there are two possible options. The *first option* is a capital cost of between \$ 240 / KW installed and \$ 815 / KW installed with a battery life of 15 years (existing life of Alpha batteries). The *second option* is a higher capital cost of between \$480/KW installed to \$1,630/KW installed with a battery life of 30 years. Given that the existing capital costs of Alpha battery is approximately \$3,200 / KW installed with 15 year life, this represents a significant reduction (*nearly 67% to 83% reduction*).

Similarly the target cost estimates for **Beta Battery** show that if we combine the operating and capital cost, Beta Battery is economically viable for the best case scenario in summer. However, to achieve year-round profitability (i.e. profits even in winter) the operating cost target estimate is \$2,650/day and the capital cost target estimate is \$2,453/day. This implies that the operating costs need to come down from approximately \$36/KW-year to \$16/KW-year (**approximately 55%**) while the capital costs need to come down from approximately \$1,250/KW installed to approximately \$450 / KW installed (**approximately 64% reduction**). Hence, based this analysis we can conclude that the extent of reduction required for Beta Battery is much lesser than the extent of reduction required for Alpha battery.

Note: Once again we would like to emphasize that the cost estimates and targets developed in this section are approximate and are meant to just provide guidance for the magnitude of reduction required in the storage costs. The main focus of our thesis as discussed in Section 5.1.2 was to demonstrate that the Incremental Gross Profit of wind plant-plus-storage unit can be improved significantly by applying supply chain management techniques. Also, the profit calculations do not account for fixed capacity payments, or government incentives, because these financial levers/instruments do not exist in all U.S. states and/or countries and their applicability is still not well established for storage.

Based on these results for Incremental Gross Profit, Operating Profit and Pre-Tax Profit discussed in this section we were able to generate several meaningful management insights that are discussed in the following section.

5.2 Management Insights

Our research proves that applying supply chain management techniques such as network design and inventory management policies can significantly improve wind plant and energy storage operation. In fact, we have shown that operating profits can be achieved on incremental revenue from wholesale electricity sales from storage under certain scenarios.

Our research thus provides a number of key insights into the management of energy storage with wind plants. These management insights are beneficial for wind plant operators who invest in energy storage, as well as other stakeholders in the Electricity Grid such as energy storage technology manufacturers and Independent System Operators. In this section we begin by discussing the insights for wind plant operators and then go on to discuss insights for energy storage companies and for the New England Independent Service Operator.

Management Insights – Wind Plant Operators

Our analysis and results helped to develop the following management insights for wind plant operators:

1.) Use inventory management policies for charge-discharge cycle of storage

Other research studies on energy storage have either assumed “perfect knowledge” of electricity prices in advance or have assumed the use of generic Time Shifting policies for managing the charge-discharge cycle of storage units. Many of these studies suggest a generic “charge at night, discharge during the day”-type of policy. Consequently, many of these studies have not been able to make a compelling economic case for employing energy storage.

Our results show that the use of inventory management policies for the charge-discharge cycle of storage units can lead to dramatic revenue improvements. For example, our Rapid Arb policy nets nearly a five times improvement over the naïve policy (approximately equivalent to our Simple policy) that is currently the accepted default policy in the industry. Therefore we recommend the use of inventory management policies for energy storage units.

2.) Iterate and improve inventory management policies

Our study produced three policies (Cost-Based, Max Peak, Rapid Arb) that achieved progressively improving results above our Simple policy. We have applied supply chain management concepts such as the *cost of underage* and *cost of overage* while treating our stored

electricity as a Single Period Problem (discussed in section 3.2) to come up with these policies. With more time and additional research, we are confident that we could continue refining our policies to get even better results for example by applying heuristics developed in extensions to the Single Period Problem(discussed in Section3.2). We recommend that any wind plant operator who invests in storage continuously create and evolve their policies to optimize performance. In addition, our results show that the specific parameters of the policy will be different depending on the season of the year. Hence, we recommend that the wind plant-plus-storage system operators should adjust their policies for different seasons.

3.) Locate storage units in densely-populated areas

Wind plants are typically located in remote locations with rich wind resources. Wholesale electricity prices are lower in these regions. Thus wind plants are currently bound by the prevailing lower wholesale electricity prices in these regions.

To get better value for their energy generation and selling operation, we recommend strategic placement of storage units in densely-populated areas. These areas allow the storage unit to sell their electricity at higher prices closer to high demand, thus improving overall profitability.

4.) Operate Storage Unit with a ‘Hybrid’ Policy

Our results show that even though the storage unit is owned and operated by a wind plant operator, it is more profitable to operate the storage unit in a Hybrid manner such that any shortfall between the Maximum Continuous Power Rating input to the Storage unit and the Wind Plant Output is purchased in the Real-Time market to always charge up storage to the maximum capacity.

Thus, we recommend that the storage units be always operated under a Hybrid policy to maximize the revenue and profit generation potential of the wind plant-plus-storage system.

5.) Consider selling into Real-Time Market over the Day-Ahead Market in the short term

Day-Ahead prices are on average about 2% higher than Real-Time prices in New England.

However, in our simulation runs, our Rapid Arb inventory management policy yielded results in the Real-Time market that are about 2% to 10% *better than* our results in the Day-Ahead market (on Incremental Gross Profit, depending on season). We have concluded that this result is due to our Rapid Arb policy's ability to capitalize on the greater variability in Real-Time prices (versus Day-Ahead prices). This result demonstrates that certain policies can yield better performance in the Real-Time market in New England – despite the fact that Day-Ahead prices are higher on average. Moreover, as per the current policies of the New England Independent Service Operator, battery storage units do not qualify for monthly Installed Capacity Payments. Hence, there is no additional incentive to participate in the Day-Ahead market.

6.) Use storage units to participate in Day-Ahead market in the long term

We expect that in the future battery storage units will be eligible to earn Installed Capacity Payments just like existing Pumped Hydroelectric Storage units in the New England region. This payment for installed capacity is contingent on participation in the Day-Ahead market (ISO New England Rules and Procedures, 2008). Given the current rate for Installed Capacity Payments and the rules that apply to Pumped Hydroelectric Storage units we expect that this payment could be as high as approximately \$175,000 per month (\$5,986 per day) even in the most conservative scenario. The details of the expected Installed Capacity Payments for a battery storage unit are shown in Appendix 6. Once battery storage units become eligible for such Installed Capacity Payments then it would be more advantageous to participate in the Day-Ahead market to qualify for getting this Installed Capacity Payments.

7.) Recommended size of storage unit relative to wind plant

The recommended size for storage depends on the scenario for operation. For a Linked scenario, where the input to storage is limited by the maximum power output at any instant by the wind

plant our results show that optimal size of storage would be around 20% of the wind plant capacity, provided there are no additional discounts in capital costs of storage for buying more storage units and increases the size of a facility. This result is consistent with results obtained in other research (see Section 5.1.2.3). However, as discussed in Section 5.1.2.3, when the storage unit is operated in a Hybrid scenario the benefits of storage increase almost linearly with increase in storage capacity. Realizing this benefit is constrained by following factors: 1) capital constraints, 2) technology scalability constraints, 3) nonlinear increase in costs with size, and 4) land constraints in densely-populated areas such as Cos Cob.

8.) Lobby state and federal governments and independent system operators for energy storage incentives

Every time a wind plant-charged energy storage facility discharges during a peak period (typically early or late afternoon depending on season), less fossil fuel-fired generation is needed to fulfill demand during that peak period. Yet few U.S. states have renewable production incentives that incorporate the use of energy storage units as part of a renewable energy facility. Therefore, lobbying states for incentives for linking energy storage use to Wind Plant Output is another recommendation we have for wind plant operators as well as energy storage manufacturers. Our results in this thesis do not include any incentives, yet they present a compelling case for energy storage. If incentives for storage existed, then the economics of a Linked energy storage-wind plant facility would become even more attractive.

Management Insights – Storage Manufacturers and Independent Service Operator

Based on our results we have also been able to compile some useful insights for the storage manufacturers and the Independent Service Operator.

1.) Achieve targeted cost for battery storage

Energy storage, especially utility-scale batteries, is relatively expensive because most technologies are still early-stage. There are currently very few buyers and limited number of manufacturers so benefits from economies of scale have not been fully realized. Existing research reports assess the economic viability of storage using a set of assumptions valid for a particular context. Based on our results, we have developed estimates of cost benchmarks that the storage technologies can set as their targets. This should help lead to greater adoption of storage technology.

As mentioned in Section 5.1.2, our research shows that by employing supply chain management techniques, we can improve incremental revenue and profits significantly over a simple policy. Still, achieving a Pre-Tax Profit is not possible if we do not include fixed capacity payments and government incentives. Our results in section 5.1.3 show that storage manufacturers need to reduce costs *by 50% to 80%* to achieve year-round economic viability in our best case scenario.

Note: This reduction percentage target is based on our assumptions of the current operating context and can be higher or lower depending on the choice of technology and operating context. The above percentage reduction targets do not account for fixed capacity payments, or government incentives, because these financial levers/instruments do not exist in all U.S. states and/or countries and are still not well established for storage. Our recommendation is that storage manufacturers not rely on incentives to make their technologies cost-effective since these financial levers/instruments are out of their control.

2.) Increase Cycle Life of batteries

To make energy storage more cost-effective, we have found that Cycle Life has a significant impact on whether or not a technology is economically-viable. A longer Cycle Life (the number

of full cycles to maximum Depth of Discharge available during the life of the unit) allows purchasers more revenue-earning opportunities to reach breakeven on the investment. Our research shows significant variation in service life of batteries and the extent of targeted cost reduction required is a function of battery life. For example as shown in section 5.1.3 for the Alpha battery, there is requirement of reduction of costs by more than 85% with the current Cycle Life of 15 years. However, if the Cycle Life increases to 30 years, then the required reduction percentage drops to approximately 65%. Hence, our recommendation to energy storage manufacturers is to focus on increasing Cycle Life of their batteries to as high as 30 years.

3.) Adopt and Formalize Installed Capacity Payments for Battery Storage

Our results show that an energy storage facility operated by a wind plant operator in a high demand area can help to meet energy requirements during peak hours. Hence, storage units represent installed capacity to meet peak demand. The ISO pays a monthly payment for installed capacity (available Generators) to ensure adequate generation throughout the year. However the rules for payment of Installed Capacity Charges to battery storage units are not clearly established. So we have not assumed any Installed Capacity Payments in our model.

Consequently, our results show that even in the best case scenario, the wind plant-plus-storage unit system is not able to earn a Pre-Tax Profit due to the high costs of storage.

Existing storage facilities such as Pumped Hydroelectric units do get an installed capacity payment as per the current market rules of the New England Independent Service Operator. (ISO New England Rules and Procedures, 2008). If battery storage units also start getting Installed Capacity Payments in a manner similar to Pumped Hydroelectric Storage units, then our calculations show that this could result in an additional revenue of approximately \$175,000 per month (\$5,986 per day) for a wind plant and 60MW storage unit, even in the most conservative scenario. Details of these calculations are available in Appendix 6. Combining this additional revenue with the best case operating profit numbers in Table 5-2 we calculate the Pre-Tax Profit in Table 5-3 below.

Table 5-3: Pre-Tax Profit with Possible Installed Capacity Payments

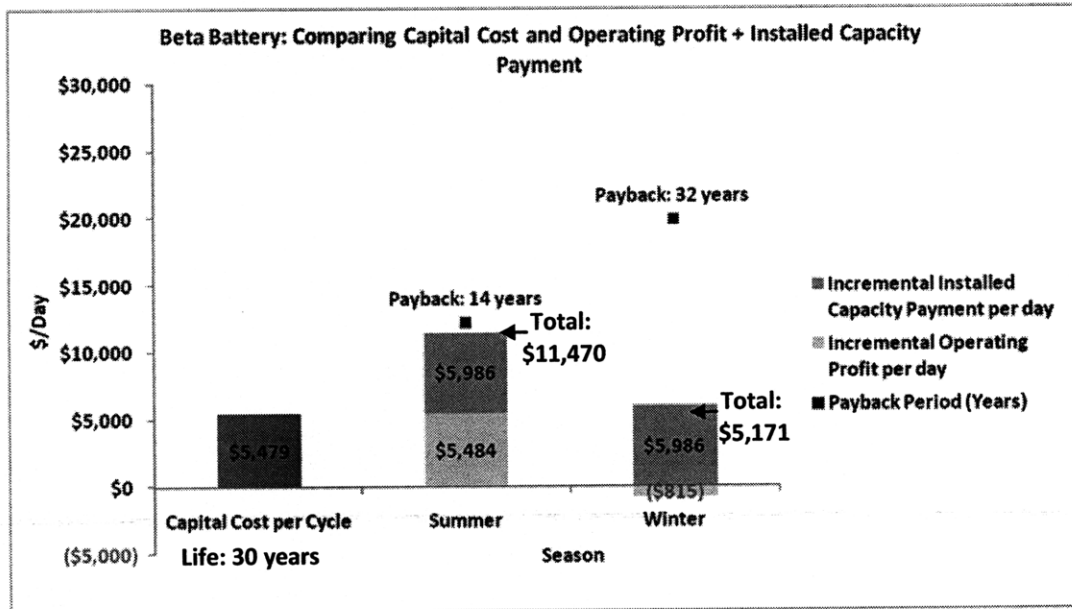
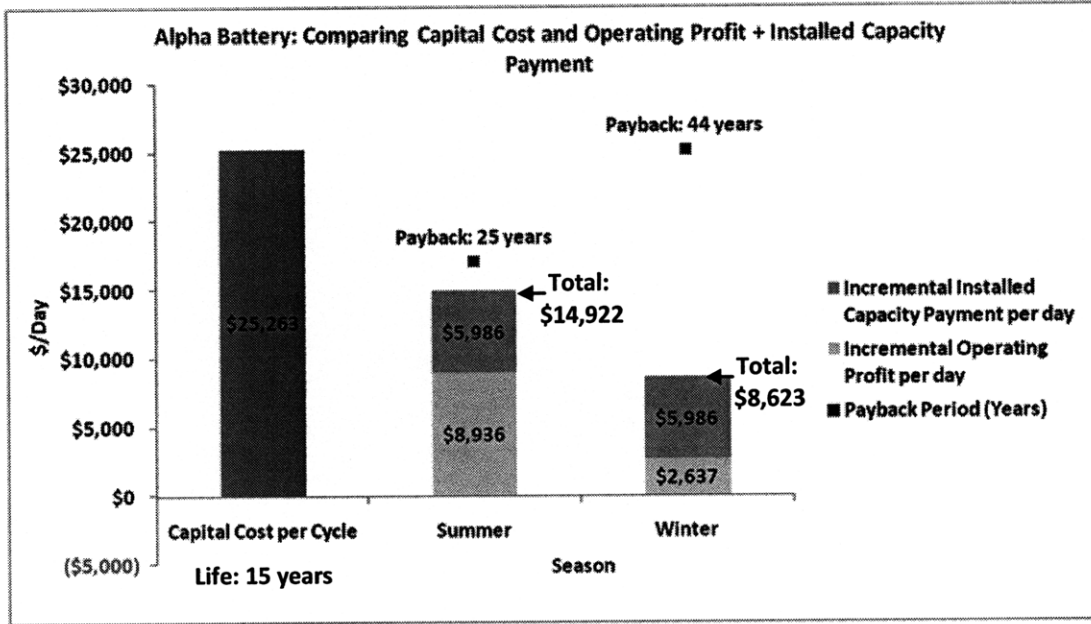
Season	SUMMER		WINTER	
	CosCob	CosCob	CosCob	CosCob
LOCATION				
STORAGE CAPACITY as % of Wind Capacity	50%	50%	50%	50%
MARKET	Real-Time	Real-Time	Real-Time	Real-Time
SUPPLY LINKAGE	Hybrid	Hybrid	Hybrid	Hybrid
Daily Operating Policy	RapidArb	RapidArb	RapidArb	RapidArb
Battery	ALPHA	BETA	ALPHA	BETA
Incremental Gross Profit per day [C]	\$11,402	\$11,402	\$5,103	\$5,103
Operating Cost of Storage per Cycle [D]	\$2,466	\$5,918	\$2,466	\$5,918
Incremental Operating Profit per day [E = C - D]	\$8,936	\$5,484	\$2,637	(\$815)
Depreciation (Capital Cost of Storage) [F]	\$25,263	\$5,479	\$25,263	\$5,479
<i>Other Income</i>				
Incremental Installed Capacity Payments	\$5,986	\$5,986	\$5,986	\$5,986
<i>Total Other Income [G]</i>	\$5,986	\$5,986	\$5,986	\$5,986
Pre-Tax Profit [H= E - F + G]	(\$10,341)	\$5,991	(\$16,640)	(\$308)

If we include the incremental installed capacity payment in the revenue to calculate Incremental Operating Profit, it increases significantly for Beta Battery to \$11,470/day (\$5,484 + \$5,986) in summer and \$5,171/day (-\$815+\$5986) in winter. From these results it is evident that given these Installed Capacity Payments, we begin to make a Pre-Tax Profit during the summer season (\$5,991/day profit) and come very close to breakeven (only \$308/day loss) during winter. This means that for the same capital costs the payback period is significantly reduced to between 14 years (based on summer) and 32 years (based on winter).

In Figure 5-15 below we compare the capital cost of Alpha and Beta Battery with the incremental operating profit and the installed capacity payment. This is then used to calculate the payback period. Given the high capital costs of Alpha Battery, the payback period using both summer (15 years) and winter (44 years) months is higher than the Cycle Life (15 years). However, for Beta

Battery the payback period based on summer results is only 14 years, while the payback period using winter results at 32 years is slightly higher than the Cycle Life of 30 years.

Figure 5-15: Capital Cost and Payback Calculation



These Pre-Tax Profit and payback period numbers represent incentive for storage companies to speed up research for reducing costs. Hence, the Independent System operator should adopt and

formalize Installed Capacity Payments for battery storage systems in line with Pumped Hydroelectric Storage systems.

5.3 Recommendations for Future work

Our recommendations for future work are discussed under two categories 1) Further research that can be used with our existing model; 2) Research that could extend our model

With the existing model, the flexibility built into our model can be used to simulate and test several other input configurations and Daily Operating Policies:

- In our model we have the option of varying several parameters of the synthesized Wind Plant Output (discussed in Section 2.2) For example, we have used the following wind plant configuration: Installed capacity- 120 MW; Individual Turbine Capacity - 1.5 MW; Hub Height - 80 meters; Wind Power Class at location – 3. We do have in our model the flexibility to test the simulation over several different values of these parameters. It will be interesting to see how our results vary with different input configurations of the wind plant.
- In addition, for both summer and winter months, further research can be done using existing data to evaluate the impact of the wind profile during a day on profitability. For example, we can compare the difference between the profitability of days with total high Wind Plant Output vs. days with high proportion of the output during the night. This analysis can be used to develop further refinement to the Daily Operating Policies.
- For market prices, we have the option of selecting different Nodal prices (such as Lakewood, ME; Cos Cob, CT; Lake Road in Providence, RI and; Kendall in Cambridge, MA. We have currently explored only Lakewood, ME and Cos Cob, CT. However, it will be interesting to see how our results vary by selection of another market. In addition, we have built into our model the flexibility of varying the market volatility. Our current set of results is based only on “regular” volatility, but they can be easily extended to a “high” or “low” volatility scenario.

- Our model can be used to test out other Daily Operating Policies. As explained in Section 3.2, several extensions to the Single Period Problem exist that have developed heuristics for optimal operations. Such heuristics could be used to develop policies that could further improve profitability. Similarly we can develop policies to incorporate other factors such as fuel price fluctuations and the impact that this will have on electricity price fluctuations. These policies can also be tested using our existing model.

Extensions to our model can be developed along the following lines

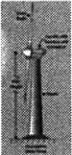
- As discussed in Section 4.3 and 5.2, our model can be extended to include the impact of Installed Capacity Payments by the Independent Service Operator and other incentives provided by the federal and state governments.
- Along similar lines our research can be extended to assess the environmental impact of storage used for meeting demand during peak hours. In the Hybrid scenario for example, we can calculate the extent of input to storage from the ‘green’ Wind Plant Output and from the electricity market. This can be used to make the case for federal and state incentives for battery storage stronger.
- For the scenario where the storage unit is located at a place different from the wind plant, under the rules of the Independent System Operator it is possible to establish ‘Bilateral Contracts’ to buy and sell electricity between the wind plant Generator and the storage unit. We haven’t included ‘bilateral contracts’ in our model but it will be interesting to examine how the price dynamic will change under bilateral contracts.
- Our model can be extended to include other electricity markets. Currently we have studied only the Time Shifting application (Section 1) and have considered only the wholesale day-ahead and real-time markets (Section 2.3). It will be instructive to examine the profitability of operation by extending participation to other markets such as ancillary services. In fact, a single storage technology can be used for both arbitrage and frequency regulation at different points during the day (Walawalkar & Apt, July 31, 2008).

- We are currently using Monte-Carlo simulation to evaluate different policies. However, it might be possible to extend this method to build an optimization based on forecasted prices. In addition, our current planning horizon of a day can also be extended to a longer period (week / month / infinite) to see the impact on our results.
- In our model we have assumed sufficient capacity of transmission to carry all the electricity output of the wind plant at all times. However, as the wind plant operates at a Capacity Factor of less than 40%, quite often there is not enough transmission capacity available to carry all the electricity output when the wind plant is producing close to peak capacity. In such a scenario when there is inadequate transmission capacity the output from the wind plant cannot be sold into the electricity market and is “spilled”. This is called Transmission Curtailment. Energy storage co-located with a wind plant helps to avoid this *Spillage* by Time Shifting the output. This benefit has not been considered in our model thus far, but it can be easily extended to include this benefit.

List of Terms

Term	Description
Base Case	To calculate the incremental revenue and profit in our model we have defined the Base Case for comparison. The Base Case is defined as scenario of the wind plant operating without access to storage i.e. the wind plant located in Maine selling generated electricity output to the Real-Time electricity market at the prevailing price for the Lakewood Node in Maine.
Capacity Factor	<p>The Capacity Factor of an electricity generating unit is a measure of the extent to which the generating unit was able to generate with respect to its capacity. It is defined as:</p> $\frac{\text{Actual amount of electricity output over a given time period (MWh)}}{\text{Theoretical maximum possible energy output over the same time period if all turbines operated at 100% capacity (MWh)}}$
Capacity of a Wind Plant	<p>The installed capacity of a wind plant is measured by the maximum possible electrical power (rate of flow of energy) that the wind plant can generate at any given point of time if all the wind turbines were operating at full capacity (see Capacity of a Wind Turbine).</p> <p>This is also called the rated capacity or installed capacity of the wind plant.</p> <p>The installed capacity of a wind plant is measured in Megawatt (MW) or Kilowatt (KW).</p>
Capacity of a Wind Turbine	<p>The capacity of a wind turbine refers to the maximum amount of electrical power (rate of flow of energy) that the wind turbine can generate at optimal wind speeds (see Power Curve of Wind Turbine)</p> <p>The capacity of a wind turbine is measured in Megawatts (MW) or Kilowatt (KW).</p>
Capacity of Storage	<p>Capacity of a Storage Unit can be defined in multiple ways:</p> <ol style="list-style-type: none"> 1. Power Capacity or Maximum Continuous Power Rating or Power Rating is measured in Megawatt (MW) or Kilowatt (KW) and represents an upper bound on the maximum amount of power that the storage unit can discharge or charge (Power is defined as the rate of flow of energy i.e. energy per unit time) When we use the term “capacity” in the context of a storage unit <u>without any qualifier</u> in this document, we mean the Maximum Continuous Power Rating 2. The maximum amount of energy that a storage unit can store is called the Energy Capacity and is measured in Kilowatt-hours (KWh) or Megawatt-hours (MWh) The Energy Capacity and Power Rating together define how much power can the storage unit deliver and for how long.
Capacity of Transmission	The capacity of a transmission line is a measure of the maximum amount of the electrical power (rate of flow of energy) that the line can carry or transfer. It is measured in Megawatt (MW) or Kilowatt (KW).
Capital cost of Storage	The capital cost of storage includes three components viz. the cost of the electrical energy storage unit, the cost of the associated power control system and the cost of the Balance of Plant (Electric Power Research Institute and U.S. Department of Energy, 2003)
Co-Located	This term is used to define one of the input options for our model where the storage unit is located alongside the wind plant in Maine.
Congestion	Congestion on the Electricity Grid is a condition that arises when one or more restrictions prevent the

Component of LMP	electricity to be carried over the grid to serve the load. The Congestion component of the nodal price reflects the marginal cost of Congestion at a given node relative to the reference node.
Cost-per-Cycle	<p>The Cost-per-Cycle for a storage unit is calculated by dividing the relevant cost by the number of charge-discharge cycles in the period being considered. For example:</p> <ul style="list-style-type: none"> • Operating Cost-per-Cycle = {Storage Operation and Maintenance Cost per year / Number of charge-discharge cycles per year under normal operation} • Capital Cost-per-Cycle = {Storage Capital Cost depreciated per year using straight line depreciation / Number of charge-discharge cycles per year under normal operation} <p>Cost-per-cycle is an important economic measurement for storage because each cycle represents an opportunity to monetize the unit and earn revenue. (Hassenzahl & Schoenung, July 2007)</p>
Cut-in Wind Speed	A technical specification of a wind turbine that determines the lowest speed below which the wind turbine does not produce any electricity output
Cut-Out Wind Speed	A technical specification of a wind turbine that determines the highest speed above which the wind turbine does not produce any electricity output
Cycle Life	Cycle Life of a storage unit defines the approximate number of charge-discharge cycles that it can undergo before failure. For storage devices cycling introduces structural, mechanical and thermal stresses which limit the number of cycles the device can withstand. For some devices such as batteries the Cycle Life also depends on the Depth of Discharge (DoD) i.e. the extent to which the device is discharged in each cycle. The Cycle Life at a deeper DoD is lower than that at a higher DoD
Daily Operating Policies	We use this term to describe a set of policies that govern the input (charging) and output (discharging) of the storage unit on a daily basis. We evolved and tested four Daily Operating Policies viz. Simple, Cost-Based, Max Peak, and Rapid Arb (described in Section 3.2)
Dashboard	The Dashboard of our model helps the user of the model to quickly select various settings for the different parameters as inputs to our model.
Day-Ahead Market	The Day-Ahead market is wholesale electricity market where Generators and loads make commitments to sell and buy electricity the following day thus creating a financially binding schedule of commitments the day before the operating day for the production and consumption of electricity (Market Rule 1 of the New England Independent Service Operator)
Depth of Discharge (DOD) for Storage Unit	The Depth of Discharge defines the percentage of the Energy Capacity of the storage unit to which it is discharged in a cycle. For example, 80% DOD means that 80% of the maximum stored energy has been discharged, so the battery now holds only 20% of its full charge
Dispatchable Asset	Very simply put a dispatchable assets on the Electricity Grid is a Generator whose electricity output can be increased or decreased at the instructions of the authority maintaining and monitoring the Electricity Grid
Dispatchable Asset Related Demand (DARDs)	A Dispatchable Asset Related Demand, simply put is a physical load that has been discretely modeled within the ISO New England's Energy Management and Settlement systems that settles at a nodal location on the Electricity Grid (Manual 35) and can be dispatched (see Dispatchable Asset)
Electricity Grid	Electricity Grid refers to the network of electrical equipment (including wires, transformers etc.) that carry electricity from the power plant over long distances (high voltage transmission lines) or distribute electricity to the end users (low voltage distribution lines). Most electricity Generators and consumers need to be connected to the Electricity Grid to be able to sell the electricity to the market or to buy electricity from the

	market.
Electricity Output	We use this term to describe the output of electrical energy from either a wind plant or from a storage unit
Energy Capacity of Storage (see Capacity of Storage)	The maximum amount of electrical energy that a storage unit can store is called the <i>Energy Capacity</i> and is measured in Kilowatt-hours (KWh) or Megawatt-hours (MWh) The Energy Capacity and Power Rating together define how much power can the storage unit deliver and for how long.
Energy Component of LMP	The component of the Locational Marginal Price (LMP, see term) that reflects the price of the electricity (electrical energy) traded. The Energy Component of the LMP at any given instant is the same across all locations in the ISO-NE (see term) region
Full Power Discharge Time	The full power discharge time (FPDT) of a storage unit links the maximum continuous power rating and the energy capacity by the formula: Energy Capacity = Maximum Continuous Power Rating * Full Power Discharge Time. Hence the FPDT defines the amount of time for which the storage unit can discharge at the power capacity given the maximum amount of energy stored.
Generator	We use the term generator to define any resource connected to the Electricity Grid that is capable of producing or produces electricity and supplies it to the Electricity Grid. Example of generators include fossil fuel fired power plants, nuclear power plants, Hydroelectric power plants and, wind plants
Hub Height	The Hub Height denotes the height above the ground at which the rotor of the wind turbine is located  {Source: http://www.daviddarling.info }
Hybrid	Hybrid refers to an input configuration in our model where the electrical energy input (charging) to the storage unit can come either from the Wind Plant Output or if the Wind Plant Output is lesser than the power capacity of the storage unit then part of the input can also come from the Electricity Grid in the form of electricity bought in the Real-Time market.
Incremental Gross Profit	Incremental Gross Profit refers to the additional profit that the wind plant-plus-storage system can earn by subtracting the cost of energy (including opportunity cost of electricity not sold by the wind plant, cost of buying electricity, penalty of not meeting commitment in Day-Ahead market and Standby Losses) from the additional revenue that it can make with storage. The incremental values are calculated with respect to the Base Case (Section 4 for more details)
Incremental Operating Profit	In our model we used a simplified definition for Incremental Operating Profit. It is calculated by subtracting the operating cost of storage from the incremental gross profit (Section 4 for more details)
Independent System Operator (ISO-NE)	The Independent System Operator of the New England region (ISO-NE) is the a regional transmission organization (RTO), serving Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont. Amongst other functions it oversees and ensures the fair administration of the region's wholesale electricity markets, and manages the regional electricity planning processes.
Installed Capacity Payments	Simply put, Installed Capacity Payments are made by ISO-NE to electricity generators based on their consistent generating capacity (or "firm" generating capacity). (Market Rules 1) These payments are a means to ensure adequacy of installed electricity generation capacity in the New England region to meet current and future requirements

Linked	Linked refers to an input configuration in our model where the electrical energy input (charging) to the storage unit can come only from the Wind Plant Output and can thus never be more than the Wind Plant Output.
Load	Load on the Electricity Grid refers to an entity that has a demand for electricity.
Load Zone	Load Zone in the ISO-NE refers to an aggregation of nodes on the Electricity Grid that lie within a specific area. There are eight load zones in the ISO-NE region viz. Maine, New Hampshire, Vermont, WC Mass, NE Mass & Boston, SE Mass, Connecticut and Rhode Island
Located	Located refers to an input configuration in our model where the storage unit is not located along side the wind plant but at a different distant location. In our model we have considered for example a storage unit located in Cos Cob, Connecticut while the wind plant is located in Maine
Locational Marginal Price (LMP)	LMP refers to the price for electricity purchases and sales at specific locations throughout the New England wholesale electricity market. It takes into account the marginal cost of electricity at different locations on the Electricity Grid in the ISO-NE region by adjusting the uniform energy cost with the variation due to different levels of Congestion and losses at different locations.
Loss Component of LMP	The component of LMP at a Node on the Electricity Grid that accounts for the marginal real electrical power losses as measured between that Node and a Reference Bus in the ISO-NE
Maximum Continuous Power Rating of a Storage Unit (see Capacity of a Storage Unit)	Power Capacity or Maximum Continuous Power Rating or Power Rating is measured in Megawatt (MW) or Kilowatt (KW) and represents an upper bound on the maximum amount of power that the storage unit can discharge or charge (Power is defined as the rate of flow of energy i.e. energy per unit time) When we use the term “capacity” in the context of a storage unit <u>without any qualifier</u> in this document, we mean the Maximum Continuous Power Rating
Model Input Configurations	Model Input Configurations refer to the various options for model inputs that can be simulated through our model. The various input configurations are discussed in detail in Section 4
Network Design Decisions	The Network Design Decisions in our model refer to the typical design decisions in a supply chain including facility role, facility location, capacity allocation, market allocation, supply allocation (Chopra & Meindl, 2004) Discussed in Section 3.1
Newsvendor Problem (See Single Period Problem)	The Newsvendor problem or Single Period Problem is a widely used model in supply chain management to determine the optimal quantity to be ordered in the face of uncertain demand and known loss of value of the item after a single period. The most often cited example is that of the problem faced by a newsvendor trying to decide how many newspapers to stock on a newsstand before observing demand. (Section 3 for details)
Node	A Node on the ISO-NE Electricity Grid is a location point where electricity is traded and a Nodal Price is established on an hourly basis
Operating Cost of Storage	The Operating Cost of storage refers to the operation and maintenance costs of the energy storage unit and the power control system. These costs are usually quoted and calculated over a time period (typically a year) (Electric Power Research Institute and U.S. Department of Energy, 2003)
Power Curve	The Power Curve of a wind turbine is a graph that indicates how large the Electricity Output will be for the turbine at different wind speeds. This curve is usually provided by the wind turbine manufacturer along with the technical specification of the turbine.
Pre-Tax Profit	In our model we use a simplified concept of Pre-Tax Profit (slightly different from the typical accounting definition). Pre-Tax Profit = Operating Profit + Additional Revenue (from Installed Capacity Payments, government incentives etc.) – Depreciation of Capital Cost (Section 4 for more details)

Pumped Hydroelectric Storage (PHES)	PHES is one of the earliest methods of storing electrical energy that first gained widespread traction in the United States in the 1960's. It involves the use of two water reservoirs. During off-peak hours water is pumped from the lower reservoir to the upper reservoir. During peak hours the water is released from the upper reservoir back into the lower reservoir during which time the water turns Hydroelectric water turbines that generate electricity
Real-Time Market	The Real-Time market in simplified terms is like a spot market for electricity. It "reconciles differences between the amounts of energy scheduled before an operating day and the actual loads of the operating day, market participant re-offers, hourly self-schedules, self-curtailments, and any other changes that impact real-time system conditions". (ISO-NE, 2009) Wind plants are currently classified as intermittent resources and participate primarily in the Real-Time market.
Renewable Energy Credits (or RECs)	RECs are tradable environmental commodities in the United States which represent proof that 1 Megawatt-hour (MWh) of electricity was renewable (generated from an eligible renewable energy resource). Typically, RECs are purchased from renewable electricity generators by non-renewable electricity generators who want to offset the carbon created by their fossil fuel-generated power. REC's are essentially a tax paid by non-renewable electricity generators to subsidize renewable generation. (Peet, Renewable Portfolio Standards Paper, 2009) and (DOE's Energy Efficiency & Renewable Energy Dept., 2009)
Replacement Interval	Replacement Interval refers to the life of a storage i.e. the period of time after which the storage unit will need to be replaced. The Replacement Interval could be determined by the Cycle Life or independently based on the physical characteristics of the storage unit. (Electric Power Research Institute and U.S. Department of Energy, 2003)
Round-Trip Efficiency	The most common way to measure efficiency of an EES system is called the AC Round-Trip Efficiency, which is defined as the AC energy output of the EES system divided by the AC energy input. There are various factors that influence the Round-Trip Efficiency of an EES system including but not limited to use to transformer for voltage step-up or down, use of AC vs. DC power, parasitic losses during standby mode and other intrinsic losses such as thermodynamic losses in batteries.
Seasonality	Seasonality refers to an input configuration option in the model where we can examine results for the winter or the summer season. The summer and winter seasons represent extremes from the point of view of wind speeds and electricity market prices. Hence, this helps us to understand year-round variation.
Single Period Problem (SPP) (See Newsvendor Problem)	The Single Period Problem or the Newsvendor problem is a widely used model in supply chain management to determine the optimal quantity to be ordered in the face of uncertain demand and known loss of value of the item after a single period. The most often cited example is that of the problem faced by a newsvendor trying to decide how many newspapers to stock on a newsstand before observing demand. (Section 3 for details)
Sodium Sulfur Battery (NaS Battery)	Sodium Sulfur batteries refers to a battery technology that consists of liquid (molten) sulfur and liquid (molten) sodium. It undergoes a reversible chemical reaction to store electrical energy during charging. The reaction can be reversed later to discharge the electricity. (Electric Storage Association) (Section 2.4)
Spillage	Spillage refers to the loss of electricity output from a generator that happens because there inadequate transmission capacity to transfer the electricity to the Electricity Grid. (see Transmission Curtailment, Section 5.3)
Standby	A storage unit is said to be in standby, when it is connected to the power system and is <u>ready</u> to charge / discharge electricity but is not actually charging / discharging.
Standby Loss	Standby Loss refers to loss of stored energy that occurs when the storage unit is in standby mode. Bulk of the Standby Losses happen as heat and are specified by the storage manufacturers as a part of the technical

	specification per module
Targeted Gross Margin	The margin goal above the purchase cost of stored electricity of a wind plant operator when selling electricity into the electricity markets
Time Shifting	This is a term used to describe the application of storage to store electrical energy during off-peak hours and sell it during the peak hours (Electric Power Research Institute and U.S. Department of Energy, 2003)
Traditional Inventory Control System	We have used this term to describe replenishment models traditionally used for inventory control of a single item with probabilistic demand. (Silver, Pyke, & Peterson, 1998)
Transmission Curtailment	Transmission Curtailment refers to the loss of electricity output from a generator that happens because there is inadequate transmission capacity to transfer the electricity to the Electricity Grid. (see Spillage, Section 5.3)
Watt / Megawatt (MW) / Kilowatt (KW)	Watt is the unit for measuring electrical power. Megawatt = 1,000,000 Watts; Kilowatt = 1000 Watt
Wind Plant (also called Wind Farm)	Wind Plant refers to a collection of wind turbines located close to each other over a geographic area to produce electricity by converting the kinetic energy of the wind. The wind plant is connected to a node on the Electricity Grid and can sell electricity to the electricity market.
Wind Plant Output	Wind Plant Output refers to the electricity output from a wind plant that can be sold to the electricity market
Wind Plant-Plus-Storage System	We use the term wind plant-plus-storage system to describe the combination of a wind plant and storage unit that from an operational perspective are considered together. The storage unit need not necessarily be co-located with the wind plant.
Wind Power Class	The historical wind speeds at a particular location are used to classify that location in terms of the richness of the wind energy resource available at the location. The different classes based on wind speed are called "wind power classes" and are available for different locations. The wind power class for different locations in Maine along with the corresponding wind speeds is available on the website of the U.S. Department of Energy (National Renewable Energy Laboratory, 2007).
Wind Power Duration Curve	The wind power duration curve is a graph that indicates the distribution of Wind Plant Output as a function of the cumulative number of hours that the Wind Plant Output exceeds a given amount over a given period.
Wind Turbine	A wind turbine is a device that captures the kinetic energy of the wind and converts it to electrical energy.
Zinc Bromine batteries / ZnBr Battery	Zinc Bromine batteries refer to a battery technology that consists of zinc and bromine as electrodes. It undergoes a reversible chemical reaction to store electrical energy during charging. The reaction can be reversed later to discharge the electricity. (Electric Storage Association) (Section 2.4)

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Appendix 1: Comparison of Storage Technologies

The following Table presents a comparison of the various storage technologies considered for Time Shifting application. This has been adapted from Walawalkar & Apt (2008) with modifications based our research. For further details and explanation of terms involved we refer the reader to the aforementioned source.

Table A1-1: Storage Technology Summary Comparison

Technology	Advantages	Disadvantages	Applications
PHES	<ul style="list-style-type: none"> Huge energy and Power Capacity 	<ul style="list-style-type: none"> Geographically limited Expensive to site and build Long construction time Large scale only 	<ul style="list-style-type: none"> Time Shifting Frequency regulation Ancillary services
CAES (below ground)	<ul style="list-style-type: none"> Huge energy and Power Capacity 	<ul style="list-style-type: none"> Geographically limited Requires fuel input Long construction time Large scale only 	<ul style="list-style-type: none"> Time Shifting Frequency regulation Ancillary services
NaS	<ul style="list-style-type: none"> High energy and power density Relatively high Round-Trip Efficiency Scalable for large applications Long Cycle Life 	<ul style="list-style-type: none"> Relatively expensive (small volume manufacturing) High temperature produces unique safety issues 	<ul style="list-style-type: none"> Time Shifting Small load leveling Peak shaving for T&D upgrade deferral
Ni-Cd	<ul style="list-style-type: none"> Mature Technology Higher energy density Better Cycle Life than lead acid batteries 	<ul style="list-style-type: none"> More expensive than lead acid Limited long-term potential for cost reductions due to material costs Toxic components 	<ul style="list-style-type: none"> Utility backup
VRB	<ul style="list-style-type: none"> Energy and power sizing are independent Scalable for large applications High energy and power density 	<ul style="list-style-type: none"> Relatively early-stage technology Relatively expensive Limited opportunities for standard sizes 	<ul style="list-style-type: none"> Time Shifting Small load leveling Peak shaving for T&D upgrade deferral
ZnBr	<ul style="list-style-type: none"> High energy and power density Relatively high Round-Trip Efficiency Scalable for large applications Long Cycle Life 	<ul style="list-style-type: none"> Relatively expensive (small volume manufacturing) Relatively high maintenance costs Corrosive and toxic materials require special handling 	<ul style="list-style-type: none"> Time Shifting Small load leveling Peak shaving for T&D upgrade deferral

Source: Adapted from Walawalkar & Apt (2008) with modifications based on our research

Appendix 2: Storage Cost Calculation Details

We present below the details of the calculation of storage costs per cycle. To maintain confidentiality of the technical and cost information provided to us by the storage manufacturers we have used the generic names of Alpha and Beta Battery to describe the two technologies that we compared.

Table A2-1: Comparison of Costs - Alpha and Beta Battery

Technology Type		Alpha		Beta	
System Capacity	<i>MW</i>	60	ρ	60	
Cycle Life	<i>cycles</i>	5700		10950	
Capital Cost			λ		Δ Δ Y
Power Control System (PCS)	<i>\$/kW</i>			\$250	
Balance of Plant (BOP)	<i>\$/kW</i>			\$0	
Overall Energy Storage System (EES)	<i>\$/kW</i>	3200		\$1,000	
Sub-Total	<i>\$</i>	\$ 192,000,000	η	\$ 75,000,000	η
Volume Discount Rate	<i>%</i>	25%		25%	
Total Capital Cost	<i>\$</i>	\$ 144,000,000	*	\$ 60,000,000	Δ
Capital Cost-per-Cycle	<i>\$</i>	\$ 25,263		\$ 5,479	
Operating Cost					
Variable	<i>\$/kW-year</i>	15			Δ
Annual	<i>per unit</i>			\$ 18,000	
Annual	<i>\$/year</i>	\$ 900,000		\$ 2,160,000	
Operating Cost-per-Cycle	<i>\$</i>	2,466		\$ 5,918	
Total Costs Per Cycle	<i>\$</i>	\$ 27,729		\$ 11,397	

ρ See Table "Alpha Battery and Beta Battery Technical Specifications" in Section 2.4 for explanation of Alpha Battery Cycle Life

λ This figure includes PCS, BOP and EES costs combined, according to company.

Y This figure is extrapolated from the low end of the company's quoted cost range of \$200-\$300 per KWh multiplied by the five-hour Full-Power Discharge time

η It is assumed that Capital cost discounts of 25% can be earned from manufacturer with volume battery purchase of at least 20 MW.

Δ Company information

* Figure only includes plant maintenance cost, according to company

Appendix 3: Flowcharts for Daily Operating Policies

We present below the flowcharts depicting the logic built into our policies for charging and discharging.

We begin with the notations used in the flowcharts then we present the flowcharts for input (charging) to storage and output (discharging) from storage for all the four policies

NOTATIONS USED IN THE FLOWCHARTS

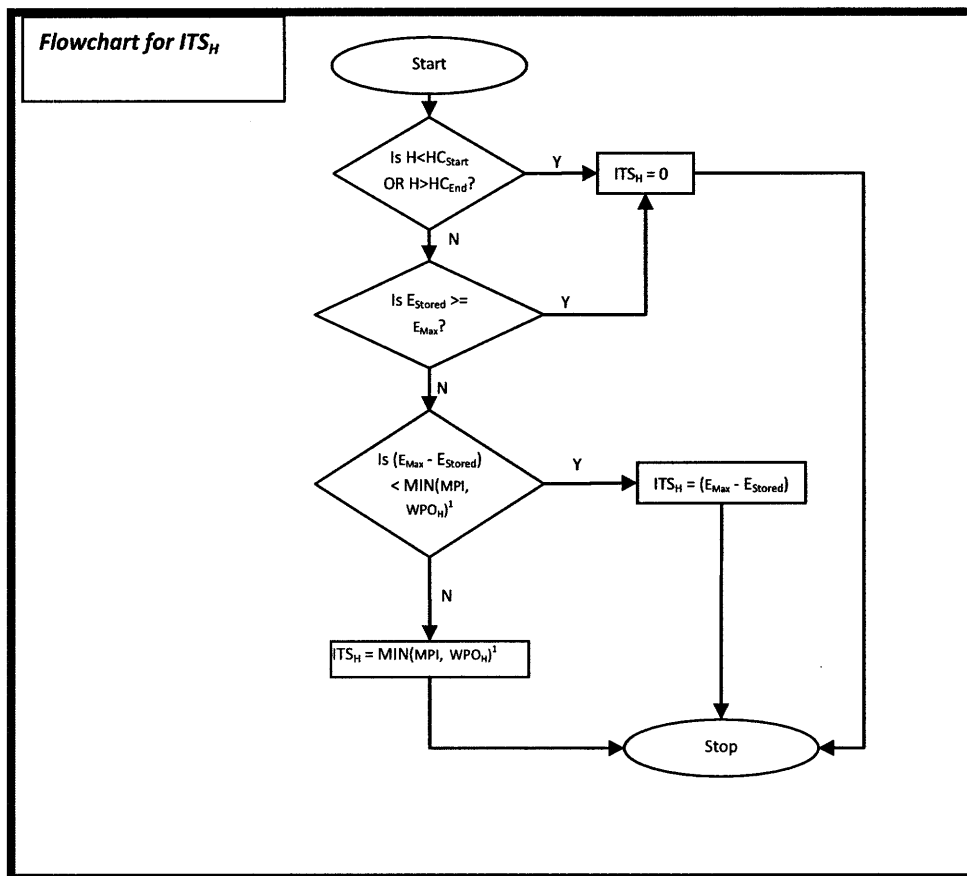
H:	The hour of the day for which decision is being made
HC _{Start} :	Hour to Start Charging (Set at 0:00 hours in most cases)
HC _{End} :	Hour to Stop Charging
HD _{Start} :	Hour to Start Discharging, if policy allows
HD _{End} :	Hour to Stop Discharging, if policy allows
H _{PeakStart} :	Hour at which (historical) Peak Hours begin (for participation in Day-Ahead Market this can be treated the same as the hour when the commitment in the Day-Ahead market begins)
H _{PeakEnd} :	Hour at which (historical) Peak Hours end (for participation in Day-Ahead Market this can be treated the same as the hour when the commitment in the Day-Ahead market ends)
P _H :	Actual Price prevailing at the hour (\$/MWh)
P _{AvgH} :	Historical Average Price for the hour H
P _{Opp} :	Weighted Average Price foregone by storing energy instead of selling to the grid during the charging hours = Opportunity Cost = $\frac{\sum_{H=0}^{H=23} P_H * ITS_H}{\sum_{H=0}^{H=23} ITS_H}$
M _{%Opp} :	% by which the (potential selling) Price in the hour should be more than the Weighted Average Price foregone (P _{Opp}) to allow discharge from storage in the hour. (e.g. can be set at 35% to recapture 25% losses due to Round-Trip Efficiency and desired gross margin of 10%)
P _{MaxPeak} :	Historical Average Maximum Peak Price per day = $Max[P_{AvgH}]_{H=0}^{H=23}$
M _{%MaxPeak} :	Maximum % by which the (potential selling) Price in the hour can be below the Historical Average Maximum Peak Price per day (P _{MaxPeak}) to allow discharge from storage in the hour.
M _{%BelowPeak} :	Minimum % by which the (potential buying) Price in the hour can be below the Historical Average Maximum Peak Price per day (P _{MaxPeak}) to allow charging to storage in the hour for Rapid Arb policy (e.g. can be set at 35% to recapture 25% losses due to Round-Trip Efficiency and desired gross margin of 10%)

OFS_H :	Energy Output From Storage (MWh) for hour H
ITS_H :	Energy Input To Storage (MWh) for hour H
RTE:	Round-Trip Efficiency of Chosen Storage (%)
MPO:	Maximum Power Output possible from Storage (MW)
MPI:	Maximum Power Input possible into Storage (MW)
WPO_H :	Wind Plant Output in the hour (MWh), also since each time interval is 1 hour this is also equal to the average power output (MW) from the plant in the hour
E_{stored} :	The amount of energy stored in storage at the beginning of the hour (MWh)
E_{Min} :	The amount of energy that should always be available in Storage below which it cannot be discharged based on Depth of Discharge (MWh)
E_{Max} :	Maximum amount of energy possible in storage system based on energy capacity (MWh)

We now present the flowcharts depicting the logic for the different policies:

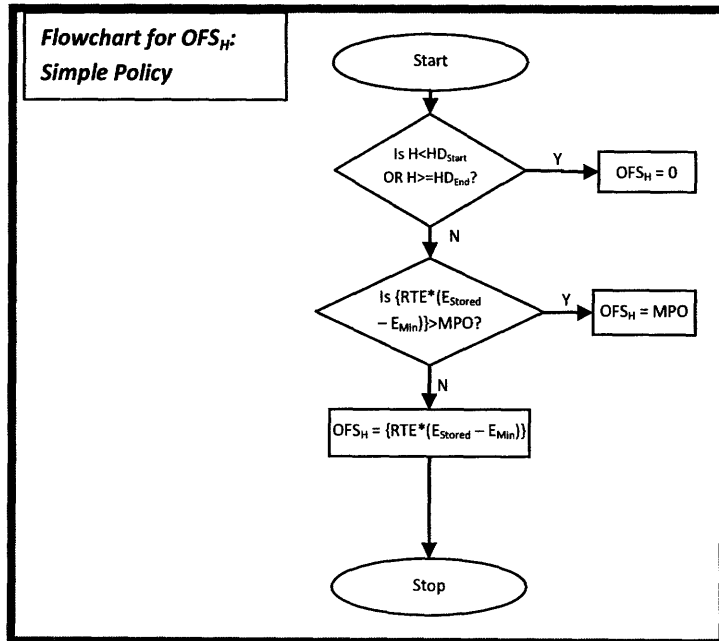
1. Policy for input (charging) to storage – common for Simple, Cost-Based, and Max Peak policies
2. Policy for output (discharging) from storage – Simple
3. Policy for output (discharging) from storage – Cost-Based
4. Policy for output (discharging) from storage – Max Peak
5. Policy for input (charging) to storage – Rapid Arb
6. Policy for output (discharging) from storage – Rapid Arb

Policy for Charging Storage: Simple, Cost-Based, and Max Peak Policy

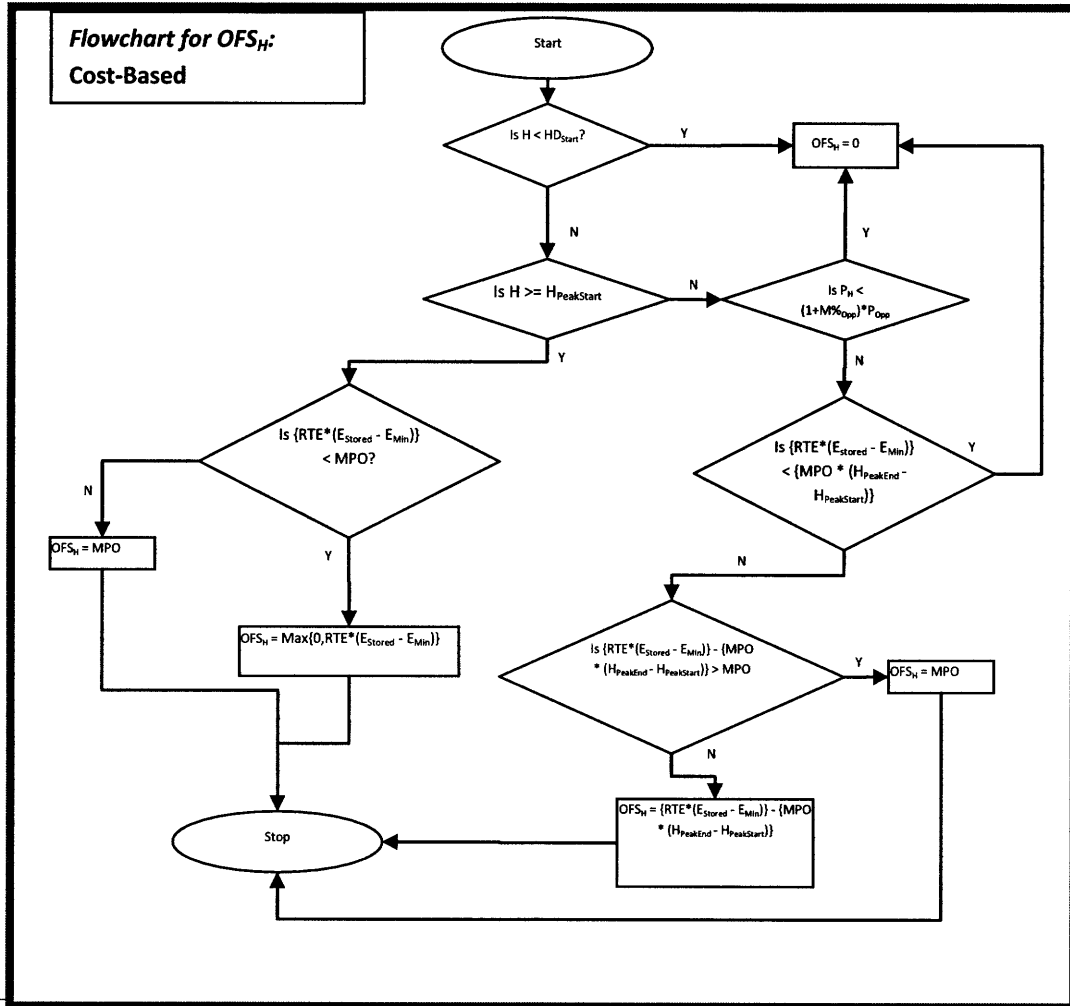


¹ For the Hybrid Policy the Right Hand Side of these equations becomes MPI instead of MIN (MPI, WPO_n)

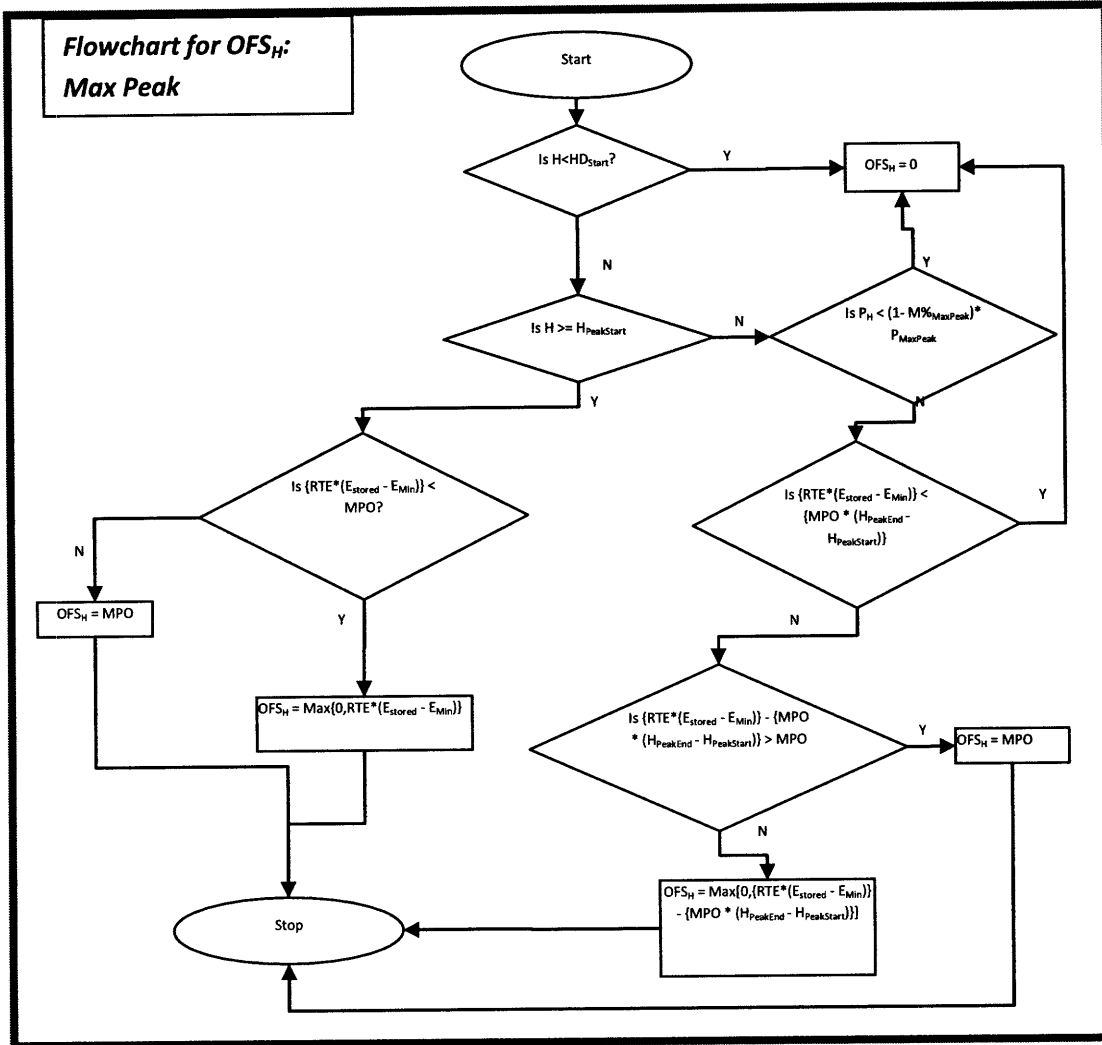
Policy for Discharging Storage: Simple Policy



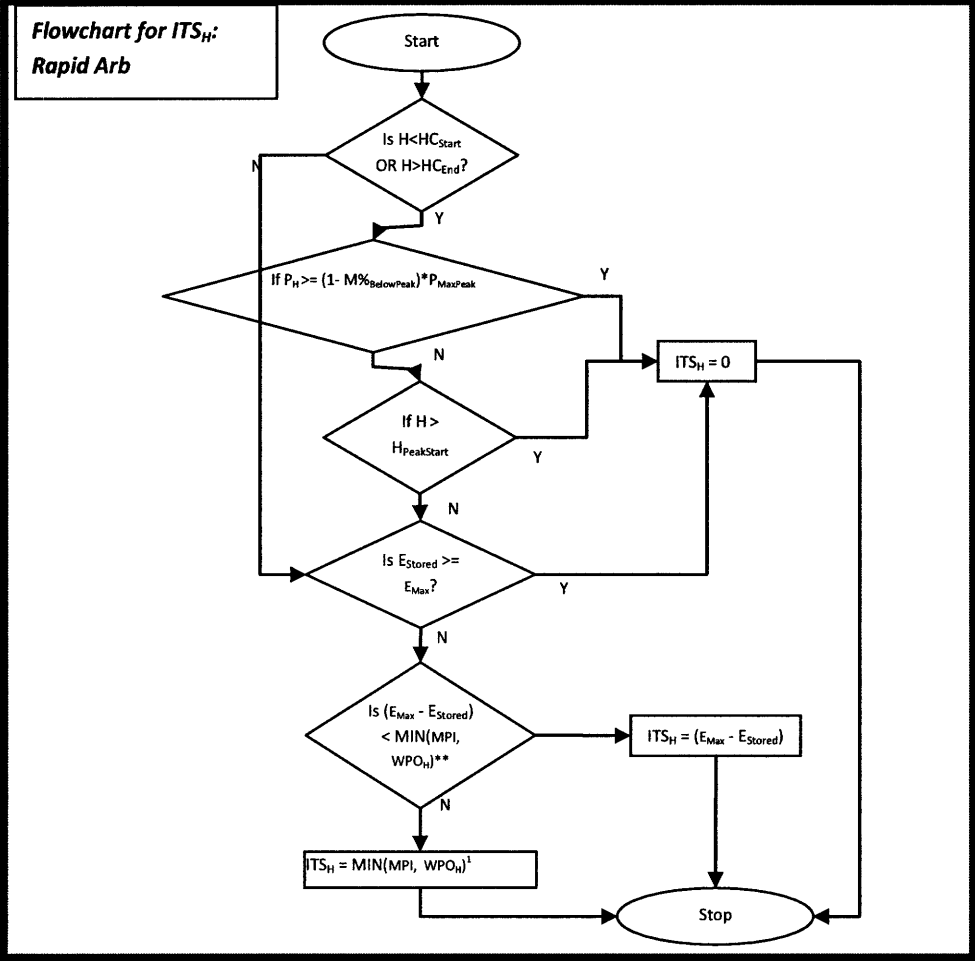
Policy for Discharging Storage: Cost-Based Policy



Policy for Discharging Storage: Max Peak

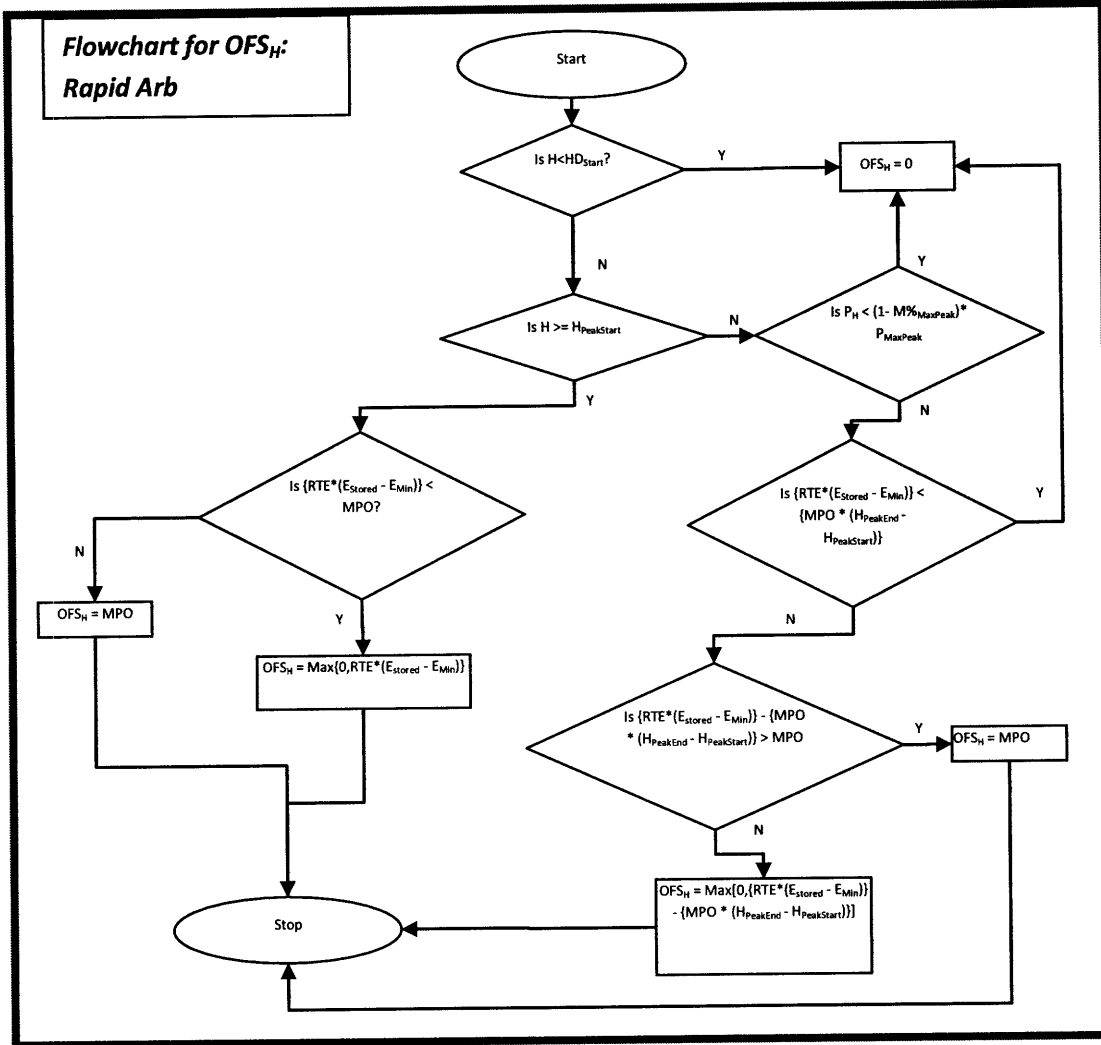


Policy for Charging Storage: Rapid Arb



¹ For the Hybrid Policy the Right Hand Side of these equations becomes MPI instead of MIN (MPI, WPO_H)

Policy for Discharging Storage: Rapid Arb Policy



Appendix 4: Shortlisted Configurations for Input to the Model

The various input configurations to the model are presented in the Table below

Configuration	1	2	3	4	5	6	7	8	9	10	11	12	13	14
LOCATION	Co-Located	Co-Located	Co-Located	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located
STORAGE CAPACITY as % of Wind Capacity	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	35%	35%	35%
MARKET	Real-Time	Real-Time	Real-Time	Real-Time	Real-Time	Day-Ahead	Day-Ahead	Real-Time	Real-Time	Day-Ahead	Day-Ahead	Real-Time	Real-Time	Day-Ahead
SUPPLY LINKAGE	Linked	Linked	Linked	Linked	Linked	Linked	Linked	Hybrid	Hybrid	Hybrid	Hybrid	Linked	Linked	Linked
Daily Operating Policy	Simple	Cost-Based	Max Peak	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb

Configuration	15	16	17	18	19	20	21	22	23	24	25	26	27
LOCATION	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob	Co-Located	CosCob
STORAGE CAPACITY as % of Wind Capacity	35%	35%	35%	35%	35%	20%	20%	20%	20%	20%	20%	20%	20%
MARKET	Day-Ahead	Real-Time	Real-Time	Day-Ahead	Day-Ahead	Real-Time	Real-Time	Day-Ahead	Day-Ahead	Real-Time	Real-Time	Day-Ahead	Day-Ahead
SUPPLY LINKAGE	Linked	Hybrid	Hybrid	Hybrid	Hybrid	Linked	Linked	Linked	Linked	Hybrid	Hybrid	Hybrid	Hybrid
Daily Operating Policy	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb	RapidArb

We ran simulations for all of these 27 input configurations for all the 190 days in summer and winter. As the technical parameters of both the Alpha and Beta Battery are the same they do not figure in the simulations for calculating the Incremental Gross Profit.

Hence total number of configurations for simulation = 27 configurations * 95 days * 2 seasons = **5,130 configurations**

Appendix 5: Results of ANOVA Test for Comparison of Policies

We present below the results of the Analysis of Variance (ANOVA) test conducted to ascertain whether there is a statistically significant difference between the incremental daily gross profit earned with the 4 operating policies viz. Simple, Cost-Based, Max Peak and, Rapid Arb. For an explanation of the policies see Section 3.2. The ANOVA results are presented for the following Model Input Configuration for both a low and high wind plant electricity output day {*Winter, Alpha or Beta, Co-loc, 50%, RT, Linked*}

Figure A5-1: One-Way ANOVA Results - Daily Operating Policies on a Low Wind Plant Output Day

{*Winter, Alpha or Beta, Co-loc, 50%, RT, Linked*}

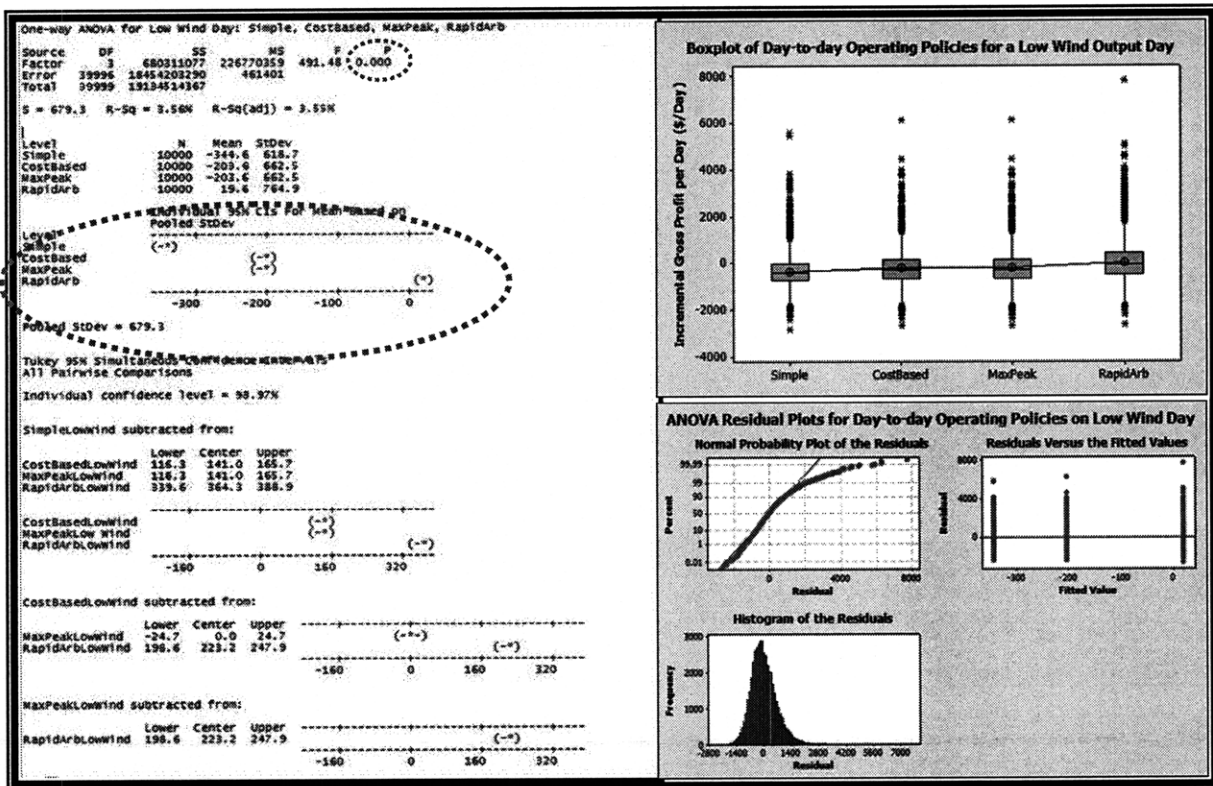
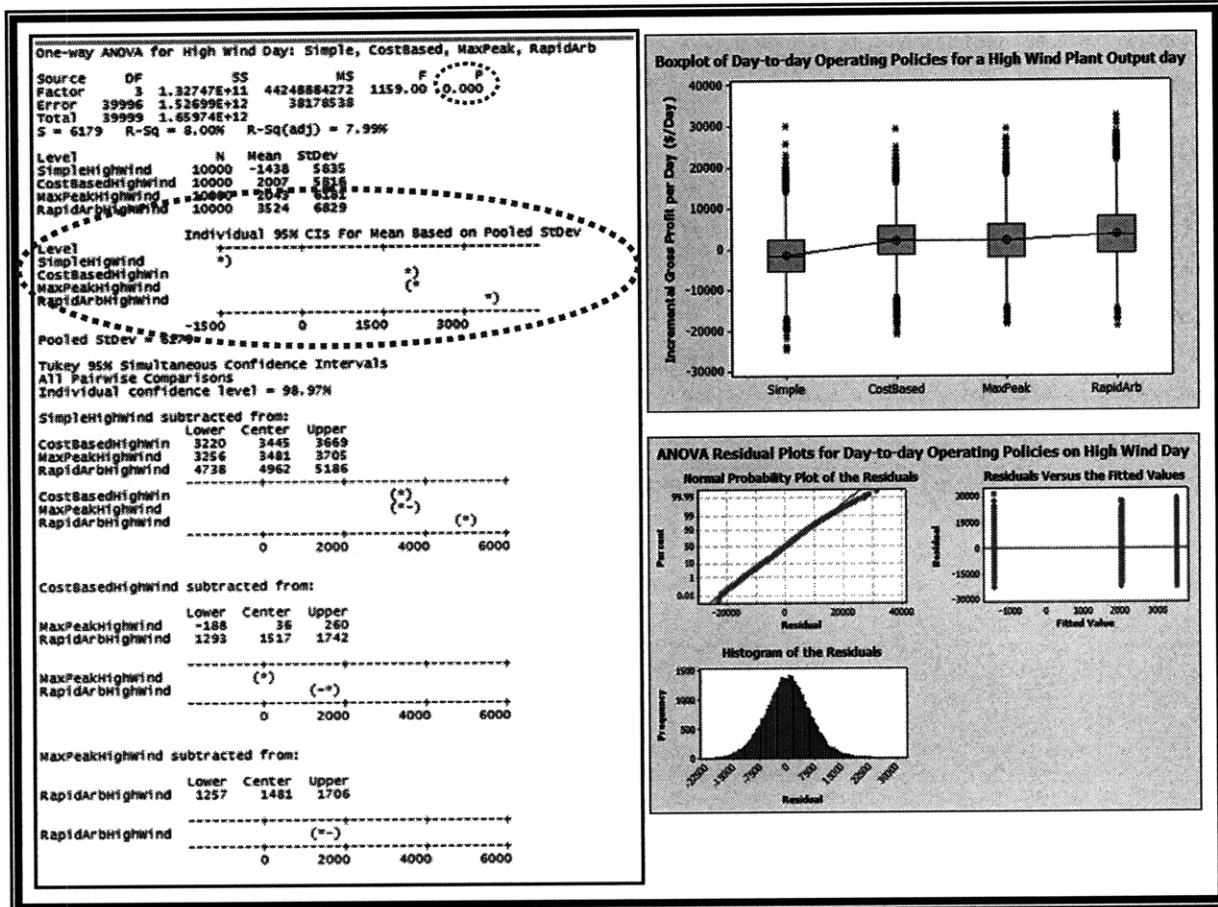


Figure A5-2: One-Way ANOVA results - Daily Operating Policies on a High Wind Plant Output Day

{Winter, Alpha or Beta, Co-loc, 50%, RT, Linked}



Inference: There is a statistically significant difference between at least one policy and the others (p value $\ll 0.01$). Based on the Tukey's Test and Individual 95% Confidence Interval Plot for the Means, the Rapid Arb Policy and the Simple Policy are significantly different from the Cost-Based and Max Peak Policy

Appendix 6: Calculation of Possible Installed Capacity Payments for Battery Storage

We present below the calculation of possible monthly Installed Capacity Payments for battery storage systems, if they were to be treated in a manner similar to Pumped Hydroelectric Storage units.

Installed Capacity Payments in the New England Region

The New England Independent System Operator (NE-ISO) ensures adequacy of generation capacity on the Electricity Grid by providing fixed payments to resources that add capacity to the network. This payment is made irrespective of the actual amount of energy that these resources provide in a given period. This payment for installed capacity will be governed by auctions held in the Forward Capacity Market starting June 1, 2010. In the interim “Transition Period” all qualified capacity resources in the NE-ISO region get paid at a Transition Rate, which is \$4.10/ KW-month currently (ISO New England, 2008). Very simply put, all qualifying resources receive this payment based on their established reliable capacity. This reliable capacity is established based on audits by the NE-ISO and based on performance data submitted by the generator. The capacity for which the payment is made is measured as the UCAP (unforced capacity) and is measured as

$$\text{UCAP} = \text{ICAP} * (1 - \text{EFORd})$$

where ICAP is the claimed installed capacity of the resource and EFORd is the Equivalent Forced Outage Rate determined based on the performance data submitted by the generator. For resources that cannot submit their performance data, the EFORd is determined by the average forced outage rate for that class of generators (ISO New England EFORd Class Averages From NERC Brochure, 2008). To earn this installed capacity payment, the resource has to necessarily commit to make an offer in the Day-Ahead. However, “intermittent resources” such as wind are exempt and receive this payment even if they do not participate in the Day-Ahead market.

Pumped Hydroelectric Storage units in the New England region are treated as “Limited Energy Resources” (ISO New England Rules and Procedures, 2008). This means they are not expected to generate electricity for all the 24 hours of a day. In fact to qualify for Installed Capacity Payments, pumped storage units have to demonstrate the claimed capacity for 4 hours during summer and for 2 hours during winter. In addition to qualify for Installed Capacity Payments pumped storage units must submit a Supply Offer for the full available capability of the unit in the Day-Ahead Market. Hence pumped storage units get Installed Capacity Payments based on their installed capacity as per the UCAP formula and the transition period payment rate described earlier.

Battery storage units are very similar in operation to a pumped storage unit in that they consume electricity from the Electricity Grid during off-peak hours and sell back the electricity to the market during the peak hours. Hence, we argue that battery storage units should also be treated as “Limited Energy Resources” and should get paid an installed capacity payment.

Estimation of Possible Installed Capacity Payments to Battery Storage

To get an estimate for the installed capacity payment we have used the following numbers:

ICAP: Installed Capacity = 60MW for our model

EFORd = Equivalent Forced Outage Rate = 27% (we picked the maximum EFORd value from the class average values provided by the NE-ISO). This helps us get a conservative estimate.

Therefore $UCAP = ICAP * (1 - EFORd) = 60MW * (1 - 0.27) = 43.8MW = 43,800KW$. There using the transition period payment rate of \$4.1/KW-month we get

<i>Monthly Installed Capacity Payment = 43,800 KW * \$4.1/KW-month = \$179,580 / month = \$5,986 / day</i>

It should be noted that this is a **conservative estimate** as we have used the worst possible value of the EFORd.