Optimal Implementation of Energy Storage Systems in Power Distribution Networks

A THESIS
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
MASTER OF SCIENCE

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June 2012

Acknowledgements

I would like to acknowledge the National Science Foundation (grant number 0831059) for financial support of my graduate research at the University of Minnesota and for the opportunity to collaborate with researchers at Tsinghua University in Beijing, China, as part of the East Asia Pacific Summer Institute.

I would like to acknowledge the support of my parents and loving wife, Kaige, without whose help it would have been impossible to pursue my passion for learning. I would like to thank my lab-mate and friend Dr. Anthony Giacomoni for providing valuable feedback on my research. I would also like to thank Professor John Gunnar Carlsson of the Industrial and Systems Engineering Department for serving as reviewer on my final oral examination committee.

Finally, I would like to thank my academic co-advisors, Professor Massoud Amin and Professor Bruce Wollenberg, for their guidance and support throughout my graduate career and for their many words of encouragement.

Abstract

A fundamental constraint in electric power system operations is the need to maintain equilibrium between supply and demand, instantaneously and all times. Energy storage systems present an opportunity to transcend the power balance paradigm by allowing energy to be stored and released at different times. The potential applications of grid-integrated energy storage systems cover the entire electric power delivery supply chain, from generation to end-use, and potential benefits range from improved frequency regulation and dynamic stability to superior utilization of renewable and distributed energy resources.

This thesis investigates the optimal planning and operation of energy storage systems in the power distribution system from the *consumer's perspective*. Two specific applications are chosen to illustrate the benefits of improved energy management and service reliability provided by energy storage systems: customer premise energy storage and distributed energy storage systems (DESS). Optimization models and solution methodologies are developed for both applications, and simulations are performed to compare and contrast various storage technologies, operational settings and solution algorithms.

The unique outcomes of this research are:

- Pareto-optimal capacity partitioning and economic assessment of customer-premise energy storage systems for multi-use applications: Section 4.9
- Optimization model and solution algorithms for prioritization of distribution system emergency backup service: Sections 5.4 – 5.6
- Optimization model and solution algorithm for determining the optimal mix and placement of distributed energy storage systems in distribution systems for reduced customer outage costs: Sections 5.7 – 5.9

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List of Abbreviations

AC	Alternating Current
ARRA	American Recovery and Reinvestment Act
BESS	Battery Energy Storage System
CAIDI	Customer Average Interruption Duration Index
CES	Community Energy Storage
C&I	Commercial and Industrial
CND	Cumulative Normal Distribution
DC	Direct Current
DESS	Distributed Energy Storage System
DoD	Depth of Discharge
DOE	Department of Energy
EDLC	Electric Double Layer Capacitor
EPRI	Electric Power Research Institute
ESCo	Energy Service Company
ESS	Energy Storage System
FACTS	Flexible AC Transmission System
FERC	Federal Energy Regulatory Commission
GLM	Generalized Linear Model
HMI	Human Machine Interface
IEEE	Institute of Electrical and Electronics Engineers

kW	Kilowatt
kWh	Kilowatt-hour
LA	Lead Acid
LBNL	Lawrence Berkeley National Laboratory
MISO	Midwest Independent System Operator
MTTR	Mean Time To Repair
MW	Megawatt
MWh	Megawatt-hour
NaS	Sodium Sulfur
PG&E	Pacific Gas & Electric
QoS	Quality of Service
RPS	Renewable Portfolio Standard
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	Supervisory Control and Data Acquisition
SMES	Superconducting Magnetic Energy Storage
SoC	State of Charge
STATCOM	Static Synchronous Condenser
T&D	Transmission and Distribution
TOU	Time of Use
UPS	Uninterruptible Power Supply
VAR	Volt-Ampere Reactive
Zn-Br	Zinc Bromine

1. Introduction

The electric power industry has always operated on the principle of instantaneously supplying demand. Everything from generation capital planning to real-time control center operations have been dictated by the necessity to maintain the balance between megawatts-in and megawatts-out across the entire network at all times. The root cause of this constraint has been the inability to store electricity at any point in the supply chain [1].

Grid energy storage systems present an opportunity to transcend the power balance paradigm by allowing energy to be stored and released at different times. The ability to move energy in time opens up a plethora of potential applications that cover the entire electric power value chain, from generation to end-use. Energy storage can be used to balance the variability of renewable generation and, properly deployed and integrated, can increase grid reliability and asset utilization [2]. As we will see, energy storage systems can also provide direct benefits to end users through reduced rates, decreased outage costs and improved power quality.

Until recently, the costs associated with implementing energy conversion and storage systems have outweighed their benefits and the investment in storage technology research and development was limited. The only storage technology that has been widely implemented is pumped hydro, which involves pumping water from a low elevation to a high elevation reservoir where it is stored and later released to turn hydro-turbines and generate electricity. The following figure shows the comparative estimates of total current electric energy storage capacity worldwide.

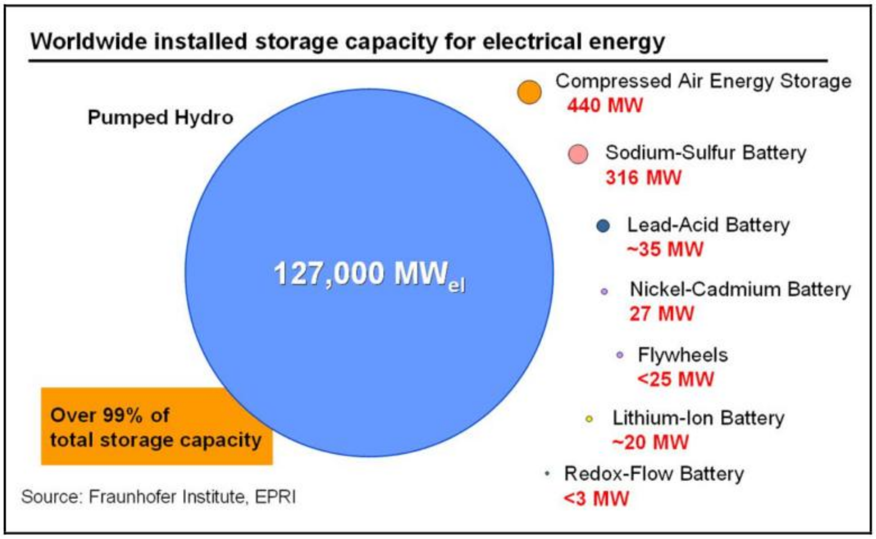

Figure 1: Worldwide Installed Storage Capacity for Electrical Energy [3]

Despite technological and economic challenges, a recent confluence of industry drivers has spurred utilities, regulators, researchers and private companies to rethink electric energy storage [4].

1.1. Industry Drivers

Recent economic, regulatory and technological trends have begun to make storage solutions economically feasible. The following trends and policies are a few of the many important industry drivers:

- **Economic**: Higher price differences between on-peak and off-peak power [4]
- **Technological**: Technological maturation of advanced battery technologies due to investments in R&D for consumer and transportation applications [4]
- **Regulatory**: A 2011 Federal Regulatory Energy Commission (FERC) mandate [5] that supports fast-ramping short term regulation resources, such as energy storage technologies.
- **Regulatory-Economic**: State-mandated renewable portfolio standards (RPS) have increased the penetration of renewable resources on the grid. In turn,

the variability of wind and solar has increased market compensation for reserve and regulation services [6].

- **Military**: Critical military installations are increasingly vulnerable to commercial electric grid outages [7], creating a need for long-duration emergency backup solutions.

In addition, federal policies such as the United States Energy Storage Competitiveness Act of 2007 [8] have helped grid storage technology development become a national imperative and federal funding has provided opportunities to test new technologies in the field. The following table summarizes the $185 million in project funding awarded for the Smart Grid Storage Demonstrations sub-category of the American Recovery and Reinvestment Act (ARRA) [9].

Table 1: ARRA-Funded Utility Energy Storage Projects [10]

Utility	Location	Rating	Technology
BATTERY STORAGE FOR UTILITY LOAD SHIFTING OR FOR WIND FARM DIURNAL OPERATIONS AND RAMPING CONTROL			
Duke Energy	Goldsmith, TX	24 MW	Proprietary
Modesto Irr. District	Modesto, CA	25MW / 75MWh	Zn-Cl Flow
SoCal Edison	Tehachapi, CA	8MW / 32MWh	Lithium Ion
FREQUENCY REGULATION ANCILLARY SERVICES			
PPL Corp/Midwest Energy	Tyngsboro, MA; Hazle Township, PA	20MW / 5MWh	Flywheel
DISTRIBUTED ENERGY STORAGE FOR GRID SUPPORT			
Painesville Municipal	5 locations in OH, PA, VA, IN, MA	1MW / 6-8MWh	Vanadium Redox
Detroit Edison	Hanover, MA; West	25kW / 50kWh (20	Lithium Ion

	Lebanon, Hanover, NH	units)	
Met-Ed	Lyons Station, PA	3MW / 1-4MWh	Supercapacitor/ Lead Acid
National Grid, Sacramento MUD	4 locations in MA, NY and CA	500kW / 3MWh (5 units)	Zn-Br Flow
Public Service NM	Alburquerque, NM	500kW / 2.5MWh	Adv. Lead Acid
COMPRESSED AIR ENERGY STORAGE (CAES)			
Iberdrola, USA	Watkins Glen, NY	150MW / 1200MWh	CAES
Pacific Gas & Elec.	Kern County, CA	300MW / 3000MWh	CAES

These industry drivers and many others are setting the stage for energy storage to become a significant new resource in the 21st century power grid.

1.2. Potential Benefits of Energy Storage

The potential benefits of energy storage cover the entire electric power supply chain and are closely tied to the application for which the system is being used. As shown below, benefits can be subdivided along two axes: discharge time and size of application.

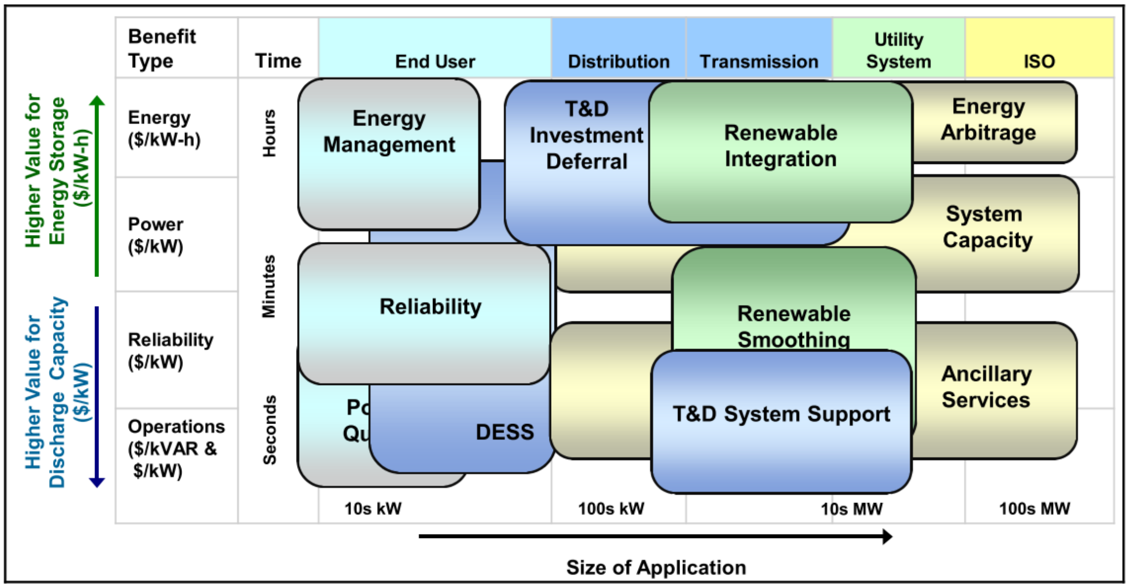

Figure 2: Operational Benefits Monetizing the Value of Energy Storage [3]

Small systems with short discharge times can be used for fast-response applications such as managing voltage spikes/sags, momentary outages and other transient events. Systems with long discharge times can help energy intensive customers reduce electric service charges by shifting demand from high cost peak hours to low cost off-peak hours. At the other end of the spectrum, megawatt-scale storage systems can earn revenue by participating directly in regulated power markets. Systems with long discharge times are often treated in a comparable manner to generators and price sensitive loads in power markets. Short-term stored energy resources, such as storage batteries and flywheels, are currently eligible to participate in the Midwest Independent System Operator’s (MISO) day ahead and real-time ancillary service markets as regulating reserves, where 1MW is the minimum offer per hour [11]. Storage systems can also be implemented to support utility transmission and distribution operations and defer capital investments.

1.3. Research Motivations for Customer Perspective Analysis

At the level of bulk power generation and transmission, the costs and benefits of energy storage systems naturally accrue to the companies that own and operate the power grid. As storage technologies are deployed at lower and lower voltages levels, however, storage system applications and benefits begin to shift from the utility to the end-user. Since consumers and utility companies that serve them operate under entirely different sets of economic incentives, a balanced assessment of storage system benefits requires framing storage system planning problems from both the utility perspective as well as the customer perspective, particularly at the distribution level. In fact, “value-based planning” is common to many engineering fields and is based on the principle of matching the level of investment with the societal benefit of the improvement [12], [13]. Despite this, the vast majority of the literature on energy storage systems neglects to incorporate customer value in problem formulation and there is a need for research in this area.

Furthermore, Smart Grid and other industry trends will introduce fundamental changes to the utility business model. Some analysts predict the rise of private third-party companies to serve a market between state regulated utilities and their present-day customers, in a process dubbed disintermediation [14]. Already, Energy Service Companies (ESCo) exist that provide “value-added” services such as planning and implementation of energy conservation projects and infrastructure outsourcing. And energy aggregators, such as EnerNOC [15], make a profit by pooling end-user demand response or distributed energy resources in return for utility or market compensation. Pacific Gas & Electric (PG&E), for instance, actively advertises a large commercial and industrial aggregator program on their website [16]: *“Acting as intermediaries between you and PG&E, aggregators offer you demand response program options not available through PG&E.”* As new players enter this consumer-centric market, customer value engineering planning methodologies will need to be developed. And while these methodologies already exist for distributed generation [17] such as diesel or gas generators, energy storage system operation varies considerably and merits investigation of its own accord.

Finally, one of the earliest adopters of energy storage systems for distribution system applications is likely to be the military, which is highly dependent on the commercial power grid. The need for decreased grid dependence has been clearly addressed by senior Department of Defense officials [7] and a report by the Defense Science Board found, "*Backup power (for critical military installations) is often based on diesel generator sets with limited on-site fuel storage, undersized for new Homeland defense missions, not prioritized to critical loads, and inadequate in duration and reliability.*" [18] Distributed energy storage systems (DESS) represent a unique approach to mitigating reliance on commercial energy infrastructure. DESS can either be sited directly at critical loads to allow uninterrupted power supply or used to allow larger groups of loads to be to ride through outages through intentionally islanding of critical sub-networks. To make this latter application practical, it is often necessary to limit backup supply to critical loads by performing Quality of Service (QoS) load shedding, a technique being investigated for Navy shipboard applications [19]. The concept of prioritized outage ride-through is investigated in detail in sections 5.4 - 5.6 of this thesis.

1.4. Objectives and Contributions

The first objective of this thesis is to define and quantify the potential customer value of energy storage systems for a specific set of applications. The second objective is to investigate the optimal planning and operation of energy storage systems from the consumer's perspective and to investigate the merits and operational idiosyncrasies of different energy storage technologies. Specifically, this work attempts to answer the following questions:

- What application areas provide the most value to the end user?
- How can we quantify the value of service reliability for individual customers?
- How should customer-premise energy storage technologies be dispatched?
- What is the effect of load and generation forecast availability and quality for energy and demand management applications?
- Does it make sense for groups of customers to pool storage resources?
- What is the optimal placement of energy storage systems in the distribution system?
- What is the importance of storage system characteristics such as capacity, power rating, cycle life and conversion efficiency?
- What are the most cost-competitive storage technologies available?

In investigating these questions, this thesis has developed the following analytical tools for customer perspective analysis:

- A mathematical model for quantifying the value of reliability and power service
- Optimization model and solution algorithms for commercial and industrial customer-premise energy storage system scheduling
- Multi-application operation via capacity partitioning for customer-premise energy storage systems
- Economic assessment of available storage system technologies for customer-premise applications
- Optimization model and solution algorithms for prioritizing outage ride-through service for end users in the distribution network
- Optimization model and solution algorithms for determining the optimal mix and placement of distributed energy storage technologies for emergency backup

1.5. Thesis Structure

This thesis is comprised of two introductory chapters and two chapters on the optimal planning and operation of energy storage systems in the distribution network. Chapter 2 first describes and classifies energy storage systems and discusses storage system applications and potential benefits. Next, a shortlist of technologies is selected to use in optimization simulations and an appropriate storage system model is developed. Chapter 3 provides the necessary background to model the customer value and storage system operating constraints by discussing electricity rate structures, distribution system operations, distribution reliability and customer outage cost estimation. Chapter 4 addresses the optimal planning and operation of customer-premise energy storage systems. Using the University Minnesota Morris as a test case, an optimization model for optimal dispatch of energy storage systems is presented and a number of simulations are carried out before making a planning recommendation based on common economic metrics. Chapter 5 investigates the optimal implementation of energy storage systems in the distribution system for emergency backup. By first addressing the issue of which customers to serve and analyzing the reliability of distribution system sub-networks, the optimal mix and placement of storage resources is determined. Chapter 6 concludes the thesis with a discussion of findings and insights.

2. Energy Storage Systems

Electric energy storage technologies consist of two fundamental stages: a grid-connected electricity conversion stage and an energy storage stage. The conversion stage is required to transform and convert three phase AC power into a form that can be transferred to and from the storage stage. Electric energy conversion is achieved either by a rotating electric machine that converts electricity directly into mechanical rotational kinetic energy, or by power electronic converters, which convert AC electricity into DC electricity and vice versa via an inverter/rectifier pair. The energy storage stage consists of the mechanisms required to deliver and accept energy from its stored state. The figure below is a conceptual diagram of the grid, conversion and storage stages.

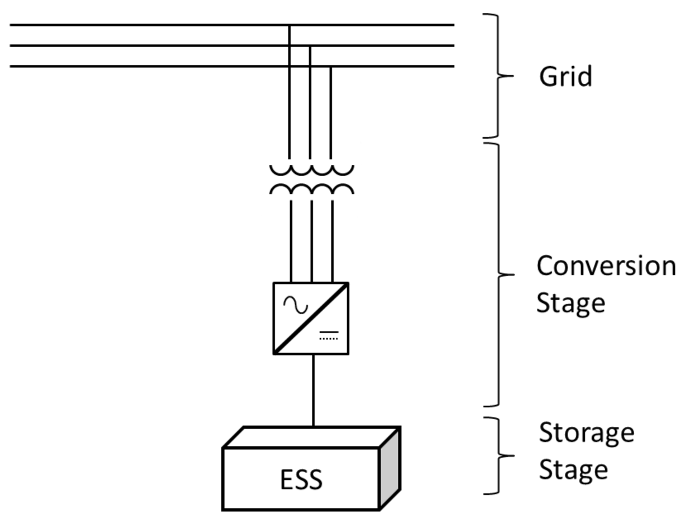

Figure 3: Grid Energy Storage System Conceptual Diagram

In addition to the conversion and storage stages, grid-tied energy storage systems also require sensing and protection subsystems to comply with utility standards for grid interconnection. At the distribution level, these requirements are outlined in IEEE standard 1547 [20]. Energy storage systems may also contain communications and control components to enable integration with utility control center Supervisory Control and Data Acquisition Systems (SCADA) systems. Internally, energy storage systems have supporting subsystems for condition monitoring and environmental control and may be equipped with a Human Machine Interface (HMI) for engineering configuration. Shown below is a generalized schematic for ABB's PCS100 Energy Storage System® [21].

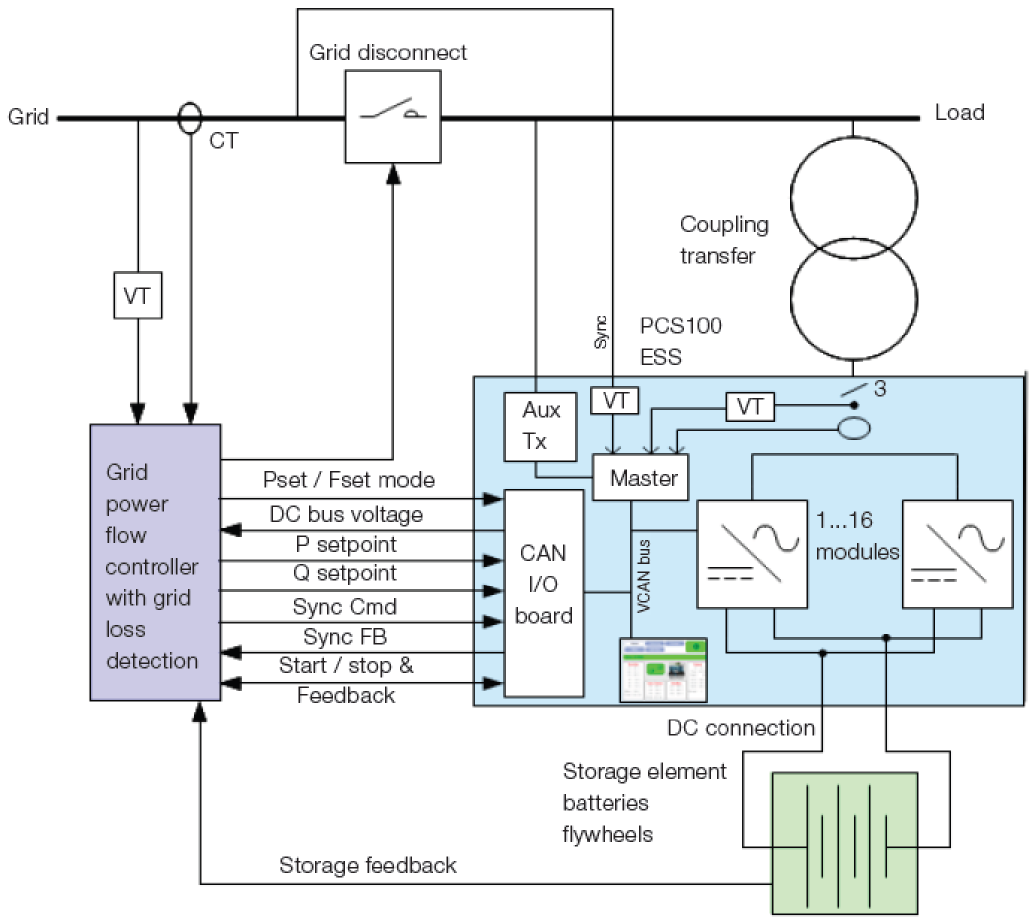

Figure 4: ABB's PCS100 Energy Storage System [21]

2.1. Parameters

The technologies used to store electrical energy are extremely diverse. Prior to comparing their characteristics and discussing their applications, it is necessary to define the following terms and parameters:

- **Available Energy Capacity, W_{op}:** The quantity of stored energy that is retrievable as electric power.
- **Rated Power, P_{rated}:** The nameplate value for the rate at which electric energy can be continually stored or extracted from the storage system, usually given in kilowatts (kW) or megawatts (MW). Also referred to as the discharge capacity.
- **Discharge Time, $t_{storage}$:** The duration of time that the energy storage system can supply rated power, given as:

$$t_{storage} = \frac{W_{op}}{P_{rated}} \tag{1}$$

- **Energy Density:** Available energy capacity per unit mass, given in W-h/kg.
- **Power Density:** Rated power per unit mass, given in W/kg.
- **Round-Trip Efficiency, $\eta_{round\text{-}trip}$:** The overall efficiency of consuming and later releasing energy at the point of common coupling with power grid. Also known as AC-AC efficiency, round-trip efficiency accounts for all conversion and storage losses and can be broken into charging and discharging efficiencies.

$$\eta_{round-trip} = \eta_{charge}\eta_{discharge} \cong \eta_{one-way}^2 \tag{2}$$

- **Cycle Life**: The maximum number of cycles for which the system is rated. The actual operating lifespan of the battery is either the cycle life or the rated lifespan, whichever is reached first.

Additional parameters and performance indices can be found in [22].

2.2. Storage Stage Technology Classification

Electrical energy storage technologies can be classified according to the form of stored energy, as listed below:

- **Electrochemical**: Electrochemical, or battery, energy storage involves the use of chemical reactions to convert electrical energy to chemical potential energy and vice versa. Energy conversion takes place in an electrochemical cell when electrons are transferred between an electrode, typically a metal or semiconductor, and an electrolytic solution containing electrically charged free ions. Electrochemical cells are aggregated in series and parallel to achieve the desired electrical characteristics. Battery energy storage systems (BESS) are characterized by high energy density, high round trip efficiency, good cycling capability, long life and low initial cost [23]. The most common electrochemistries and characteristics of battery energy storage systems used in this thesis are outlined in appendix A.
- **Electrical:** Capacitors store electric energy directly in the electric field between charged plates. The quantity of energy stored is proportional to the capacitance of the dialectric material separating the charged plates and the electric potential. Compared to batteries, electric double-layer capacitors (EDLC), or supercapacitors, have higher power densities and low energy densities.
- **Electromagnetic:** The energy stored in a current-carrying conductor is proportional to current squared and inductance. Superconducting magnetic energy storage (SMES) systems utilize DC currents in superconducting coils to store energy in a magnetic field and are characterized by high round-trip efficiency, extremely high power density and low energy density.
- **Mechanical:** Mechanical energy storage requires converting electric energy into mechanical energy and vice versa via a rotating electric machine, such as an induction machine or synchronous generator. Once in rotational kinetic

form, energy is typically converted to another form of mechanical energy such as gravitational potential energy. The following system are the most common types of mechanical grid energy storage:

- Compressed Air Energy Storage (CAES): Electric machines are used to power turbo compressors to compress large volumes of air to high pressures and temperatures. Pressurized air is then released and fired with natural gas to drive turbines and generate electricity.
- Flywheel Energy Storage: Electric machines and power electronics are used to accelerate a mechanical device with a high moment of inertia to very high speeds. Energy is stored in the device as rotational kinetic energy.
- Pumped Hydro: Electricity is used to pump water from a low elevation to a higher elevation reservoir. Later, stored water is released to turn turbines and generate electricity, similar to a conventional hydroelectric plant.

2.3. Technology Comparisons

The next section highlights the salient characteristics of different storage technologies by comparing them along different axes.

- **Power Rating and Capacity**

The two most important operating characteristics of energy storage systems are the energy capacity (kWh) and power rating (kW). The following figure from the Energy Storage Association, and international trade association, shows the discharge time and power rating of installed systems worldwide as of November 2008.

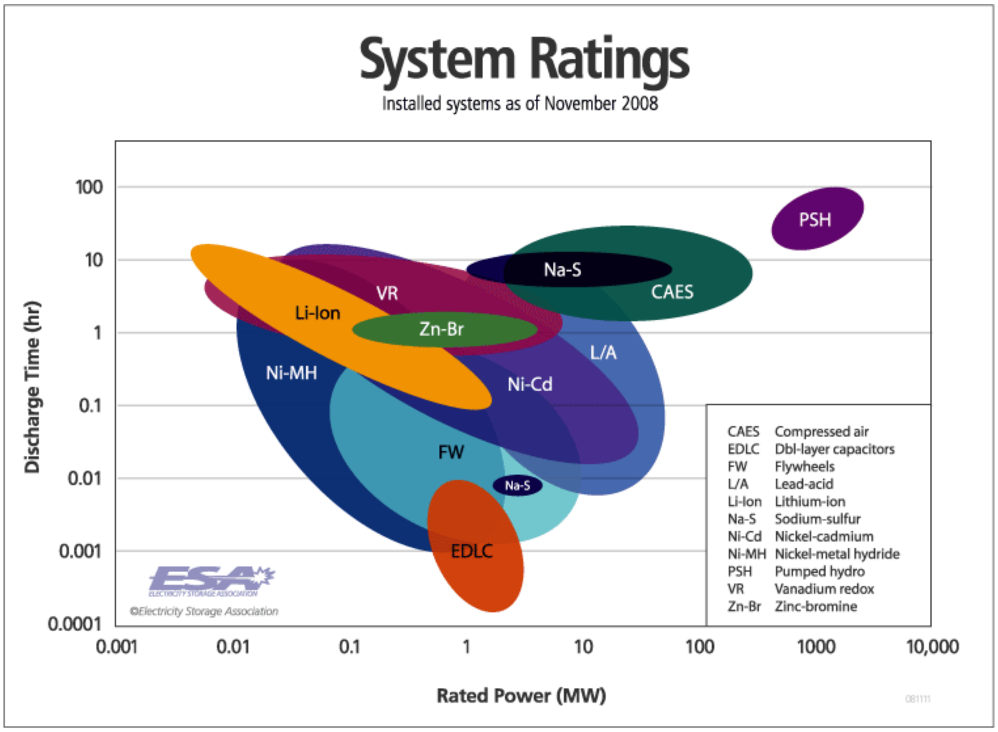

Figure 5: Ratings of Installed Energy Storage System [24]

- **Efficiency, Cycle Life and Cycle Cost**

A major limitation for certain applications, such as energy management, is the fact that the operating lifespan of an energy storage system is reduced if the system prematurely reaches the end of its cycle life. Furthermore, the cycle life is dependent on the average depth of discharge at which the system is cycled. As depth of discharge increases, cycle life is reduced.

Cycle life and round trip efficiency for number of energy storage technologies are depicted in the figure below assuming an average depth of discharge (DoD) of 80%.

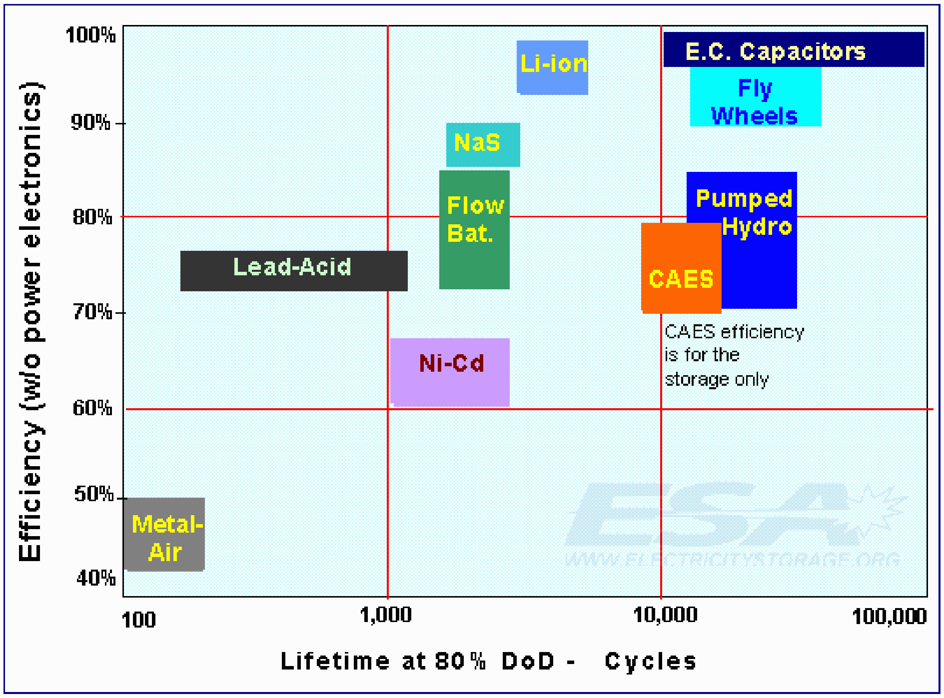

Figure 6: Efficiency vs. Cycle Life [24]

An extension of cycle life is cost per cycle, or cycle cost, which is defined as the capital cost per kWh capacity divided by the cycle life times the efficiency:

$$C_{cycle} = \frac{Capital\ Cost/W_{op}}{\eta * Cycle\ Life} \tag{3}$$

Cycle cost weighs the actual cost of the storage system with the cycle life and efficiency and is one of the most important metrics used in selecting storage technologies for cycle-intensive applications [24].

2.4. Energy Storage Applications

The uses of energy storage systems can be subdivided into generation and system-level applications, transmission and distribution applications and end-use applications. The following table developed by EPRI [3] summarizes ten applications in these three categories.

Table 2: Energy Storage System Application [3]

VALUE CHAIN	APPLICATION		DESCRIPTION
Generation & System Level Applications	1	Wholesale energy services	Utility-scale storage systems for bidding into energy, capacity and ancillary services markets
	2	Renewables integration	Utility-scale storage providing renewables time shifting, load and ancillary services for grid integration
Transmission and Distribution (T&D) System Applications	3	Stationary storage for T&D support	Systems for T&D system support, improving T&D system utilization factor, and T&D capital deferral
	4	Transportable storage for T&D support	T&D system support and T&D deferral at multiple sites as needed
	5	Distributed Energy Storage Systems (DESS)	Centrally managed modular systems proving increased customer reliability, grid T&D support and potentially ancillary services
	6	Energy Service Company (ESCo) aggregated services	Residential-customer sited storage aggregated and centrally managed to provide distribution system benefits
End-user applications	7	C&I power quality and reliability	Systems to provide power quality and reliability to commercial and industrial customers
	8	C&I energy management	System to reduce Time of Use (TOU) energy charges and demand charges for C&I customers
	9	Home energy management	Systems to shift retail load to reduce TOU energy and demand charges
	10	Home backup	Systems for backup power for home offices with high reliability value

At the generation and system level, many energy storage system applications parallel those of traditional synchronous generators such as power energy and capacity market services as well as ancillary services such as frequency regulation [25]. There are also megawatt-scale applications for supporting intermittent renewable generation, such as mitigating the severity of weatherinduced ramps and shifting energy output from low price periods to high price periods, a practice known as energy arbitrage [26].

Transmission system support includes a diversity of applications such as reactive power support and bus voltage control, frequency regulation and power electronics applications such as Flexible AC Transmission System (FACTS) and Static Synchronous Compensators (STATCOM) [27]. The distribution system has additional applications in voltage regulation and reactive power control. T&D deferral refers to the use of energy storage systems to meet capacity requirements that would otherwise require additional capital investments, the most common example of which is using energy storage systems to reduce peak loads thereby avoiding the need for additional peak-time generation capacity.

As discussed in the introduction, this thesis investigates the customer-perspective value of energy storage systems. The majority of benefits that accrue directly to end-users occur at the distribution level, corresponding to application areas 5-10. This thesis specifically investigates commercial and industrial (C&I) applications and distributed energy storage systems (DESS), which are discussed in detail in the next two sections.

2.4.1. Customer Premise Applications

Customer premise energy storage systems are located on the customer side of the meter and provide energy services directly to the end-user. Residential systems have power ratings of 1–10 kW with single phase connection at 120 or 240 V. Commercial and industrial systems range from 10 kW to megawatt levels and would be connected at the appropriate voltage for the customer class [28] . Storage system energy capacity, power rating and cycle capability requirements depend on the specific application area, five of which are summarized below:

- **Energy Management:** Shifting load from one price period to another, thereby reducing energy charges. Energy management, also known as energy arbitrage, is only possible for customers charged according to a Time of Use (TOU) rate structure, discussed in section 3.1, or with real-time pricing.

  - Requirements: Medium energy capacity, medium power rating, high cycle life

- **Demand Management:** Reducing peak consumption during a given period of time, thereby reducing demand charges, discussed in section 3.1. Also known as customer-perspective “peak shaving”.
  - Requirements: High power rating, medium energy capacity
- **Emergency Backup:** Supplying backup power to customers in the event that grid power is unavailable. Outage-related costs are avoided by allowing the customer to “ride through” extended outages, defined as longer than one minute.
  - Requirements: High energy capacity, medium power capacity
- **Power Quality:** Filtering voltage spikes/sags, flickers and other transient events to provide pure sinusoidal AC power to loads. Power quality applications also include the ability to ride through momentary outages, typically defined as less than one minute, which result from reclosers or reclosing circuit breakers attempting to clear temporary faults [29].
  - Requirements: Fast response (i.e. high power capacity)
- **Utility Services:** Provide load control, reactive power support or other distribution system support services to the local utility in return for reduced rates or other compensation.
  - Requirements: Vary depending on service.

Given the high cost of present-day energy storage technologies, customer-premise systems are only practical for customers that are highly dependent on electric power. Examples include data centers that require reliable, high quality power or energy-intensive industrial plants located in areas with high peak-time electricity prices. While the requirements of each application area vary, energy storage systems are oftentimes used to meet multiple operational objectives. Uninterruptible Power Supplies (UPS), for instance, are used to improve both power quality and reliability. This thesis investigates energy storage systems that provide energy management, demand management and emergency backup services, both individually and simultaneously.

2.4.2. Distributed Energy Storage Systems (DESS)

Also known as Community Energy Storage (CES), distributed energy storage systems are implemented in the “last mile” of the distribution grid near the customer but on the utility side of the meter. While the definition and specification of DESS are still evolving, these systems would provide peak load management, reactive power support, voltage control [30] or other utility services and would be controlled in real-time using substation or feeder load signals [28]. With the proper relaying and protection schemes, they could also allow non-faulted subsections of the grid to operate in islanded mode during system outages [31]. DESS applications are closely related to those of microgrids, which are defined as an aggregation of loads and micro-sources that operate as a single, self-controlled system and supply reliable, high-quality power to end-users, even in the case of a grid-side outage [32]. In addition to local uses, DESS is also being considered for aggregated use for frequency regulation and participation in capacity and ancillary service markets.

One approach to implementing DESS is to use many smaller systems that are connected at the secondary (customer voltage) at pad-mounted transformers and are rated for 25-200kW with discharge times of 2-4 hours [28]. This approach is shown in the conceptual diagram below, developed by American Electric Power and a consortium of other utilities and vendors [33].

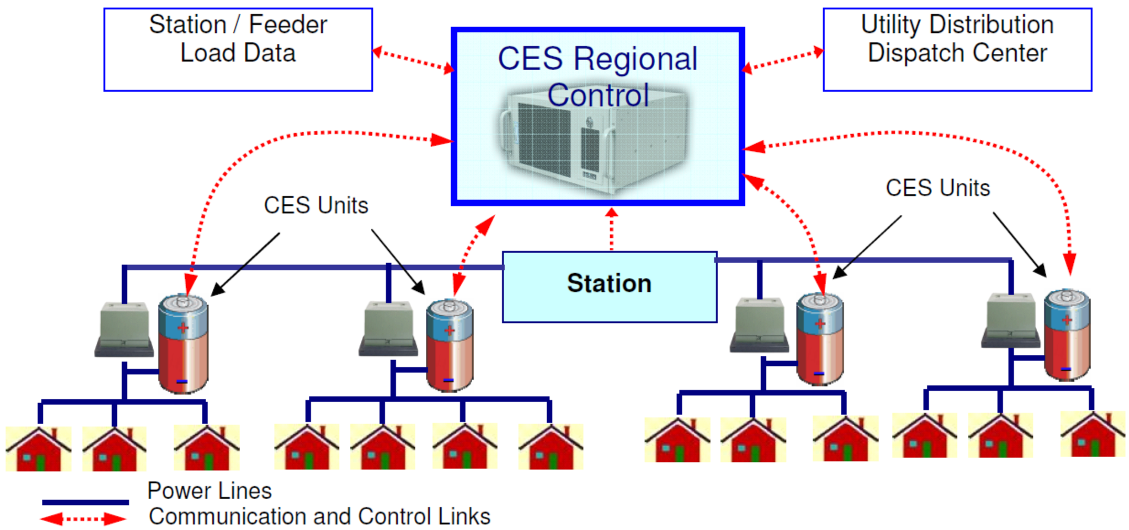

Figure 7: Distributed Energy Storage System Architecture [33]

Another approach is to implement larger 200-5000kW systems that directly support three-phase feeder sections, microgrids or distribution substations. This thesis investigates the use of large systems to provide emergency backup power to groups of customers separated by feeder sectionalizing devices.

2.5. Storage System Selection

Following to the requirements detailed in the previous sections, a shortlist of energy storage systems was compiled for use in optimization simulations of customer premise and DESS applications. The high energy capacity needed to support emergency backup for extended periods of time precluded the use of flywheel, SMES or super-capacitors. Also CAES and pumped hydro are used for very large applications and tend to be site specific and, as a result, only battery energy storage system technologies were selected for simulations. BESS system parameters and prices were obtained from a white-paper on the value of energy storage systems [3] written by the Electric Power Research Institute (EPRI). For a detailed description of individual BESS technologies, see Appendix A.

Table 3: BESS Selected

	Maturity	Energy Capacity (kWh)	Rated Power (kW)	η (%)	Life (cycles)	Cost ($/kWh)	Cycle Cost (¢/kWh)
Advance Lead-Acid 1	Demo-Comm	5000	1000	85	4500	600	0.1569
Advanced Lead-Acid 2	Demo-Comm	1000	200	85	4500	720	0.1882
Sodium Sulfur	Comm	7200	1000	75	4500	500	0.1481
Zinc Bromine Flow 1	Demo	625	125	62	12000	485	0.0652
Zinc Bromine Flow 2	Demo	2500	500	62	12000	440	0.0591
Vanadium Flow	Demo	1000	285	67	12000	1085	0.1350
Lithium Ion	Demo	625	175	87	4500	1085	0.2771

It is important to note that battery systems are modular and can be configured for larger and smaller sizes and that the systems listed above are a representative selection for the specific applications under investigation. Other assumptions made in determining system parameters are discussed in detail in [3]. Capital costs include costs of power electronics, installation costs, project contingency costs that depend on technical maturity, step-up transformer, grid-connections according to utility standards and Smart Grid communication and controls.

Now that candidate system parameters and prices have been obtained, the next step is to develop a model for BESS operation.

2.6. Battery Energy Storage System Generic Model

The level of detail required to model a physical system depends on the phenomena under study. In order to simulate dynamic behavior, for instance, one generally requires a specific model for each storage technology. Generic models have been developed, however, for sub-classes of storage systems that utilize fewer and more accessible parameters [34]. The following dynamic battery model [35], for instance, only requires the manufacturer's discharge curve and a nominal cell efficiency to determine all parameters.

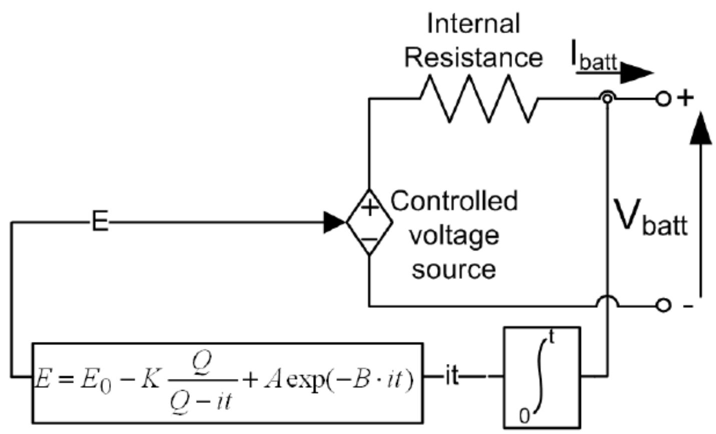

Figure 8: Generic Battery Model for Dynamic Simulations [35]

Here, E_o is an ideal internal voltage, Q is the battery capacity in amp-hours, R is the internal resistance and K, A and B are empirical constants measured from the discharge curve. While many simplifying assumptions are made, this model accounts for the non-linear relationship between terminal voltage and capacity as well as internal losses. Exact voltages and currents can be determined as a function of time and capacity, which is necessary to enforce realistic operating constraints.

Despite the relative simplicity of this model, discharge curves are difficult to obtain for proprietary, grid-scale BESS cells, flow batteries would require model modifications and additional energy collection and conversion elements, such as cables and power electronics, would need to be modeled separately. In addition, since the optimization problems and simulations developed in this thesis are used for long-term planning and operation horizons, which extend from weeks to years, a simpler model is used which can be applied to any type of storage system. The only state variable is energy stored, W_{st}, and the only control variable is power entering the system, P, which can be positive or negative. The model can be thought of as a reservoir of liquid as shown below.

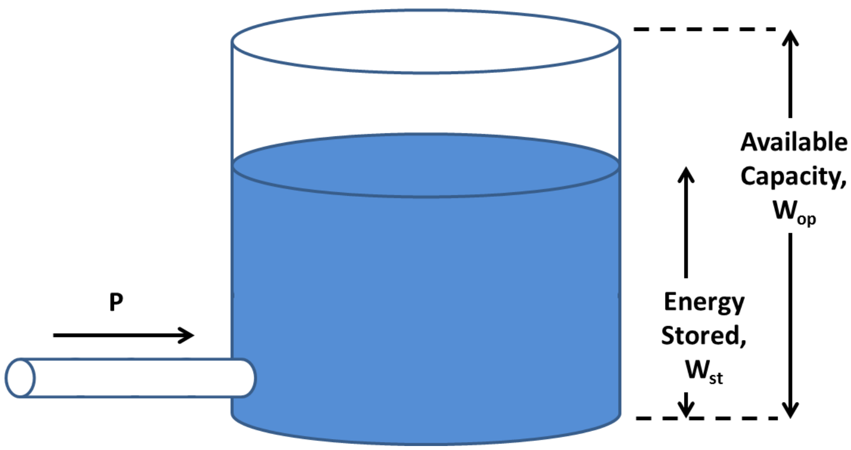

Figure 9: Generic Storage System Model

Mathematically, the relationship between energy and power is expressed as follows:

$$\frac{dW_{st}}{dt} = \eta P \tag{4}$$

where η is the one-way conversion efficiency. Equivalently:

$$W_{st} = W_{st}(t_o) + \int_{t_o}^{t} \eta P d\tau \tag{5}$$

This model makes a number of simplifying assumptions, the most important of which are listed below:

- **Assumption 1**: The efficiency of the entire conversion and storage process is aggregated into one value which remains constant with respect to energy stored and power flow. In reality, there is typically a specific operating region during which the change in efficiency is small, as depicted in the figure below for lead acid batteries.

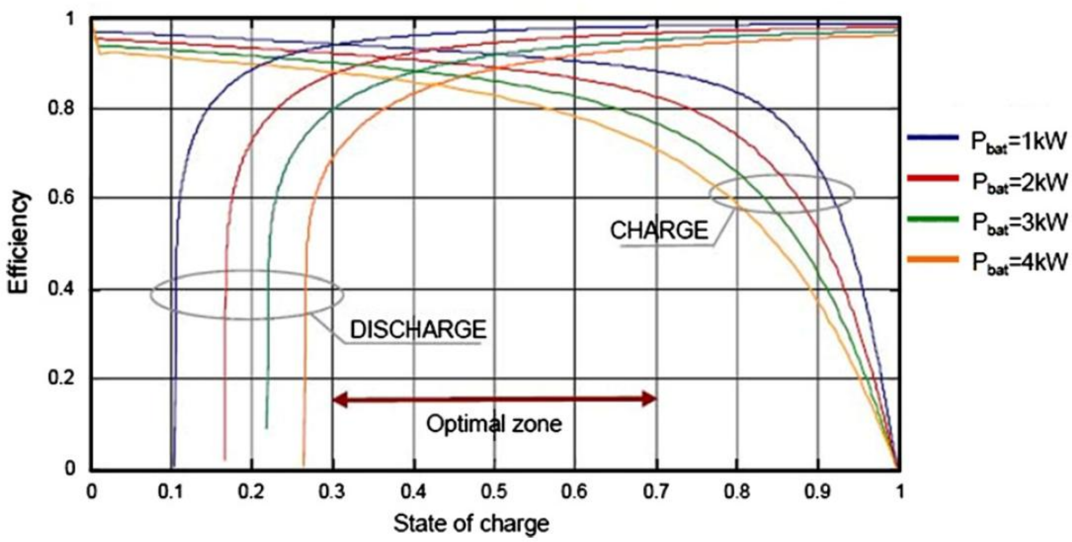

Figure 10: Efficiency of a 48V 15kWh Lead Acid Battery [36]

As addressed below, BESS operation is assumed to be limited to a standard operating region, where non-linear efficiency effects are minimal.

- **Assumption 2**: The model "normalizes" available system capacity to a specific operating region in order to account for all operating constraints. For example, lead acid storage batteries are often specified by the manufacturer not to exceed a maximum depth of discharge of 80%. Hence a lead acid BESS with a total energy capacity of 100kWh would be modeled with an available energy capacity, W_{op}, of 80kWh, since the last 20kWh would be "off limits". Accordingly, the operating constraints of all systems modeled are:

$$0 < W_{st} < W_{op} \tag{6}$$

$$-P_{rated} < P < P_{rated} \tag{7}$$

One justification for these simplifications is that energy storage system vendors are often required by utilities and grid operators to provide fixed capacity and power rating limits, keeping non-essential operating parameters "under the hood". Short-term energy storage resources that participate in MISO's ancillary services market, for instance, are required to provide hourly maximum energy storage level, minimum and maximum MW regulation limits, and an energy storage loss in addition to their MW regulation bids [11].

According to the operating region defined above, the magnitude of energy stored and released in one complete charge/discharge cycle is equal to twice the available capacity. For discrete increments in stored energy, the number of cycles is thus:

$$N_{cycle} = \frac{\Delta W_{st}}{2W_{op}} = \frac{\eta P}{2W_{op}} \tag{8}$$

By extension, the total kWh energy losses incurred by cycling are given as:

$$P_{loss} = W_{op}(1 - \eta^2)N_{cycles} \tag{9}$$

3. Power Distribution Systems

A quantitative estimate of customer value is a pre-requisite for formulating "value-based" capital planning or customer-perspective optimization problems. And, an understanding of the physical context of energy storage systems is required to describe operational constraints. This chapter presents the following analytical tools used in objective function and constraint modeling: commercial and industrial (C&I) customer electricity rate structures, distribution system operations, distribution reliability analysis and customer outage cost modeling.

3.1. C&I Customer Electricity Rate Structures

Commercial and industrial customers are defined as business customers that subscribe to a non-residential electricity service. While practices vary from utility to utility, C&I retail rates typically include a fixed monthly service charge as well as fees based on the amount of real energy consumed, maximum demand during a given time period and power factor.

Depending on the customer's service agreement, energy is either charged at a flat $/kWh rate, which may vary from season to season, or according to a Time of Use (TOU) rate structure, where the price per kWh varies with time of day. In the bulk power system the price of supplying and transmitting power is generally higher during periods of high demand as more expensive units are brought online to meet load and transmission networks become congested. Consequently, TOU rate structures are an important tool for utilities to give consumer's the incentive to reduce consumption during peak-hours, when the utilities costs are highest.

In addition to energy costs, C&I customers also incur a demand charge that is proportional to maximum kW power demand during one billing cycle, where demand is defined as the load average over a specified time period, say 15 minutes or 1 hour. Utilities level demand charges to recover the fixed costs associated with the system capacity necessary to produce and deliver electricity.

Finally, customers are also charged an additional fee if the average power factor of power consumed is below a certain value. This reflects the fact that supplying reactive power reduces network efficiencies and requires additional capacity, which comes at a non-negligible cost to the utility.

In general, there is a clear economic incentive for C&I customers to manage peak-time demand, as is evidenced by the demand charge and TOU rate structure. One approach to reducing peak hour consumption is to engage customers in demand response or load management programs, whereby certain large loads are remotely shut off or shifted to non-peak hours [37]. Energy storage systems provide another means of shifting energy from one price period to another and can be used to significantly reduce monthly service charges.

3.2. Distribution System Operations

Electric power distribution systems are designed to accept electric energy from the bulk transmission system and distribute it to consumers over a wide geographic area. Networks are typically radially connected where power flows “downstream” from the substation along high-voltage feeders and branches into one, two and three-phase laterals to serve different areas. Distribution transformers are situated at different points along the laterals and act to step down distribution voltages to service voltages that are connected directly to customer premises via secondary lines. Distribution systems have the following operational constraints:

- Thermal ratings and other factors affect the ampacity of conductors, which is the maximum rated current of the conductor. Ampacity, in turn, is used to determine “normal” and “emergency” operating limits for line current and power flow.

- Line voltages are regulated so that service voltages remain within regulated limits for acceptable power quality. In the United States, most utilities use the ANSI C84.1 ranges for service entrance: 114 to 126V, or +/- 0.05 per unit.
- Most distribution systems, apart from urban underground mesh networks, must remain radially connected at all times.

Line flows and voltages in the distribution system are non-linearly dependent on electrical connectivity, the loads and generators connected, line impedances and resistances, autotransformer tap positions and other factors. Power engineers utilize power flow analysis software tools to determine currents and voltages at all points in the network and determine if there are any limit violations that require corrective action.

3.3. Distribution Reliability

The reliability of distribution systems is heavily influenced by the radial nature of the network. Distribution protection devices, for instance, are coordinated so that if a short circuit is experienced at a particular location in the network, upstream protection devices will disconnect faulted sections network and leave a subset of customers in service. The following sections provide an introduction to system-perspective and customer-perspective reliability analysis techniques.

3.3.1. Reliability Indices

The following variables are fundamental to distribution system analysis:

- **Failure rate, λ**: The average number of times per year a network component is expected to fail
- **Repair time**, r: Also known as Mean Time to Repair (MTTR), the average number of hours required to repair a network component
- **Unavailability**, $U = \lambda r$: The number of hours per year that a network component is out of service. The product of failure rate and repair time.

- **Load Point, s**: A collection of electrically connected customers

$$\sum N_s = Total\ Number\ of\ Customers \tag{10}$$

$$\sum N_s \lambda_s = Total\ Annual\ Customer\ Interruptions \tag{11}$$

$$\sum N_s \lambda_s r_s = \sum N_s U_s = Total\ Annual\ Customer\ Interruption\ Duration \tag{12}$$

The variables and summations above are used to calculate the following system-wide reliability metrics:

- **System Average Interruption Frequency Index (SAIFI):** The average number of interruptions per customer served.

$$SAIFI = \frac{\sum N_s \lambda_s}{\sum N_s} \tag{13}$$

- **System Average Interruption Duration Index (SAIDI):** The sum of interruption durations averaged over all customers.

$$SAIDI = \frac{\sum N_s U_s}{\sum N_s} \tag{14}$$

- **Customer Average Interruption Duration Index (CAIDI):** The average interruption duration experienced by a customer during an outage. As opposed to SAIDI, CAIDI gives a relative understanding of system reliability from the customer perspective.

$$CAIDI = \frac{\sum N_s U_s}{\sum N_s\, \lambda_s} \tag{15}$$

3.3.2. Distribution Reliability Analysis

Radial distribution networks consist of a set of series components between substation and load point. Since the failure of any component in series leads to an outage at the load point, classical analytical reliability assessment techniques approximate load point reliability indices by summing the failure rates and repair times of all series components upon which it depends [38]. Indices for each load point are then summed and used to calculate system wide indices according to the equations above.

More advanced reliability assessment techniques, such the state duration sampling methods, take into account the probability distributions of failure rates and repair times and can be used to calculate the probability distributions of load point indices.

3.3.3. Customer Perspective Reliability Modeling

Given detailed knowledge of network topology, protection schemes and equipment reliability, the techniques discussed above can be used to determine the reliability of individual load points. In cases where these detailed data are unavailable, it is necessary to determine expected outage data using alternative approaches. EPRI researchers have developed a method [3] of estimating customer-perspective (i.e. load point) outage duration and frequency probability distributions given SAIDI and SAIFI, indices which most utilities are required to track. The four step approach is outlined below.

1. SAIDI and SAIFI outage metrics for the utility in question are used to calculate CAIDI.
2. The probability that an outage will be of a given duration are estimated according to a left-skewed distribution. A customer weighting of how many customers will experience outages of each duration is then applied to reflect the fact that a greater number of customers experience outages of shorter duration while fewer customer experience outages of longer duration.
3. Next, the outage probability and the customer weighting are adjusted to yield a CAIDI similar to the system-wide CAIDI. This step is performed by noting that customer weighting is analogous to number of customers and

duration weighting is analogous to failure rate, the ratio of which equals CAIDI as shown below:

$$\frac{\sum N_s \lambda_s r_s}{\sum N_s \lambda_s} = \frac{\sum CW_s * DW_s * r_s}{\sum CW_s * DW_s} = CAIDI \tag{16}$$

where, DW_i is the duration weighting and CW_i is the customer weighting of outage length i.

4. The customer perspective outage probability for a given outage duration is then the normalized product of outage duration and customer weighting. When multiple by SAIFI, this yields the expected number of outages of a given duration that the customer will experience in a year.

While the EPRI developed methodology is a powerful tool in determining the value of service reliability, its accuracy hinges on two critical assumptions:

- **Assumption 1 - Outage duration distribution**: Outage duration depends on network topology, event type, time to repair and other factors. An accurate and consistent model of outage duration distributions has yet to be presented in the literature. Empirical evidence has shown that outages tend to follow a left-skewed distribution, although logarithmic or Weibull specifications do not yield satisfactory results [3]. A 2009 paper done for NREL done by GE Global Research [39] on two anonymous U.S. utilities shows outage lengths with the highest probability between 30 minutes and 2 hours, and outages of longer duration have increasingly lower probability. These empirical findings are used as the basis for duration weighting assumptions in this thesis.

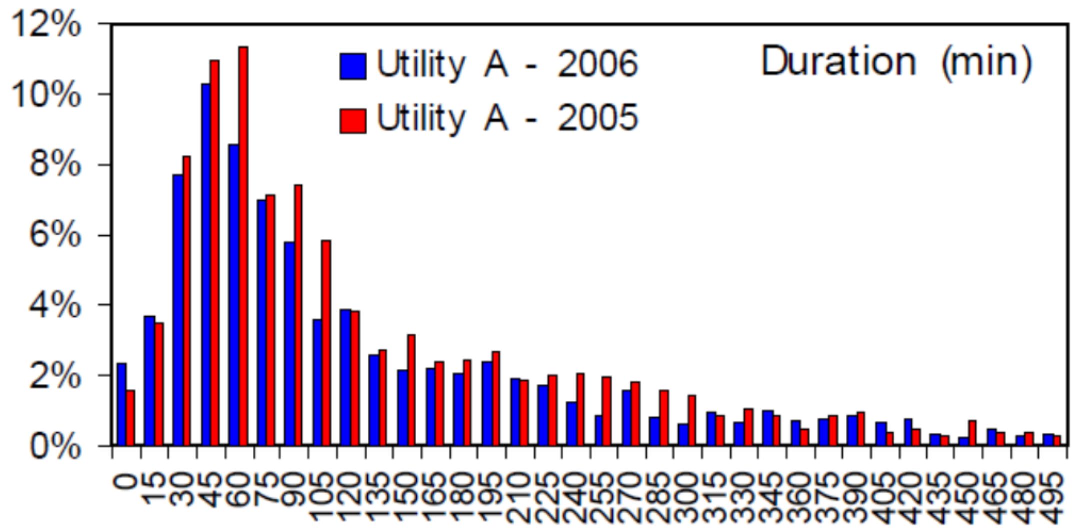

Figure 11: Recorded Outage Durations for two U.S. Utilities [39]

- **Assumption 2 – Customer Weighting:** It is also necessary to estimate the percentage of customers that will experience a given length outage. As a rule of thumb, the shorter the outage, the more customers are affected. One reason could be that it is more common to have outages further out on radial distribution lines, where outages last longer than central outages at a substation, but affect fewer customers [39]. This rule of thumb is applied in estimating customer weightings in this thesis.

3.4. Customer Outage Costs

One approach to determining the value of reliability and power quality is to estimate the customers' economic losses that result from service interruptions and power quality events, such as lost productivity, spoiled goods or damaged equipment. In 1994, Goel and Billinton [40] first suggested the use of a mathematical model for the expected customer cost of a power interruption, which known as a customer damage function (CDF). They originally described this equation as a simple linear relation between average interruption cost and outage duration. A more general customer damage function was proposed by EPRI in 1995 [41] and is of the following form:

$$\begin{aligned} \boldsymbol{E}(\boldsymbol{C_i}) = \boldsymbol{f}(&\boldsymbol{interruption\ attributes},\\ &\boldsymbol{customer\ characteristics},\\ &\boldsymbol{environmental\ attributes}) \end{aligned} \tag{17}$$

Where E(C_i) is the expected cost of the outage for customer *i* in dollars per event. Interruption attributes include interruption duration, season, time of day, whether or not advance notice was given, day of the week, etc. Customer characteristics include customer type, industry, annual energy demand, etc. Environmental attributes include temperature, frequency of storms, and other factors that may increase or decrease customer costs. The choice of variables depends on the particular customer damage function, but should include those factors that have been shown in interruption cost surveys to have a large influence on outage costs.

This thesis makes extensive use of customer damage functions developed by Lawrence Berkeley National Labs (LBNL) and is presented in the report, “Estimated Value of Service Reliability for Electric Utility Customers in the United States” [12]. In order to create the functions, LBNL researchers synthesized 28 customer value service reliability studies conducted by 10 major utilities from 1989 to 2005 into a normalized meta data set for statistical analysis. The regression of these data was then guided by the following two salient characteristics:

- There were many instances where the cost of an outage was reported as $0, indicating that the customer perhaps didn’t experience an outage during a given year or did not report it.
- The distribution of outage costs is generally lognormal.

The model developed is composed of two parts: an indicator function to determine the probability that the cost of outage was greater than zero, and a Generalized Linear Model (GLM) using a lognormal distribution. Mathematically, this is expressed as follows:

- **Indicator Function:**

$$P(C_i > 0) = \mathrm{cnd}(\boldsymbol{\beta}_1^T \boldsymbol{X}_i) \tag{18}$$

- **Generalized Linear Model:**

$$E(C_i) = \exp(\boldsymbol{\beta}_2^T \boldsymbol{X}_i) \tag{19}$$

Where *cnd()* is a cumulative normal distribution, $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$ are vectors of attribute coefficients for the indicator and GLM functions respectively, and $\boldsymbol{X_i}$ is the vector of independent variables for customer *i* for the given outage. The combined model is thus:

$$\tilde{C}_i = \hat{P}_i * \hat{C}_i \tag{20}$$

It is important to note that the LBNL customer damage function is a fundamentally probabilistic model where each expected cost of outage value has an associated variance. However, for the sake of simplicity and exposition, the optimization techniques presented in this thesis are performed deterministically over the expected cost of outage.

The table below shows average values of customer variables, $\overline{X}_\iota$, and attribute coefficients obtained from the regression for medium and large C&I customers.

Table 4: Medium and Large C&I Customer Damage Function Regression Data [12]

VARIABLE	AVERAGE	COEFFICIENT
Interruption Characteristics		

Duration (minutes)	122.1	0.009
Duration squared	14,908.3	-9.01E-06
Outage occurs in morning	46.0%	0.019
Outage occurs in afternoon	40.4%	0.280
Outage occurs in evening	3.1%	0.306
Outage occurs on weekday	93.7%	0.252
Warning given	8.8%	-0.088
Summer	85.8%	-0.077
Customer Characteristics		
Log of Annual MWh	8.9	0.451
Back-up Gen. or Power Conditioning	37.2%	0.080
Back-up Gen. and Power Conditioning	8.4%	0.127
Interactions		
Duration x Log of Annual MWh	266.6	-2.09E-04
Duration Sq. x Log of Annual MWh	32,545.8	1.73E-07
Industry		
Mining	1.4%	0.430
Construction	0.9%	1.579
Manufacturing	28.6%	1.289
Telco. & Utilities	7.2%	0.815
Trade & Retail	25%	0.273
Financial, Insurance & Real Estate	3.8%	1.225
Services	25.2%	0.522
Public Admin.	1.8%	0.617
Industry Unknown	4.7%	1.076

For the sake of functional analysis, the variables in the LBNL customer damage function can be subdivided into attributes that change for a given outage (duration), those that change over a longer time-scale (time of day, season) and those that may be fixed for a given simulation (customer characteristics and industry). Since the average outage duration is just over two hours, it is reasonable to consider outage duration as the single independent variable with all other variables constant. Functionally, the generalized linear model of the damage function reduces to a single variable non-linear function of the following form:

$$C_i(t_o) = \alpha * \exp((\beta_1 - \gamma\beta_2)t_o + (-\beta_3 + \gamma\beta_4)t_o^2) \tag{21}$$

Where, α, is lumped coefficient, γ is the log of annual MWh consumption and β_1, β_2, β_3, $\beta_4 > 0$ are the relevant attribute coefficients. Due to weighting of terms, the function typically contains a negative term in the exponent and is non-convex. Illustrated below are curves of the expected cost of outages by industry in US 2008$ for medium and large C&I customer given a summer weekday afternoon outage:

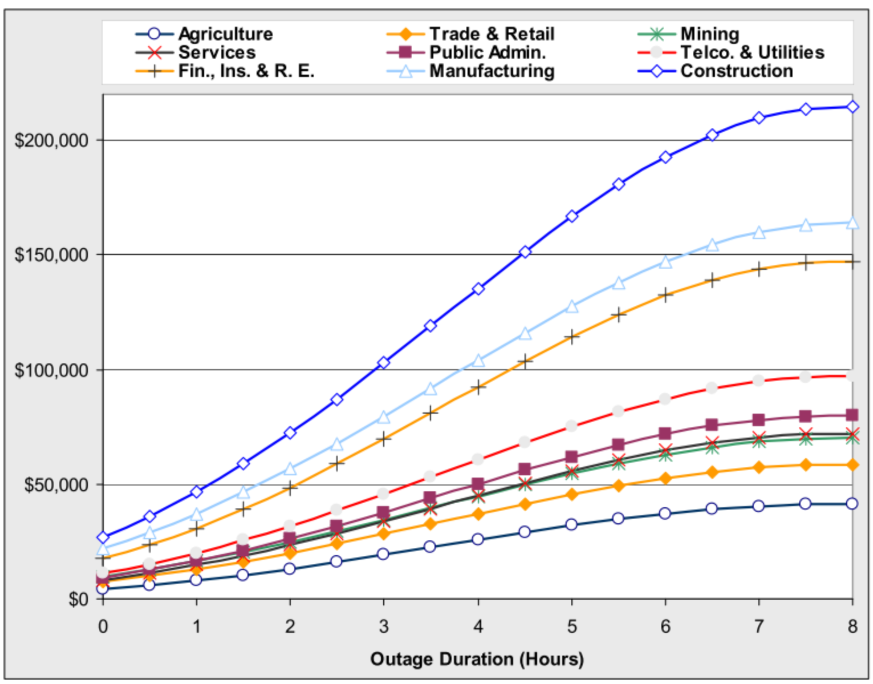

Figure 12: Outage Costs for Medium and Large C&I Customers as a Function of Outage Duration [12]

LBNL's customer damage functions synthesize empirical data from ten years of outage cost surveys. A number of insights can be gained from these functions, such as:

- Compared to C&I customers, residential customer outage costs are low
- All customers have a non-zero initial outage cost (i.e. short outages are expensive).
- Incremental outage costs are the greatest during outage hours two to five

Another important metric used in outage cost analysis is the ratio of interruption cost to average kW demand. Data from a previous LBNL report [42] clearly indicate that certain customer groups are "hit harder" by outages.

Table 5: Average Outage Costs [42]

$/kW	15 min	30 min	1 hr	2 hrs	4 hrs	8 hrs
Residential	$ 0.05	$ 0.60	$ 2.60	$ 3.95	$ 5.30	$ 5.60
Small C&I	$ 8.65	$ 16.01	$ 23.37	$ 48.91	$ 117.76	$ 189.23
Large C&I	$ 4.79	$ 7.46	$ 10.12	$ 17.96	$ 36.94	$ 68.36

The fact that C&I customers, particularly small C&I customers, experience high costs of outages per kW demand is an important observation that will be investigated in the optimal implementation of DESS.

4. Customer-Premise Energy Storage

4.1. Overview

This portion of the thesis is dedicated to determining the optimal dispatch of customer-premise energy storage resources for large commercial and industrial (C&I) customers and as well as optimal BESS capacity partitioning for multiple application uses. The University of Minnesota Morris (UMM), a small residential campus of 1,800 students in rural Minnesota, was chosen for simulations due to the fact that historical meter data is readily available, the utility rate structure is well known and the campus has significant onsite renewable generation. As discussed previously, the desired benefits of the proposed storage system are to reduce power service charges and the cost of service interruptions. First, the university's electric service rate structures, customer damage function and reliability model are discussed. A multi-objective optimization model is presented and an operational strategy to partition battery capacity according to operating objective is proposed. Then, a Dynamic Programming algorithm for optimal BESS dispatch is detailed and used to determine optimal energy and demand charge savings. Simulations are then performed to analyze the sensitivity of a number of parameters, including forecast error, energy conversion efficiency, cycle life and capacity partitioning. With the knowledge gained from this analysis, the optimal ratio of partitioned capacity is determined for a range of storage capacities as well as their overall economic competitiveness.

4.2. UMM Power System

The UMM Campus was one of the first public colleges in the U.S. to generate on-site renewable power from local resources. Presently, UMM owns and operates a biomass gasification plant fueled by crop residues from nearby farms, solar thermal panels, a solar photovoltaic system and two 1.65MW wind turbines [43]. UMM's wind turbines operate at a capacity factor of approximately 0.4, with a typical week's output shown below.

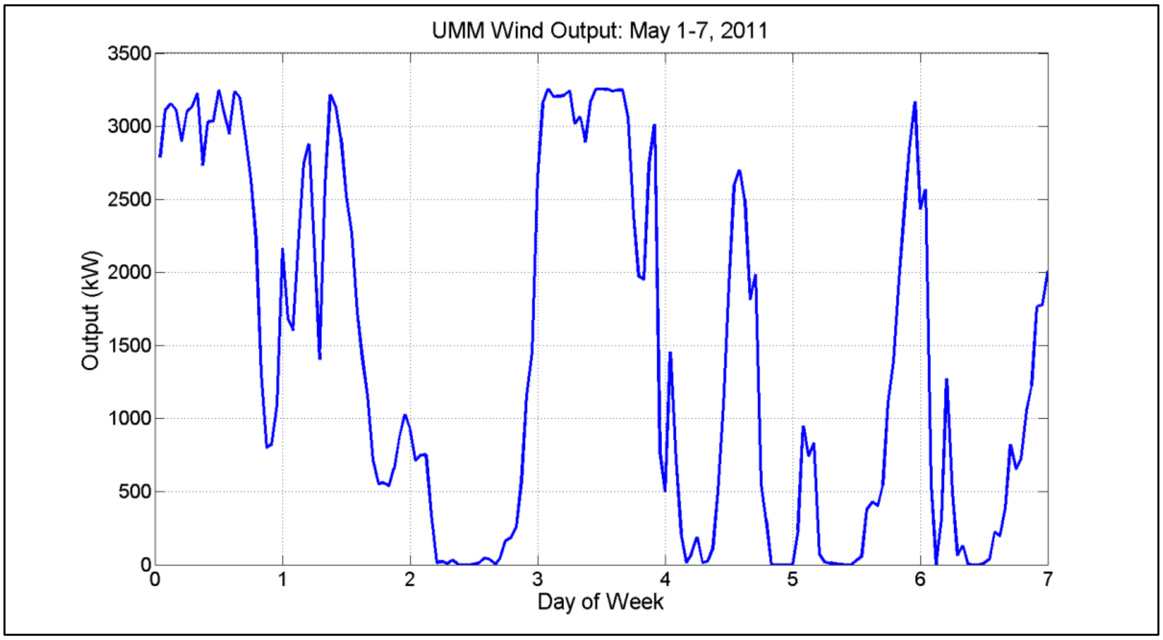

Figure 13: UMM Wind Output May 1-7, 2011

UMM is served by Otter Tail Power Company (OTPC), an investor owned utility with approximately 129,300 customers in Minnesota, North Dakota and South Dakota. If wind generation exceeds local demand, power is sold back to OTPC at a fixed rate. UMM's power system is modeled as single bus with two wind generators, a medium voltage connection with OTPC and an aggregate campus load, which peaks at approximately 1.5MW and accounts for all other local generation sources. An MV90 metering system collects real and reactive power interval data for the campus load, the wind generation and the net tie line flow with OTPC. As a large C&I customer, the proposed energy storage system for the UMM campus is a battery energy storage system (BESS) as previously discussed. The BESS is connected directly to the campus bus, with the direction of power flow defined as positive during charging. The system one line diagram is shown below.

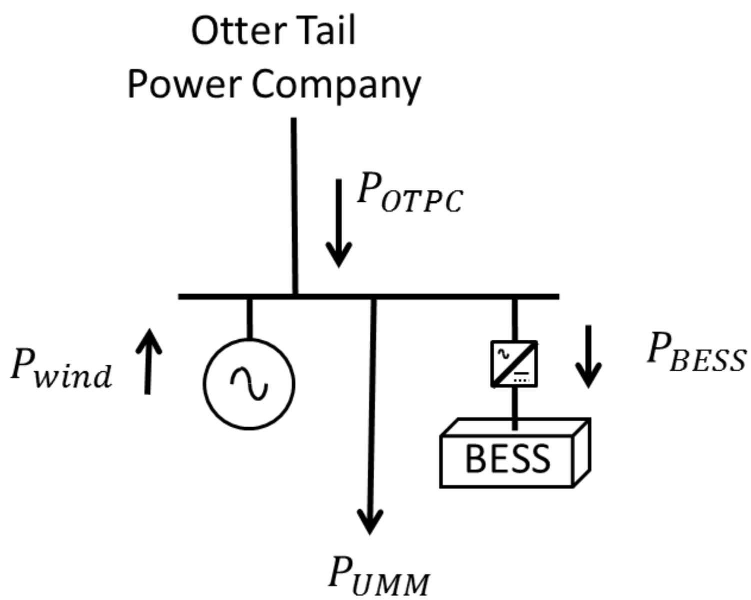

Figure 14: UMM Proposed Power System

The power balance equation at any given time, *t*, for the UMM power system model is given as:

$$P_{OTPC,t} = P_{UMM,t} - P_{wind,t} + P_{BESS,t} \tag{22}$$

4.3. UMM Rate Structure

UMM currently subscribes to a large general service rate schedule, which is regulated by the Minnesota Public Utilities Commission [44]. The following “flat” rates apply to customers with primary three-phase service voltages of 2,400V up to 69,000V and whose maximum demand requirement is greater than 20 kW.

Table 6: OTPC Large General Service - Primary Service Rate Schedule

Monthly Charges	Rate	
Customer Charge, C_c	$40.00 (one time)	
Facilities Charge (per annual max kW), C_f	$0.12/kW	
	Summer	***Winter***
Energy Charge, C_e	4.477 ¢/kWh	4.821 ¢/kWh
Demand Charge, C_d	6.93 $/kW	5.76 $/kW

For this rate schedule, the demand charge consists of the maximum average kW measured for one hour during a monthly billing cycle plus an adjustment for excess reactive power demand, which occurs when power factor dips below 0.707 for more than one hour. The mathematical expression includes constant terms, a summation over hourly demand periods and a maximum term as shown below:

$$Cost_{flat} = C_c + D_f C_f + \sum_{t=1}^{T} P_t C_e + (\max\{P_t\} + PF)C_d \tag{23}$$

P_t is the average kW demand during hour $t \in T$, D_f is the previous year's peak demand and *PF* is the excess reactive demand penalty.

In addition to the flat energy rate large general service, OTPC offers a Time of Use (TOU) rate schedule, where energy and demand charges vary between three price periods: On-peak, Shoulder and Off-peak.

Table 7: OTPC Large General Service - TOU Primary Service Rate Schedule

Monthly Charges	Rate	
Customer Charge, C_c	$60.00	
Facilities Charge (per annual max kW), C_f	$0.12/kW	
Energy Charge	***Summer***	***Winter***
On-peak	7.067 ¢/kWh	6.251 ¢/kWh
Shoulder	5.228 ¢/kWh	4.742 ¢/kWh
Off-peak	2.376 ¢/kWh	3.546 ¢/kWh
Demand Charge	***Summer***	***Winter***
On-peak	5.32 $/kW	4.94 $/kW
Shoulder	1.61 $/kW	0.82 $/kW
Off-peak	0.00 $/kW	0.00 $/kW

The rates can be expressed mathematically as:

$$Cost_{TOU} = C_c + D_f C_f + \\ + \sum_{p=1}^{P} \sum_{t=1}^{T} P_{t,p} C_{e,p} + \sum_{p=1}^{P} \left(\max\{P_{t,p}\} + PF_p \right) C_{d,p} \tag{24}$$

Where *p = 1, 2, 3* indicate the on-peak, shoulder and off-peak price periods, respectively, and there are different energy and demand charges for each interval. The figure below depicts the price periods graphically for the summer and winter seasons.

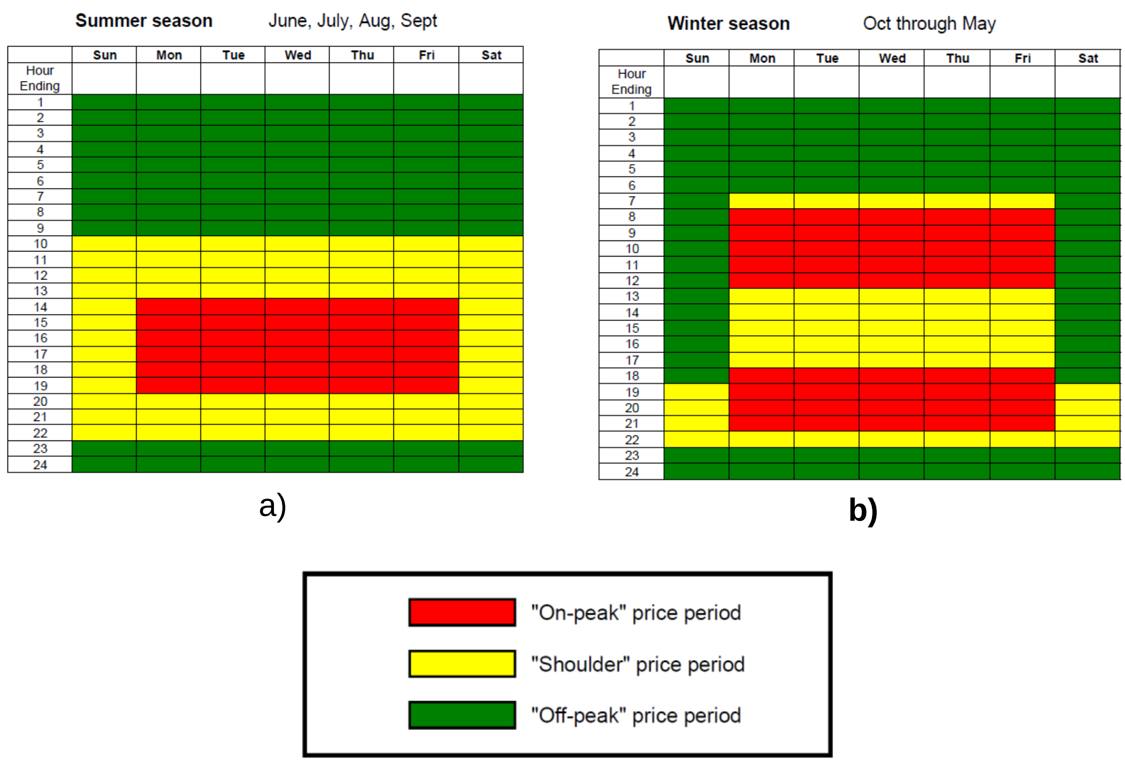

Figure 15: OTPC Large General Service TOU Price Periods a) Summer, b) Winter [44]

In addition to the rates detailed above, OTPC has an agreement with UMM to pay for excess wind generation at a fixed rate. Since the agreed upon rate is confidential, we assume that UMM is recompensed C_{gen} = \$0.05/kWh for energy sold back to OTPC. In order to account for the discontinuity in cost for net negative and positive tie flow, we divide P_{OTPC} into two separate variables:

$$if\ P_{OTPC} > 0, \qquad P_{LOAD} = P_{OTPC}; P_{GEN} = 0 \tag{25}$$

$$if\ P_{OTPC} < 0 \qquad P_{GEN} = P_{OTPC};\ P_{LOAD} = 0 \tag{26}$$

4.4. UMM Customer Damage Function

The outage cost model for UMM is based on the LBNL customer damage functions discussed in section 3.4. UMM subscribes to a large general service at a medium voltage and has a peak load of 1.5MW, hence it is classified as a large C&I customer. Since the characteristics of the outages expected to be experienced throughout a year are unknown and difficult to accurately model, average values are chosen for outage time of day and season. Additionally, of the C&I sectors modeled by the LBNL CDF, the university most closely fits the description of “Public Administration”. With these chosen parameters, UMM’s customer damage function is shown below.

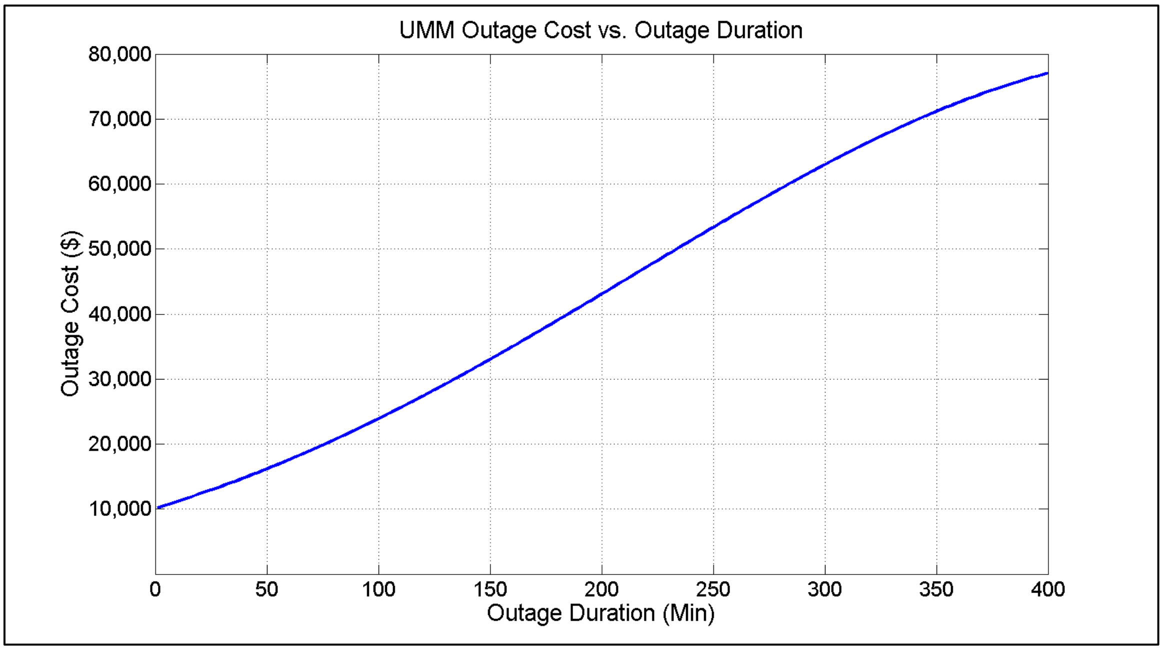

Figure 16: UMM Customer Damage Function

4.5. UMM Reliability Modeling

The customer-perspective reliability model discussed in section 3.3.3 is used to determine the number of outages of a given duration that UMM campus can expect to experience in a given year. OTPC’s system-wide reliability metrics for 2009 and 2010 are publically available [45] and summarized below:

Table 8: OTPC Reliability Indices [45]

Year	SAIDI	SAIFI	CAIDI
2009	84.8	1.5	57
2010	62.1	1.09	56.9
Average	73.5	1.3	57

The follow table illustrates the chosen outage duration bins, average outage duration, duration weighting, customer weighting, customer perspective outage probability and the expected number of outages per year used in determining UMM's outage statistics.

Table 9: OTPC Customer Perspective Outage Model

	0-15m	15-30m	30m-1hr	1-2hr	2-4hr	4-8hr	8-24hr	1-3 days	>3 days
Average Duration (min)	10	22.5	45	90	180	360	960	2280	10800
Duration Weighting (%)	8	20	35	23	8	2	1	1	2
Customer Weighting (%)	23	21	20	17	13	3	2	1	0
Outage Probability (%)	10	23	39	22	6	0	0	0	0
Outages Per Year	0.132	0.301	0.501	0.280	0.074	0.004	0.001	0.001	0

The same outage statistics are plotted below.

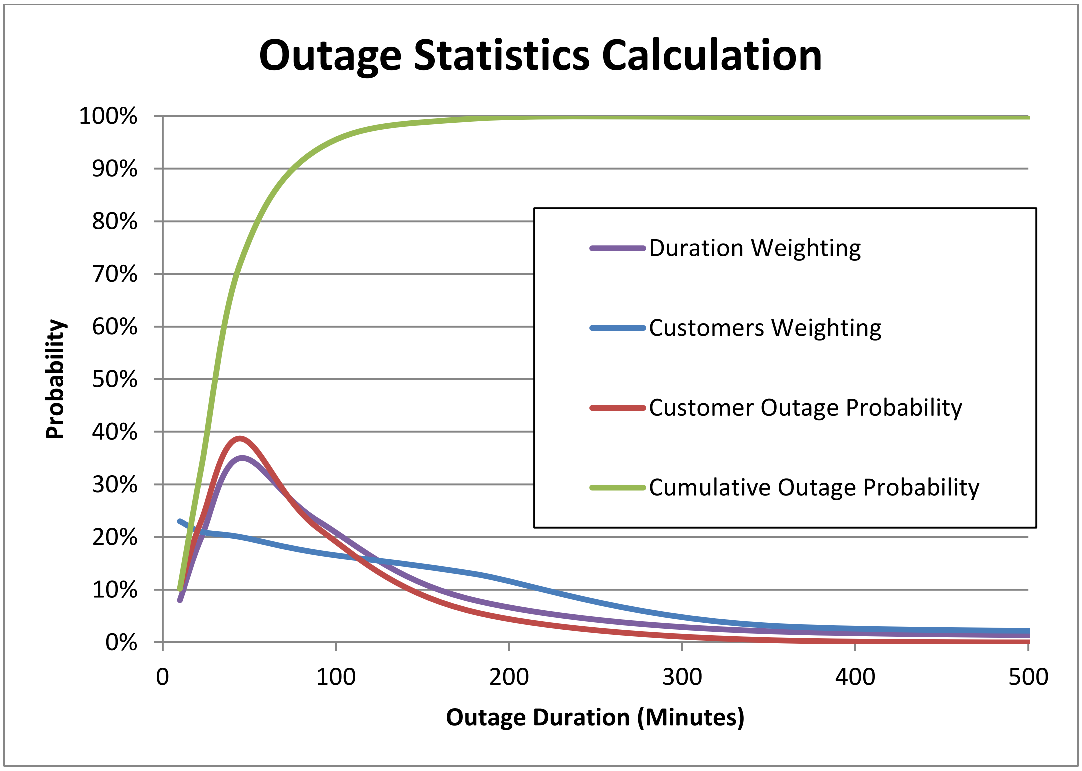

Figure 17: UMM Outage Statistics

The expected cost of outages is determined by multiplying the cost of the average outage duration for a given bin, as calculated by the customer damage function, by the expected number of outages a year. The minimum capacity required to ride through the outage is calculated assuming that the load remains constant at UMM's average value of 875kW and wind generation is not being supplied. While the required ride-through capacity varies considerably with net demand during the outage, we continue with a deterministic approach of calculating expected values using average quantities.

Table 10: OTPC Customer Perspective Outage Model

	0-15m	15-30m	30m-1hr	1-2hr	2-4hr	4-8hr	8-24hr	1-3 days	>3 days
Average Duration (min)	10	22.5	45	90	180	360	960	2280	10808
Outage Cost ($)	11,171	12,617	15,488	22,233	38,968	72,552	0	0	0
Outages/Year	0.132	0.301	0.501	0.280	0.074	0.004	0.001	0.001	0
Expected Outage Cost ($)	1,472	3,796	7,765	6,227	2,903	312	0	0	0
Min ride-through capacity (kWh)	146	328	646	1313	2625	5250	0	0	0

The following plot shows the outage costs that the university can expect to avoid as a function of storage capacity values.

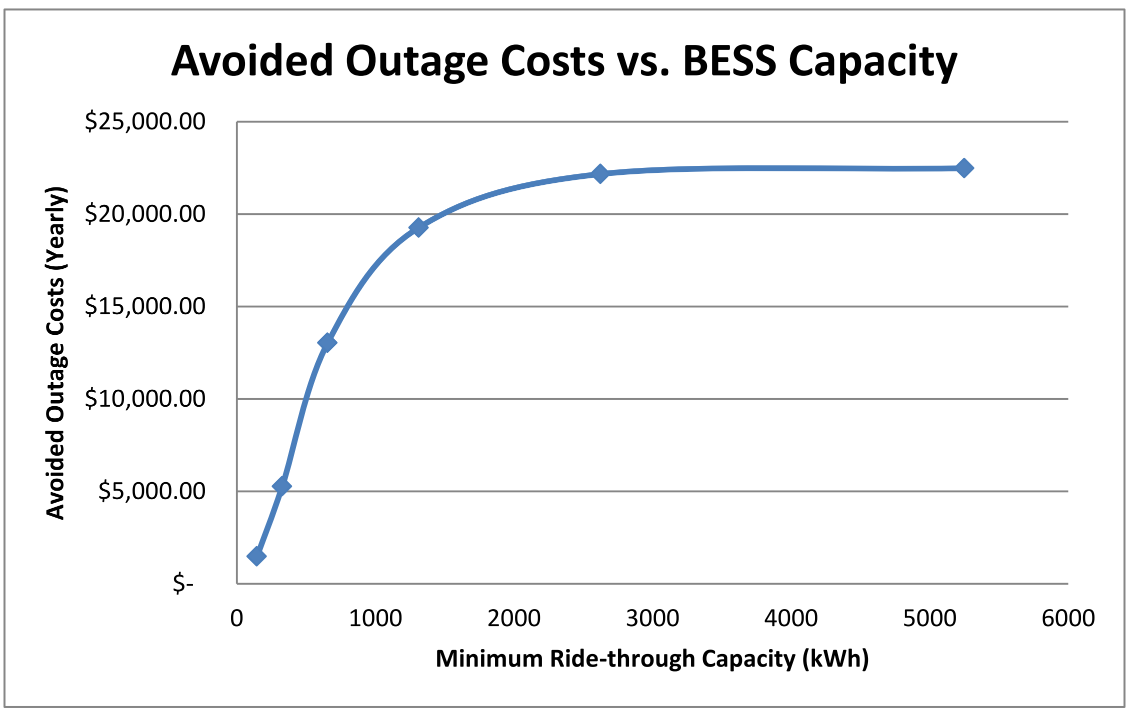

Figure 18: UMM Avoided Outage Costs vs. Ride-through Capacity

With this data, we can define a general piece-wise linear function that relates the cost of outages to available capacity devoted to emergency backup.

$$Cost_{OUTAGE} = f\left(W_{op}\right) \tag{27}$$

4.6. Optimization Model

As we have seen, UMM's annual power-related costs are the yearly service charge it pays OTPC in addition to outage-related costs, which are approximately $22,500 a year. Accordingly, an energy storage system should be implemented to achieve one or more of the following three objectives: minimize outage costs, minimize energy charges and minimize demand charges[1]. Qualitatively, these objectives are achieved by using available storage capacity to ride through outages, charging and discharging to shift net power consumption from high-cost periods to low-cost periods and reducing monthly peak demand, respectively. The objectives and constraints are formulated mathematically and discussed below:

- **Objective 1: Minimize Outage Costs**

$$\underset{W_{op}}{\text{minimize}}\, f\left(W_{op}\right) \tag{28}$$

  Where W_{op} is the available energy of the storage system

- **Objective 2: Minimize Energy Costs (Emin)**

  Given W_{op},

$$\underset{W_{st,t}}{\text{minimize}} \sum_{p=1}^{P} \sum_{t=1}^{T} P_{LOAD,t,p}\, C_{e,p} - \sum_{t=1}^{T} P_{GEN,t} C_{gen} \tag{29}$$

[1] Reactive charges were extremely small for all simulations performed and were neglected in the optimization model.

Where W_{st} is the stored energy in the BESS at time t and corresponds to the hourly charge/discharge schedule of the battery. It is important to note that the P_{UMM} and P_{wind} terms that make up P_{LOAD} and P_{GEN} are not known but are rather forecasted over the time period in question.

- **Objective 3: Minimize Demand Costs (Dmin)**

Given W_{op},

$$\underset{\mathrm{W_{st,t}}}{\text{minimize}} \sum_{p=1}^{P} \max\{P_{LOAD,t,p}\}\, C_{d,p} \tag{30}$$

Similar to the previous objective, the optimal solution will be the BESS's dispatch schedule.

- **Operating Constraints:**

The operating constraints of the BESS for energy and demand cost minimization are exactly the same as those developed in section 2.6.

$$0 < W_{st} < W_{op} \tag{31}$$

$$-P_{rated} < P < P_{rated} \tag{32}$$

4.7. Solution Algorithms

The approach adopted in this thesis for determining optimal BESS implementation is to first solve the dispatch scheduling problem for energy and demand minimization over a set of different storage system capacities and technologies. These discrete values are then combined with outage cost minimization to determine a set of pareto-efficient solutions to the longer term multi-objective planning problem of optimal BESS sizing and technology selection.

4.7.1. Dynamic Programming for BESS Dispatch

Objective functions two and three are linear programs except for a discontinuity at $P_{OTPC} = 0$ and, since they are simply two line items on the monthly bill, they can be treated with equal weight. Dynamic programming, a numerical approach to solving optimization problems, was chosen because the problem has the property of optimal sub-structure. That is, all that is needed to determine the optimal solution at a given time, t, is the optimal solution up to t-1 and the possible paths from the t-1 solution to t solutions. Dynamic programming also efficiently handles non-linear objective functions and constraints, which would be critical if the more dynamic detailed battery model is implemented. As a numerical method, dynamic programming is also particularly well suited to digital computation and can be implemented with a series of nested loops. The dynamic programming approach to optimal BESS dispatch scheduling has been implemented by a number of researchers [46], [47] and bears close resemblance to the short-term hydrothermal scheduling problem [48]. Dynamic programming has obvious shortcomings, however, such as the fact that the discretization of the available battery capacity leads to a non-optimal solution and that computational time-cost grow precipitously with problem dimensionality. These problems can be partially mitigated through the judicious selection of algorithm parameters.

The master theorem of dynamic programming, developed by Richard Bellman in the late 40s and early 50s [49], states that that "an optimal policy must only contain optimal sub-policies". In other words, complex problems of specific forms can be broken up into sub-problems that can be solved separately and then compared and combined to form the solution to the original problem. When applied to the BESS dispatch problem, time is discretized along one axis and available capacity is discretized along the other, by evenly dividing the total capacity into discrete values. Given N_W discrete capacity values, the incremental distance between values is:

$$\Delta W = \frac{W_{av}}{N_W} \tag{33}$$

In our case, the discrete time step is chosen to be one hour to align with demand intervals, as defined by OTPC. Also, since the demand is assessed once a month, the simulation necessarily runs for the entire month. There were 31 days in May 2011 data used for simulations, hence there are total of 744 time steps.

The master theorem indicates that the optimal dispatch schedule for the entire month can be determined from the optimal dispatch schedules of shorter time periods. The recursive algorithms for energy minimization, demand minimization and combined energy and demand minimization are given below for time step *t* in price period p going from capacity step *i* to capacity step *j*, where $Cost^*_{t,p,j}$ is the minimum cost, $Ecost_{t,i\text{->}j}$ is the energy charge, $P_{t,i\text{->}j}$ is the net tie-line demand, $D_{t,p,j}$ is the demand, $Dcost_{t,p,\,i\text{->}j}$ is the demand charge, $Dcost^*_{t,p,j}$ is the optimal demand charge and $options_i$ is an array of candidate solutions.

- **Energy Minimization Algorithm (Emin)**

$$Cost^*_{t,j} = min\{Cost^*_{t-1,i} + Ecost_{t,i\to j}\} \tag{34}$$

- **Demand Minimization Algorithm (Dmin)**

$$Cost^*_{t,p,j} = min\left\{max\{Cost^*_{t-1,p,i}, Dcost_{t,p,i\to j}\}\right\} \tag{35}$$

- **Energy and Demand Minimization (EDmin)**

$$\begin{array}{l} for\ i = 1{:}\, N_W \\ \quad if\ P_{t,i\to j} > D_{t-1,p,i} \\ \qquad options_i = Cost^*_{t-1,p,i} + Ecost_{t,i\to j} + Dcost_{t,p,i\to j} - Cost^*_{t-1,p,i} \\ \quad else \\ \qquad options_i = Cost^*_{t-1,p,i} + Ecost_{t,i\to j} \\ end \\ Cost^*_{t,j} = min\{options_i\} \end{array} \tag{36}$$

4.7.2. Optimal Capacity Partitioning

The dynamic programming algorithm will produce an optimal solution to the Emin, Dmin and EDmin problems for a given BESS and results in a reduction in monthly service charge. However, simply using the BESS for emergency backup during outages, which are assumed to occur at a frequency and duration developed in section 4.5, also leads to savings. In order to achieve the maximum amount of savings for a given technology, it is possible to partition BESS capacity according function, as shown below.

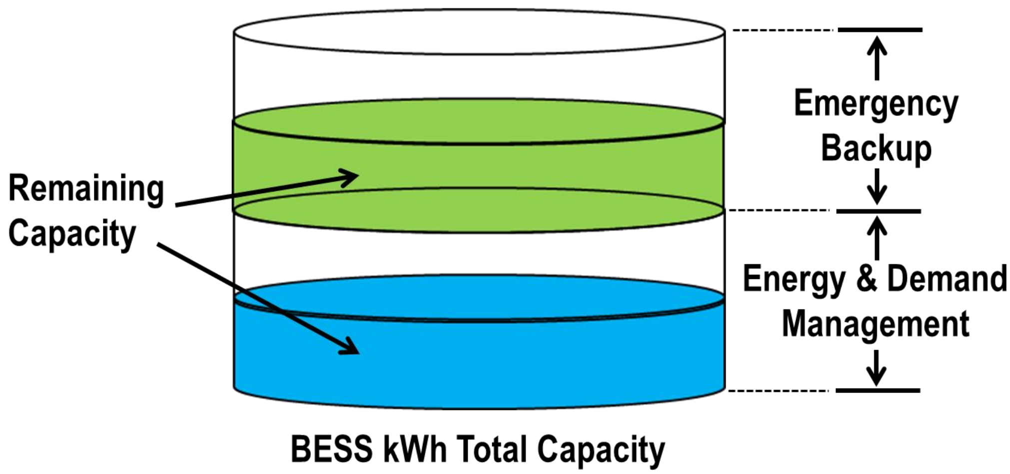

Figure 19: BESS Capacity Partitioning

By varying the ratios of capacity dedicated to one application or the other, one can arrive at a set of pareto-efficient solutions to this multi-objective problem. Practically speaking, outages are a very rare event. The vast majority of the time capacity partitioning has the added benefit of reducing the maximum depth of discharge for energy and demand management, which cycles the battery on a daily basis, and can potentially extend the cycle life of the battery. Furthermore, when outages do occur, the unused portion of the EDmin partition will naturally be re-allotted to supplement the emergency backup capacity, thereby providing an additional design margin for interruption ride-through.

4.8. Optimal Dispatch Simulations

Optimal BESS scheduling simulations were performed on historical meter data from the month of May, 2011. Wind and load data were used as forecast inputs and the number of discrete capacity steps was set to 100. The lead acid 2 (LA2) BESS was chosen as an initial candidate, which has a 1000kWh available energy capacity, 200kW power rating and 0.85% round trip efficiency. Preliminary simulations are performed to illustrate the characteristics and potential savings of different optimization objectives in four different scenarios: flat rates - no wind, flat rates – with wind, TOU rates – no wind, TOU rates – with wind. While the optimization model is formulated as a minimization problem, results are presented as savings with respect to a base case where no storage unit is present. In this way, savings can be entirely attributed to the BESS and benefits are clearly exposed.

4.8.1. Energy Cost Minimization

To illustrate the nature of the energy cost minimization solution, we must consider a scenario where UMM is charged according to TOU rates and no wind is present. The following plot shows BESS output, UMM load and net tie flow over the first two days of the month, which are a Sunday and a Monday.

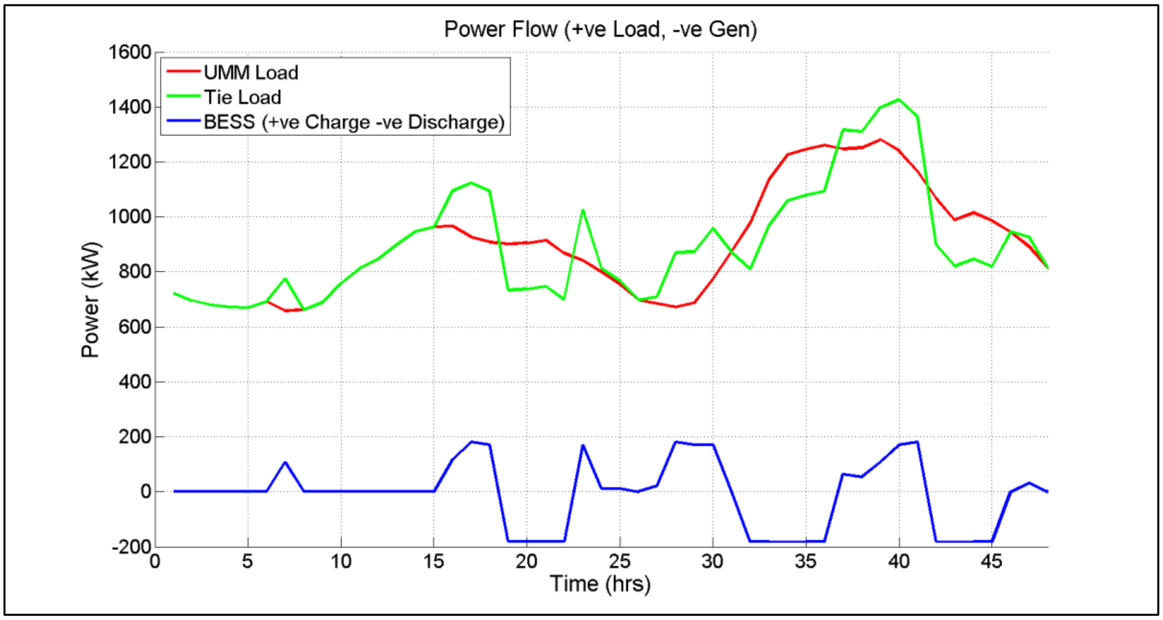

Figure 20: LA2 Emin Power: TOU, No Wind

Keeping in mind that energy is the area under the dispatch curve, we can clearly see that the BESS is actively shifting energy from one time period to another, and more so on Monday than Sunday. The same dispatch schedule depicted in terms of stored capacity and TOU energy charges clarifies the “reasoning” behind the dispatch decisions, which is to charge before peak hours and discharge during peak hours.

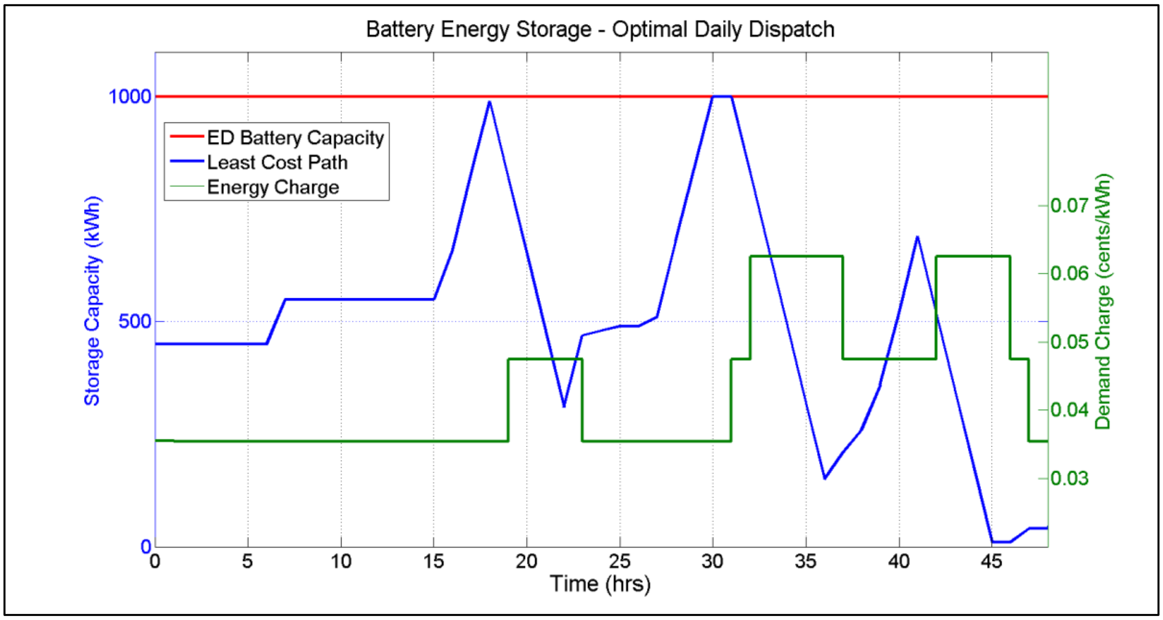

Figure 21: LA2 Emin Stored Energy: TOU, No Wind

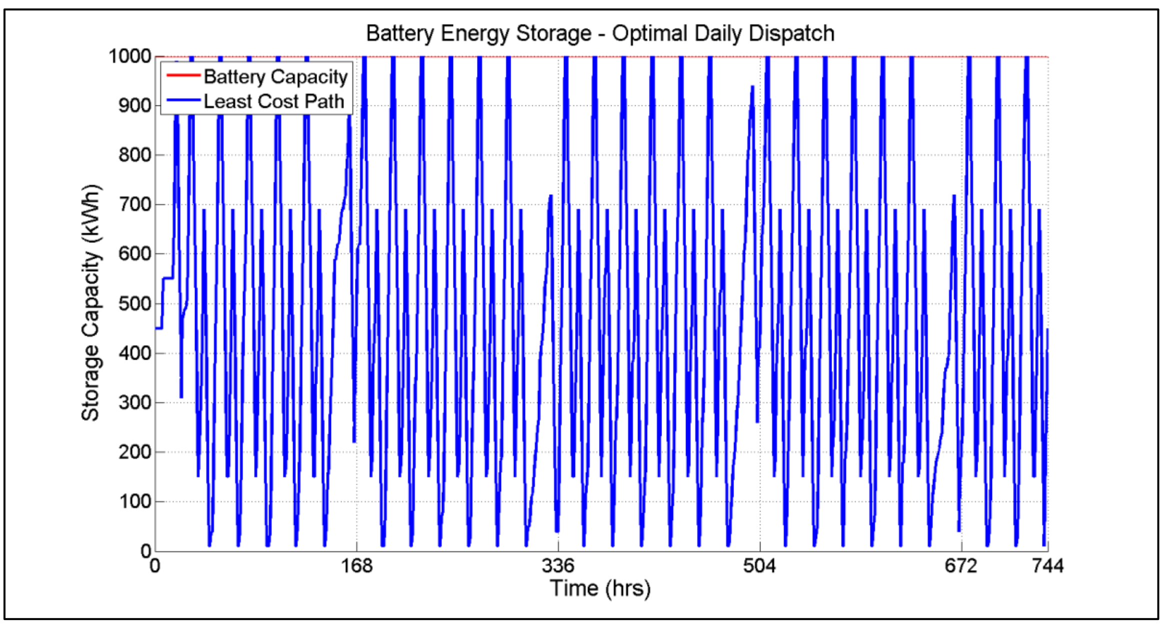

Figure 22: LA2 Emin Monthly Stored Energy: TOU, No Wind

On a monthly basis, we see that the battery is heavily cycled, with a total of 46.24 cycles.

4.8.2. Demand Cost Minimization

In order to illustrate the effect of demand cost minimization, consider a flat rate - no wind scenario. The following plots show BESS output over the first two days and the entire moth, respectively

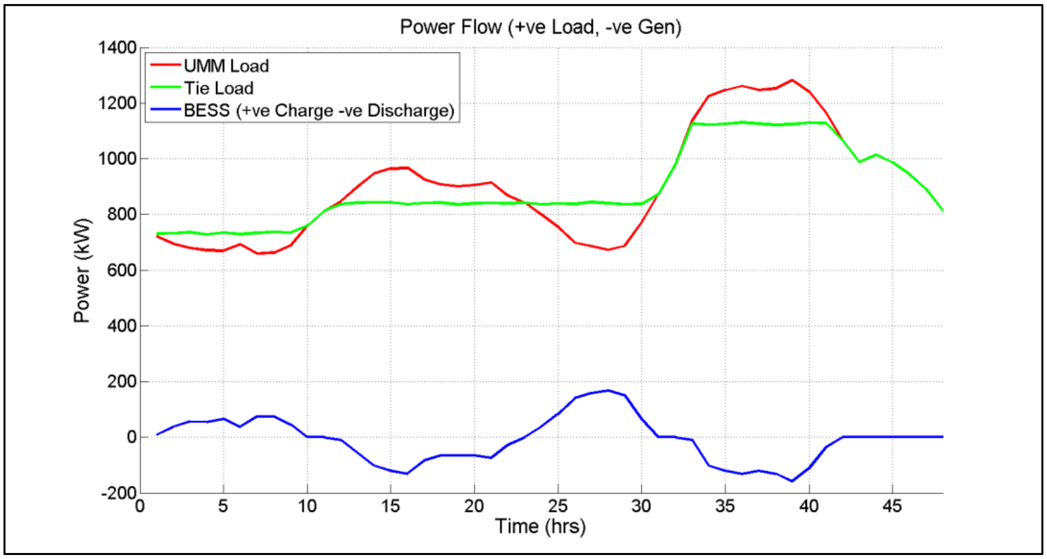

Figure 23: LA2 Dmin Power: Flat, No Wind

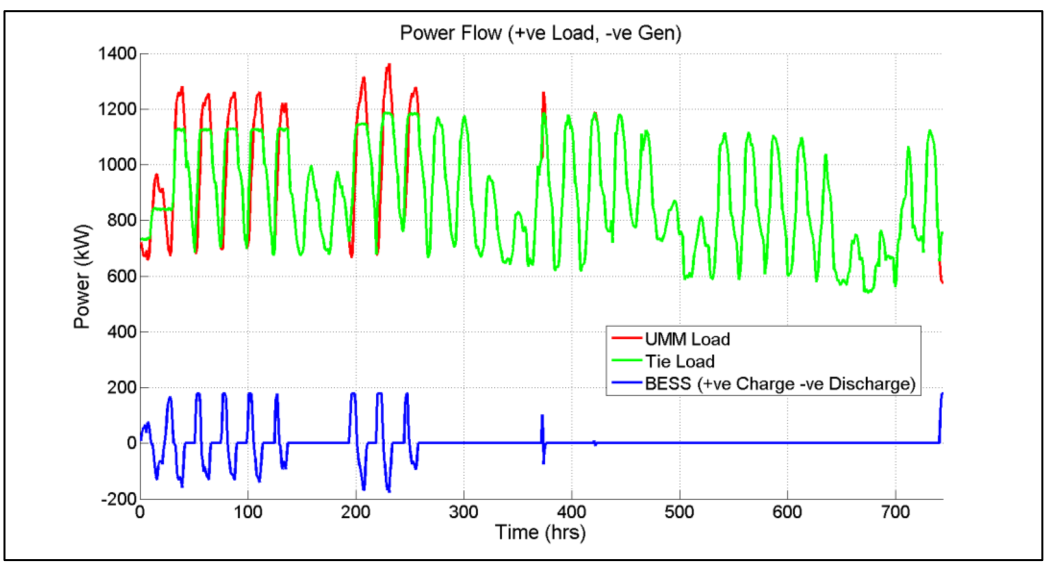

Figure 24: LA2 Dmin Monthly Power: Flat, No Wind

It is easy to see how the BESS control objective is to “shave peak” and one can visually confirm that monthly tie line demand is significantly reduced. By extension, in a TOU setting, the peak and shoulder demands are both included in the minimization (there is no charge for off peak demand). We also see that the battery is cycled significantly less than during the Emin simulation, since the daily peak demands are lower in the latter half of the month.

4.8.3. Energy and Demand Cost Minimization

The energy and demand cost minimization algorithm, EDmin, combines both objectives into one problem to provide a global solution. The following plot shows the EDmin solution for a TOU - no wind scenario.

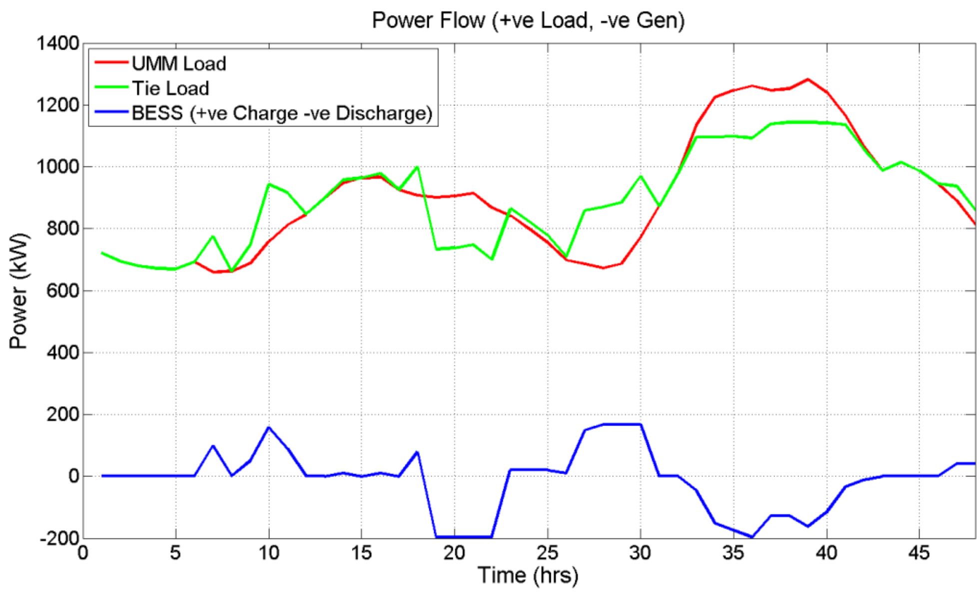

Figure 25: LA2 EDmin Power: TOU, No Wind

Although at this point it is difficult to qualitatively intuit the reasons for hourly control decisions, we can see that Monday’s peak load is reduced and that energy appears to be shifted during certain hours. The following table summarizes the energy and demand savings realized by each of the optimization methods over all four scenarios to more clearly illustrate the savings.

Table 11: UMM Morris Optimal Dispatch Comparison Table - Lead Acid 2

Simulation Parameters	Base Cost	E Min Savings	D Min Savings	E&D Min Savings
Flat Rates, No Wind				
Energy	$ 31,325	---	$ -60	$ -60
Demand	$ 7,854	---	$ 967	$ 967
Total	$ 39,179	---	$ 907	$ 907
Savings		**0%**	**2.31%**	**2.31%**
TOU Rates, No Wind				
Energy	$ 31,529	$ 639	$ 77	$ 546
Demand	$ 7,624	$ 718	$ 861	$ 959
Total	$ 39,152	$ 1,357	$ 938	$ 1505
Savings		**3.47%**	**2.40%**	**3.84%**
Flat Rates, With Wind				
Energy	$ 7,590	---	$ -19	$ -19
Demand	$7,206	---	$ 892	$ 892
Total	$ 14,796	---	0	0
Savings		**0%**	**5.90%**	**5.90%**
TOU Rates, With Wind				
Energy	$ 7,957	$ -518	$ 33	$ -511
Demand	$ 7,075	$ 667	$ 874	$ 932
BESS Revenue	---	$ 1042	$ 28	$ 1024
Total	$ 15,032	$ 1191	$ 935	$ 873
Savings		**7.92%**	**6.22%**	**9.61%**

Theoretically, the objective function evaluated at the optimal solution should be at least as good as both the Emin and the Dmin solutions alone. In a flat rate scenario, the EDmin solution is equivalent to the Dmin solution, since no savings can be realized from energy arbitrage. With TOU rates, the EDmin solution is superior to both the Emin and Dmin solutions alone. In general, the highest percentage savings are achieved in cases where wind is present and the majority of the savings come from demand charge reductions and additional revenue earned by the BESS. This latter phenomenon is explored in the following section.

4.8.4. BESS Revenues

Given the fact that the BESS has a non-negligible round trip efficiency and no external source of energy, it may come as surprise that it can generate a revenue from energy sales. The reason is because UMM's wind generation capacity is very large and frequently meets and exceeds local demand, leading to a "no-load" scenario. During off-peak hours, when no demand charge is incurred, the energy charge (3.546 ¢/kWh) is actually lower than the sell-back price (5 ¢/kWh). This rate structure has consequently created an incentive for the BESS to purchase as much energy as possible and immediately sell it back during off peak hours. This phenomenon is llustrated below for a TOU – With Wind Scenario.

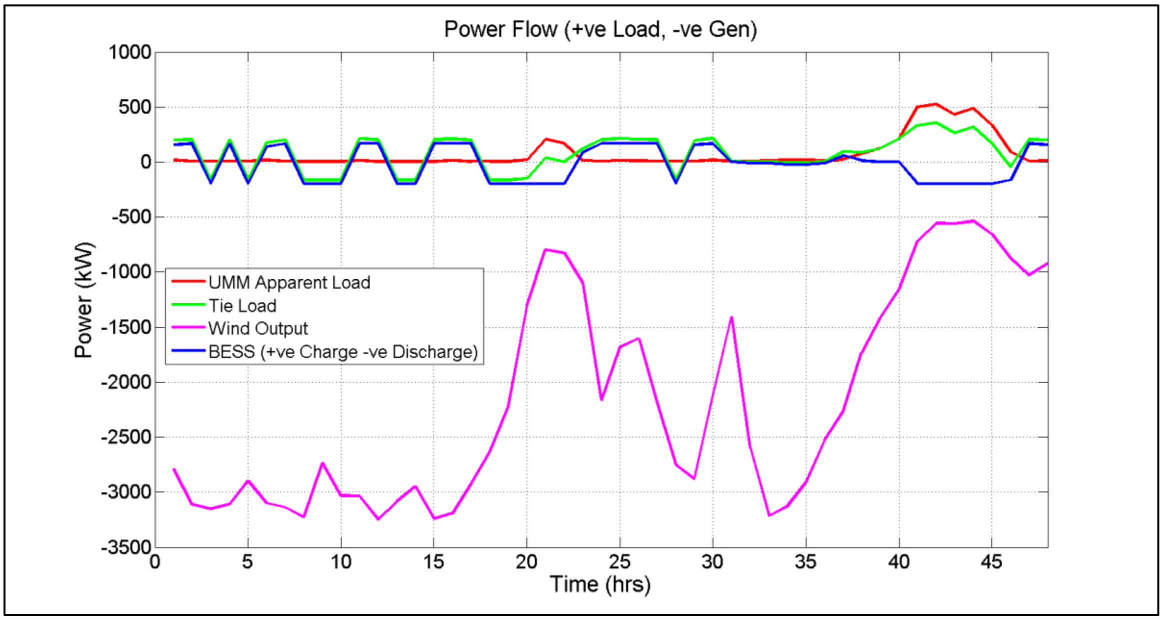

Figure 26: LA2 EDmin Power: TOU, With Wind

Notice that hours 0-18 correspond to off-peak hours where the apparent UMM campus load is close to zero due to high wind output. We see that the BESS cycles at peak power rating during this period to “make a few extra bucks”. This is even more apparent from the jagged plot of stored energy.

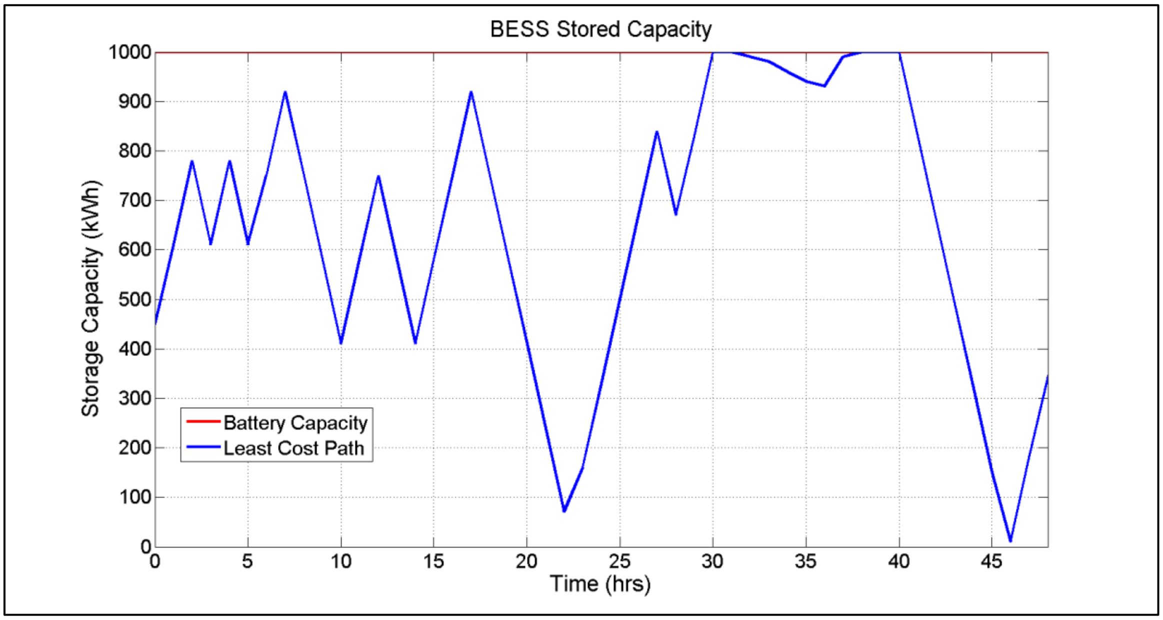

Figure 27: LA2 EDmin Stored Energy: TOU, With Wind

This behavior illustrates two important phenomena. First, that certain rate structures contain loopholes that encourage unnecessary charge/discharge cycles at cost to the utility. Second, that the optimization model as formulated does not penalize excessive cycling, other than through the effect of cycling losses.

4.8.5. The Effect of Forecast Error

Upon first glance, one might assume that the Achilles heel of the proposed dispatch algorithm is the fact that it requires an accurate load and wind generation forecast. To test this hypothesis, a normally distributed error is introduced into the forecast data, a technique that has been used in the past for determining the value of bulk energy storage in power systems with large penetrations of wind [6]. The error is defined as the maximum error of the forecast at a given time, which is given as a percent and set to three standard deviations from the mean. As an example, the following plot shows a 30% wind forecast error.

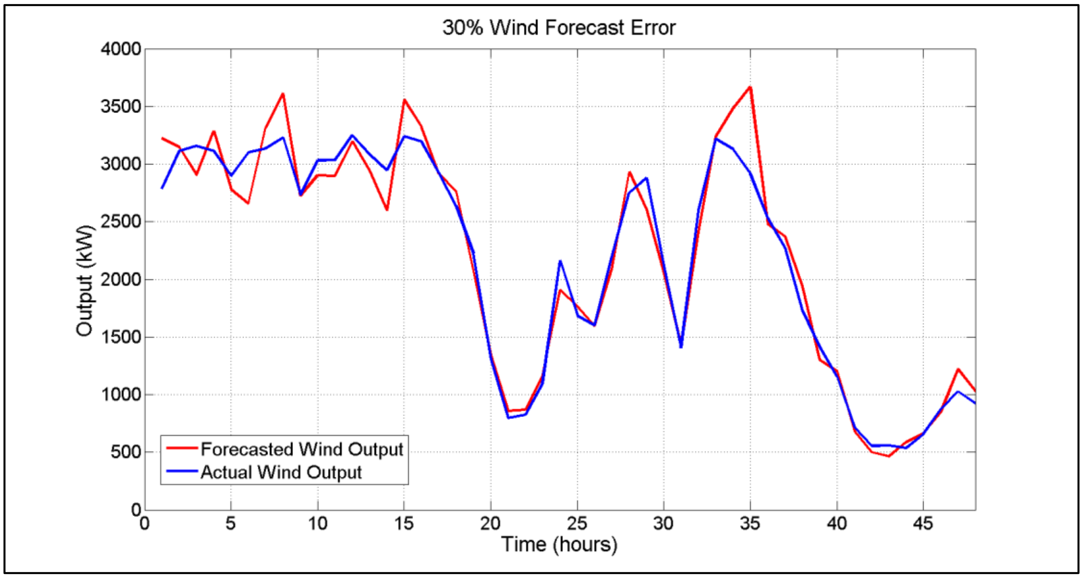

Figure 28: 30% Wind Forecast Error

Simulations were run for Emin, Dmin and EDmin algorithms to determine the effect of equal load and wind forecast errors for a TOU scenario. Results are summarized below.

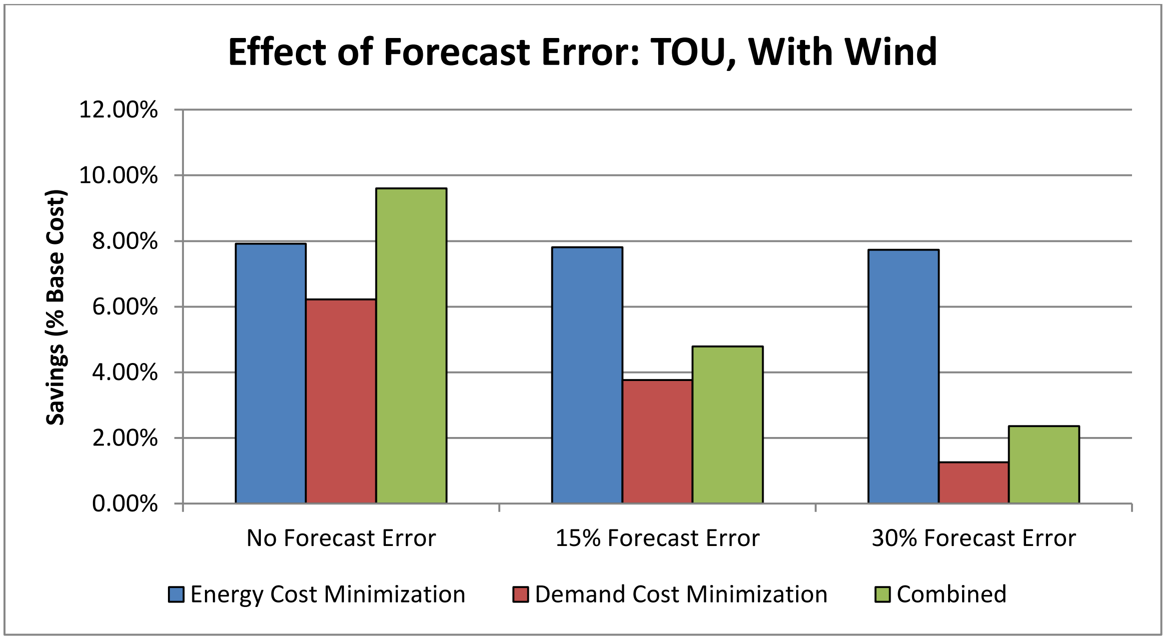

Figure 29: Effect of Forecast Error on Savings

We see that the energy cost minimization solutions only decreases slightly with forecast error and demand and combined minimization solutions decrease significantly. This is due to the fact that energy savings are slowly accumulated over the entire month, while demand savings are based on assumption of the monthly peak demand and achieved by limiting daily peaks that surpass a certain level.

4.8.6. Effect of Energy Conversion Efficiency on Losses

BESS conversion efficiency has a major impact on the optimal dispatch behavior, savings and energy losses. To observe and analyze this effect, an EDmin optimization is performed over a range of efficiencies, from 0.5 to 1, for a TOU - with wind scenario. The effect of conversion efficiency on number of cycles is shown in the figure below.

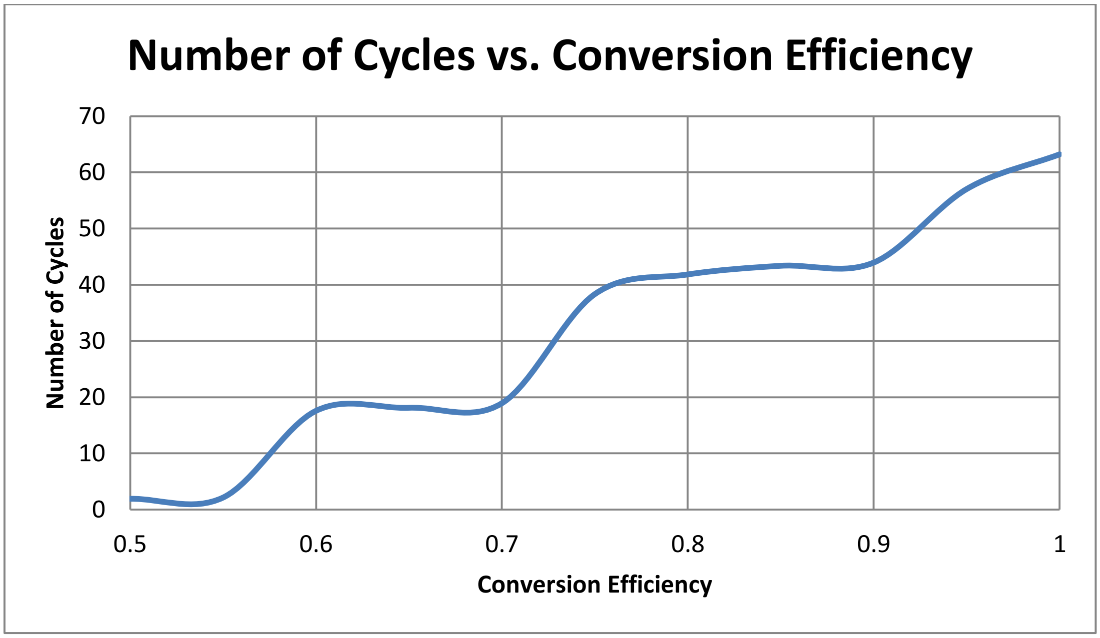

Figure 30: LA2 Effect of Conversion Efficiency on Cycling: TOU, With Wind

In general, the number of cycles in the optimal dispatch schedule increases with conversion efficiency, although the relationship is certainly not linear. The reason for this behavior is only clear after looking at the ratio of BESS revenues for different efficiencies, as shown below.

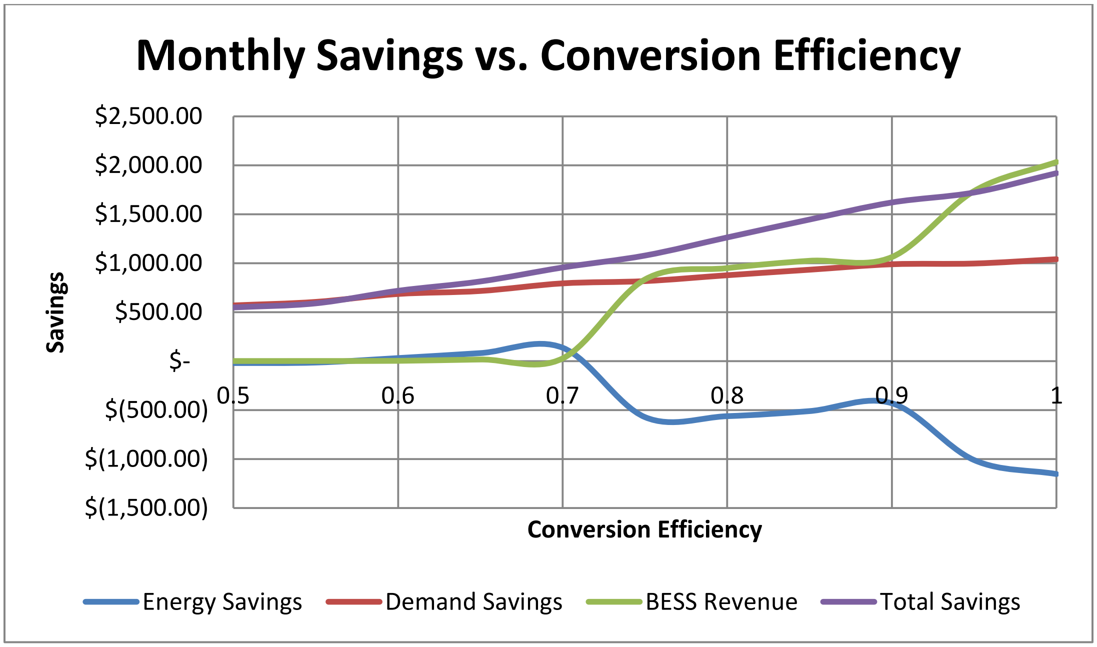

Figure 31: LA2 Effect of Efficiency on Savings: TOU, With Wind

When conversion efficiency is low, the majority of savings are from less cycle-intensive demand charge reductions. Likewise, the additional energy charges incurred from inefficient cycling outweigh the potential savings of TOU energy arbitrage, hence the energy minimization objective is abandoned. For higher conversion efficiencies, there is a steady climb in demand savings and there is a play-off between maximizing energy savings and maximizing sell-back revenues. In this scenario, the additional sell-back revenue wins out as conversion efficiency exceeds 0.7.

Recall that accumulated energy losses depend on available capacity, roundtrip efficiency and the number of cycles.

$$P_{loss} = W_{op}\left(1 - \eta_{roundtrip}\right)N_{cycles} \tag{37}$$

Since the number of cycles increases for high efficiencies in the EDmin simulation however, there is a non-linear relationship between conversion efficiency on BESS-induced losses, which is depicted below.

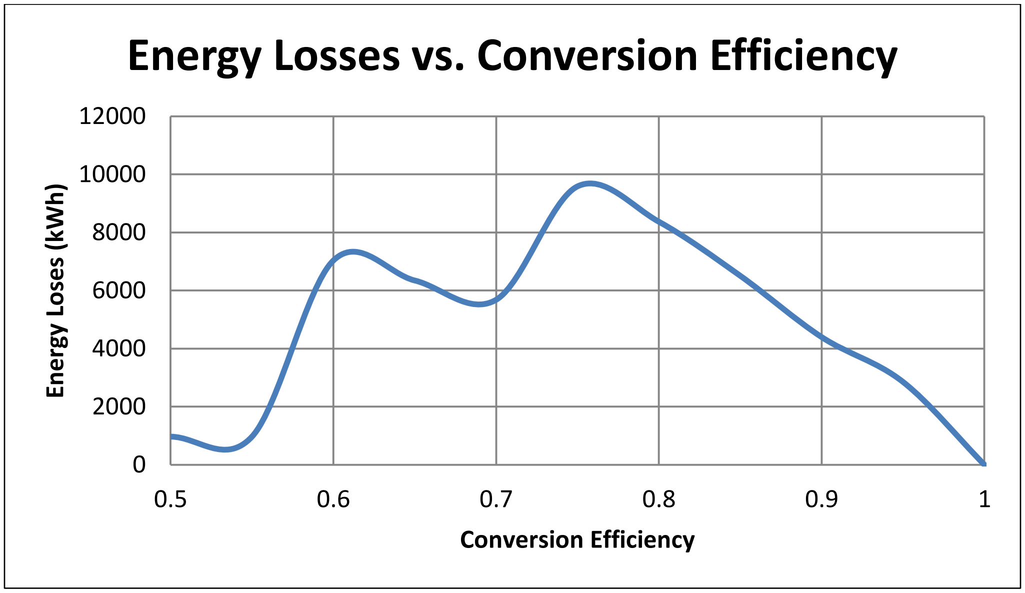

Figure 32: LA2 Impact of Efficiency on Energy Losses: TOU, With Wind

4.8.7. Cycling and BESS Lifetime

As shown, cycling increases for high efficiency BESS that can achieve savings from energy arbitrage or energy sell-back. Excessive cycling can have a detrimental impact on the operational lifespan of BESS, however, and should be limited to acceptable limits in order to maximize lifetime savings. One approach to limiting cycling is to introduce a penalty factor into the objective function that incurs a cost for each cycle. Since the penalty factor will only have a virtual effect on the objective function value, the actual savings accumulated will only be penalized by the reduction in cycling. The penalty factor term introduced into the EDmin objective function is expressed as the incremental cycle times the penalty factor, *PF*, as shown below.

$$Cost_{cycle} = -\frac{\eta P_{BESS,t,p}}{2W_{op}} * PF \qquad (38)$$

The following figures show the physical effect of the penalty factor on BESS operation.

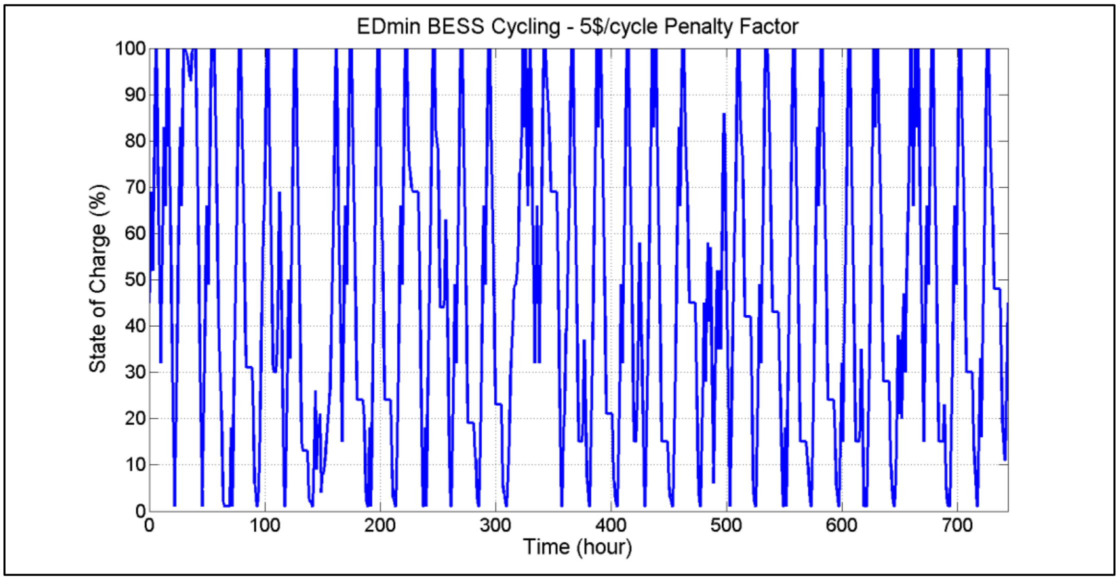

Figure 33: BESS Cycling – 5$/Cycle Penalty Factor

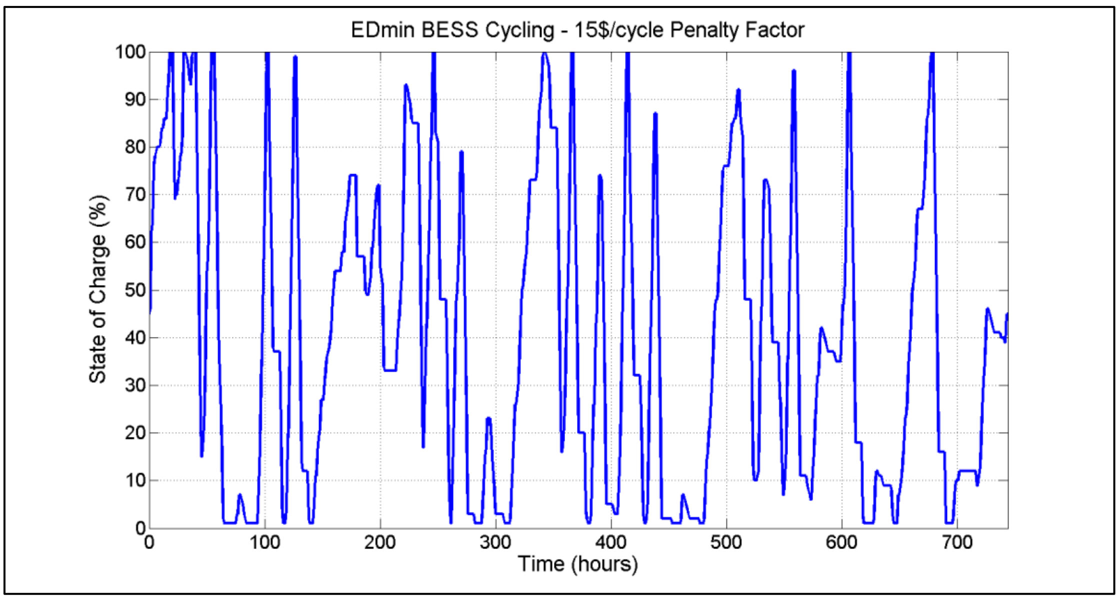

Figure 34: BESS Cycling – 15$/Cycle Penalty Factor

To illustrate the effect of the penalty factor on BESS lifetime and lifetime savings, consider a Lead Acid 2 BESS with a rated lifespan of 15 years and a cycle life of 4500 cycles. For planning purposes, assume that there is no inflation and that the average monthly savings for the next 15 years are equivalent to the May 2011 savings, which are determined in a TOU – with wnd scenario. The maximum number of average cycles per month before the BESS cycle life starts reducing its rated lifespan can be calculated as:

$$N_{max\ cycles} = \frac{Cycle\ Life}{Lifespan} \tag{39}$$

The maximum number of monthly cycles for the LA2 BESS is 25. The following table illustrates the impact of cycling on lifetime and lifetime savings, which were obtained by varying the penalty factor.

Table 12: Effect of Cycling on Lifespan and Lifetime Savings

Penalty Factor ($/cycle)	Cycles Per Month	Actual Lifespan (yrs)	Lifetime Savings
0	43.4	8.65	$ 149,923.23
2	43.3	8.65	$ 150,038.07
4	42.8	8.76	$ 151,798.49
6	42.2	8.89	$ 153,721.27
6.5	40.0	9.37	$ 160,494.00
7	38.6	9.73	$ 165,401.56
7.5	29.6	12.66	$ 205,493.42
7.6	27.8	13.48	$ 216,713.59
7.7	18.8	15	$ 228,810.60
7.8	18.7	15	$ 228,796.20
8	18.8	15.00	$ 228,762.00

It is evident that, without the penalty factor, the actual life of the LA2 BESS is shortened by almost half and savings are significantly reduced. As expected, the maximum lifetime savings occur when the monthly cycles are kept closest to the maximum value of 25, which occurs at a penalty factor of 7.8 $/cycle and yields a lifetime savings of $228,810.

The table also illustrates a major limitation of using a penalty factor to enforce constraints: it is difficult to control the constrained variable. Over the range of values calculated above, the number of cycles drops precipitously for penalty factors greater than 6 $/cycle and the optimum value needs to be obtained by iterative search methods.

4.9. Capacity Partitioning

For this part of the analysis, available BESS capacity was divided in two and dedicated to emergency backup and energy and demand management applications in varying proportions. As a first approximation for planning purposes, EDmin savings amounts from May 2011 were extrapolated over the entire year. Outage savings were accrued if the BESS emergency backup capacity exceeded the minimum ride-through capacity for a given outage duration, as calculated in section 4.5. This simplified technique using expected outage frequencies and costs was used to prevent making further assumptions required for more in-depth outage modeling.

Results are first shown in detail for the Lead Acid 2 BESS for a TOU case with no wind so that the opportunistic battery sell-back cycling effect discussed in section 4.8.4 does not occur. Also, the cycling penalty factor is not included due to the difficulties discussed in the previous section. Once the LA2 BESS has been examined in detail, all candidate technologies are compared and contrasted and the overall competitiveness of each technology is determined.

4.9.1. Lead Acid 2 Capacity Partitioning

For this simulation, the 1000kWh available capacity of the LA2 BESS was divided into ten discrete segments and the proportions dedicated to the EDmin application and to emergency backup were varied. For example, when the battery capacity is divided equally between applications, EDmin yearly savings are $14,576 and avoided outage costs are $9,335. The latter value was calculated by noting that 500kWh emergency backup capacity could be used to ride through all 0-30 minute outages in addition to some slightly longer outages, the accumulative savings of which are obtained by a piece-wise linear extrapolation of the discrete values in table 10.

The resulting savings are shown below, where the x-axis is kWh capacity dedicated to EDmin with remaining capacity devoted to emergency backup.

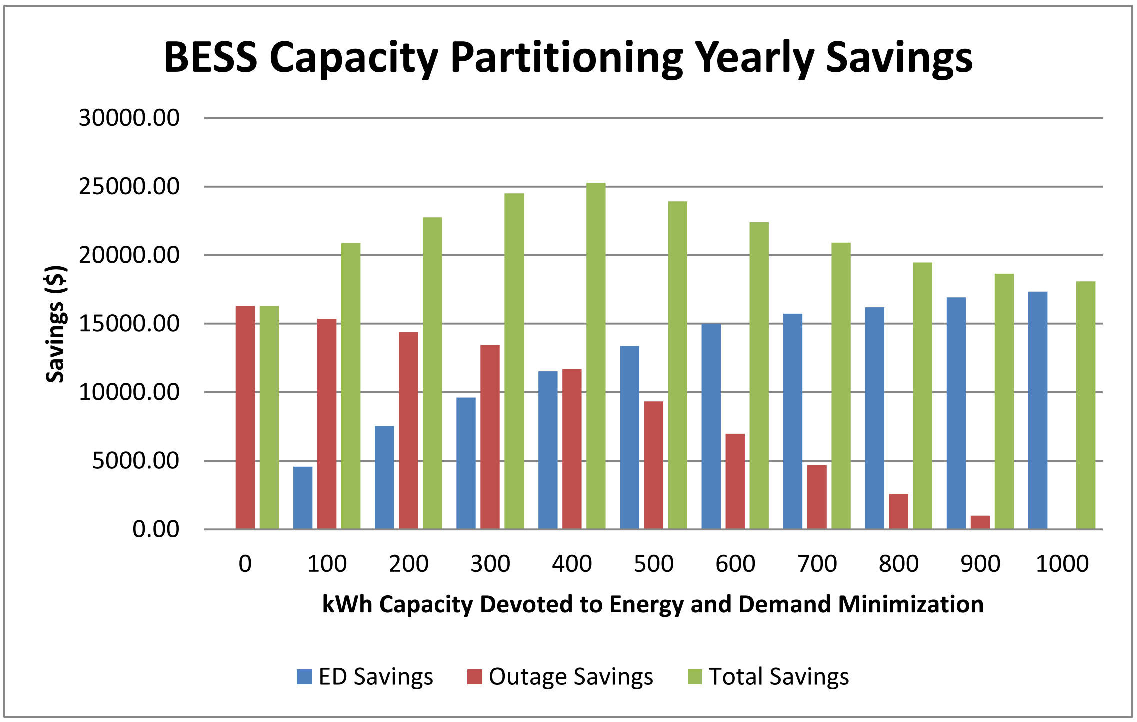

Figure 35: LA2 Capacity Partitioning Yearly Savings

Assuming that avoided outage cost and EDmin savings are treated with equal weight, we see that a maximum value of occurs at 400kWh for EDmin, 600kWh for emergency back-up and yields annual savings of $25,265. Another visualization is the multi-objective pareto-efficiency curve, shown below, which bulges outwards due to the fact that results are formulated in terms of maximized savings and can be used to determine pareto-efficient values in cases where outage cost savings and EDmin savings are treated distinctly.

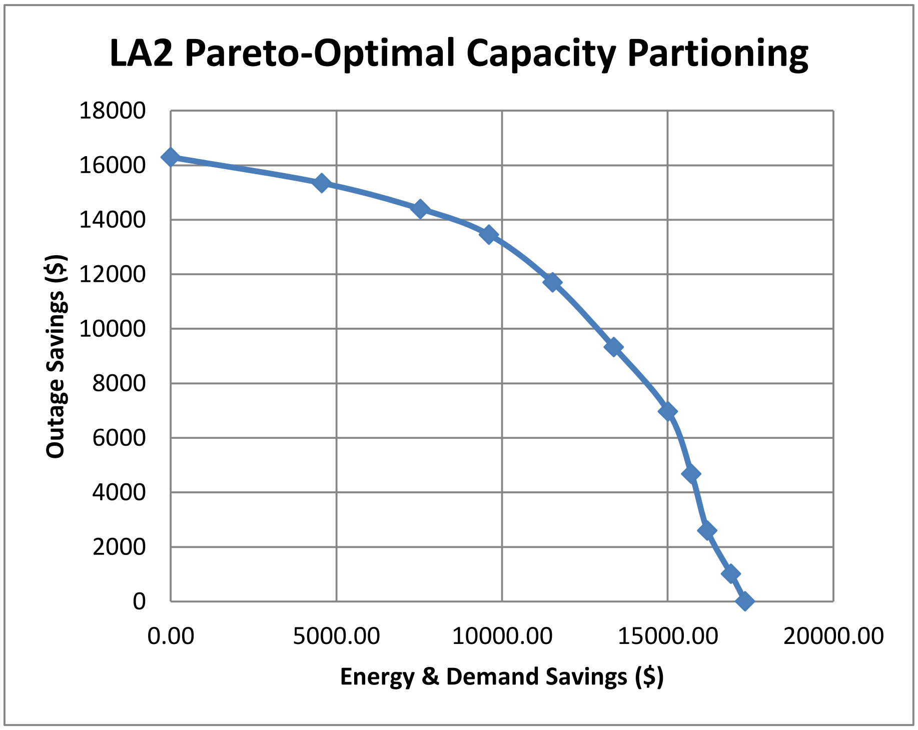

Figure 36: LA2 BESS Pareto-Efficient Capacity Partitioning

4.9.2. Capacity Partitioning Technology Comparisons

The following table compares the optimal values of all selected BESS technologies by treating EDmin and outage cost savings equally. The Return on Investment (ROI) is calculated using a simple cash flow definition neglecting economic depreciation and O&M costs.

$$ROI = \frac{Gross\ Cash\ Flow}{Gross\ Investment} \tag{40}$$

The gross investment is the capital cost of the BESS, which is the $/kWh value of the BESS multiplied by the available capacity.

Table 13: Optimal BESS Capacity Partitioning Technology Comparison

BESS	η	Available Capacity (kWh)	EDmin Capacity*	Emerg BU Capacity*	Yearly Savings*	ROI
LA1	85%	5000	80%	20%	$ 92,486	***3.08%***
LA2	85%	1000	40%	60%	$ 25,265	***3.51%***
NaS	75%	7200	80%	20%	$ 87,589	***2.43%***
Zn-Br1	62%	625	20%	80%	$ 14,167	***4.67%***
Zn-Br2	62%	2500	40%	60%	$ 37,856	***3.44%***
Van Flow	67%	1000	40%	60%	$ 22,530	***2.08%***
Li-Ion	67%	625	30%	70%	$ 21,632	***3.19%***

The average ROI of all the systems is 3.2%. With a 15 year lifespan with no O&M costs, none of the BESS will be able to pay back the initial capital investment, indicating the fact that the storage systems are still too expensive for the University of Minnesota Morris. It should be noted, however, that flow technologies like Zn-Br and Vanadium Redox batteries also have extremely high life cycles, which would make them even more competitive if limits were imposed on monthly cycling.

Analyzing some of the individual technologies, we see that Lead Acid 1 and the Sodium Sulfur battery both achieve large yearly savings due mainly to Energy and Demand minimization. Despite this, they both achieve less than average ROI due to their high cost. Also, the fact that only 20% of their available capacity is dedicated to emergency backup illustrates the fact that UMM's incremental yearly outage costs due to long term outages are small and fewer savings can be achieved from additional outage ride-through capability.

The smaller Zinc-Bromine 1 BESS is the most competitive candidate technology, with an ROI of 4.67%, due to its low capital cost of $303,125. Despite this, the payback period for UMM is over 21 years, hence is not economically attractive

5. Distributed Energy Storage

5.1. Overview

This section of the thesis is dedicated to investigating two problems: the optimal subset of distribution customers to receive emergency back-up service during an outage and the optimal the mix and placement of storage units in the distribution system for intentional islanding of sub-networks during outages. The former problem's objective is to minimize aggregate outage costs and it can be formulated as a non-linear, non-convex integer program. Simulations are used to compare and contrast two solution methodologies. The second problem of the optimal mix and placement of energy storage resources is investigated over a long-term planning horizon by using classical distribution system reliability analysis techniques. Individual distribution system feeder segments separated by sectionalizing switches become candidates for storage-enabled islanding during outages. A resource allocation problem is formulated as another non-linear integer program that leverages the techniques developed for the optimal subset problem. Before discussing the optimization models, however, the test system used for simulations is introduced.

5.2. 123 Node Test Feeder System Overview

The IEEE 123 Node Distribution Test System [50] is a three-phase unbalanced radial distribution feeder with 85 loads. Test system data contain technical parameters for loads, transformers, voltage regulators, switches, capacitor banks as well as detailed phasing and conductor information for overhead and underground lines. No customer information is included in the specification, however, so it was necessary to create detailed customer information for use in estimating outage costs. The following assumptions were made in creating the customer data:

- **Assumption 1**: The load factor of all customers is 0.45, a value that is typically use for distribution transformer loading assumptions [51]. The average kW demand for each load was given as the peak load, provided in the test feeder data, and the load factor.
- **Assumption 2**: All loads are assumed to remain constant during the outage and equal to their average kW demand. This is a reasonable assumption for planning purposes over long time horizons.
- **Assumption 3**: Residential, small C&I and large C&I customer sub-classes are assumed to each represent 36%, 35% and 29% of all load, respectively and each sub-class average per customer kW consumption is 1.33kW, 8.7kW and 75kW, respectively. These values are in close agreement with nationwide data [52], except for industrial customer average demand, which was assumed to be half the average value since large industrial customers typically connect directly to the sub-transmission network and since the transformer kVA ratings provided for the test system would not support very large loads.

The detailed customer information developed can be found in Appendix B. High-level system characteristics are summarized in the following table.

Table 14: 123 Node Test System Overview

SYSTEM CHARACTERISTICS	
Voltage (kV)	4.16
Number of Loads	85
Peak Load	3490 kW at 0.88 PF
Average Load	1570 kW

Number of Customers	513
Large C&I Customers	10
Medium C&I Customers	62
Residential Customers	441

5.3. 123 Node System Reliability Analysis

The 123 node system contains a three-phase feeder backbone and a number of one, two and three phase laterals that taps off the mains. There are three-phase switches at certain points along the feeder mains that are used to sectionalize the network during an outage, and sub-divide the mains into five subsections as shown below.

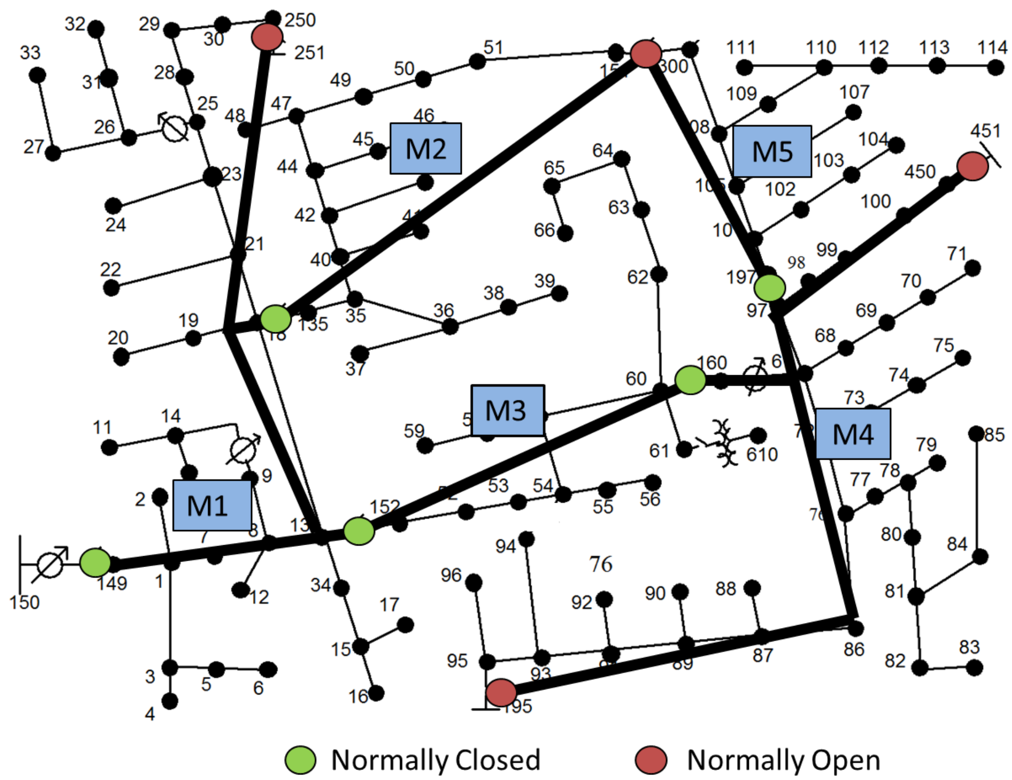

Figure 37: Test System Feeder Mains Topology and Switches

The electrical connectivity of the feeder mains can be represented by the following one-line diagram, which clearly shows five separate sub-sections.

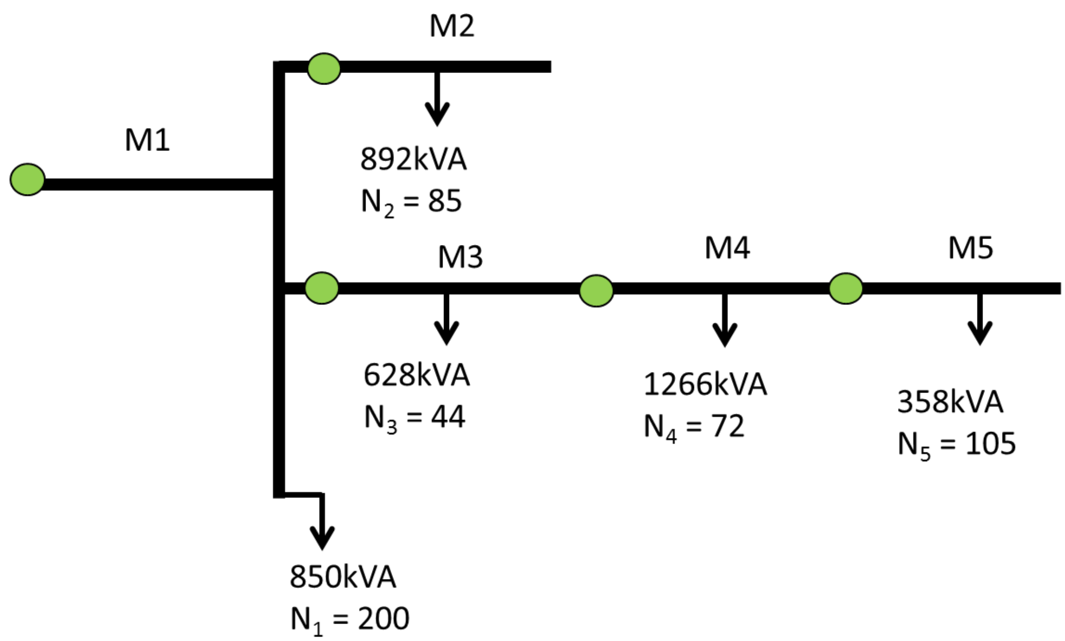

Figure 38: Feeder Main One-Line Diagram

Distribution protection schemes typically consist of an overcurrent relay and feeder circuit breaker at the substation, reclosers and sectionalizers on feeder mains and fuses at lateral connections and at specific equipment. Assuming that the normally-closed switches in the 123 node test feeder all time-coordinated reclosers, then faults that occur at a given sub-section of the feeder main will only outage that particular section and all downstream sections, leaving upstream sub-networks connected to the source. Implementing the techniques discussed in section 3.3.2, the following reliability statistics are determined for feeder sections with a mean failure rate of 2 failures per year and a mean time to repair of 1.5 hours.

Table 15: Feeder Section Reliability Analysis

	Feeder Section 1			Feeder Section 2			Feeder Section 3			Feeder Section 4			Feeder Section 5		
	N1: 200			**N2:** 85			**N3:** 44			**N4:** 72			**N5:** 112		
Failure Mode	λ (f/y)	r (h)	U=λr (hr/y)	λ (f/y)	r (h)	U=λr (hr/y)	λ (f/y)	r (h)	U=λr (hr/y)	λ (f/y)	r (h)	U=λr (hr/y)	λ (f/y)	r (h)	U=λr (hr/y)
M1	2	1.5	3	2	1.5	3	2	1.5	3	2	1.5	3	2	1.5	3
M2				2	1.5	3									
M3							2	1.5	3	2	1.5	3	2	1.5	3
M4										2	1.5	3	2	1.5	3
M5													2	1.5	3
Total	Σ λ	ΣU/Σλ	Σ U	Σ λ	ΣU/Σλ	Σ U	Σ λ	ΣU/Σλ	Σ U	Σ λ	ΣU/Σλ	Σ U	Σ λ	ΣU/Σλ	Σ U
	2	1.5	3	4	3	6	4	3	6	6	4.5	9	8	6	12
Cust Type	**LCI**	**SCI**	**Res**	**LCI**	**SCI**	**Res**	**LCI**	**SCI**	**Res**	**LCI**	**SCI**	**Res**	**LCI**	**SCI**	**Res**
No. Cust	0	11	189	4	4	77	2	14	28	4	33	35	0	0	112
Cost by Type	0	11365	817	9847	1593	192	22067	27652	181	60403	103120	297	0	0	1127
Total Cost	**2 x $ 12,183**			**4 x $11,632**			**4 x $49,900**			**6 x $163,820**			**8 x $1,127**		

- **Reliability Indices**

$$SAIFI = \frac{\sum \lambda_i N_i}{\sum N_i} = 4.37 \quad SAIDI = \frac{\sum U_i N_i}{\sum N_i} = 6.56 \quad CAIDI = \frac{SAIDI}{SAIFI} = 1.5 \tag{41}$$

5.4. Prioritized Ride-through Optimization Model

The optimal subset problem can be stated as follows: *Given an outage of a specific length and an energy storage system of specific capacity and location, determine the optimal subset of customers to ride through the outage to minimize all customers' outage costs*. The motivations for addressing this problem were discussed in section 1.3 and section 3.4, where it was shown that some customer groups have low outage costs per average kW demand and would be consuming valuable storage system energy during outages for a minimal increment in aggregate outage cost savings. In other words, from the point of view of the collective of all consumers, it is best to reserve storage capacity for those that need it most.

Physically, providing selective power can be realized at the level of the customer premise interconnection with the grid, i.e. the meter. Many smart meters currently being deployed have a remote connect-disconnect functionality that could potentially be leveraged to disconnect a group of customers. The idea of "intelligent load shedding" in distribution networks has been researched in the past [53], [54] and Quality of Service (QoS) load shedding is being investigated for naval shipboard applications by the Office of Naval Research [19].

Mathematically, the optimal subset problem can be expressed as follows.

$$\underset{X \in \{X_1..X_N\}}{\text{minimize}} \sum_{n=1}^{N} CDF_n \left(t_{out} - X_n \frac{W_{op}}{\sum_i^N X_n P_n} \right) \qquad s.t.$$

(1) $$X_n \in \{0,1\} \; \forall \, n \tag{42}$$

(2) $$\textstyle\sum_i^N X_n P_n < P_{rated}$$

(3) *Power System Operating Constraints*

Where, n is the load index $n \epsilon \{1 \ldots. N\}$, $CDF_n(\ldots)$ is the Customer Damage Function, t_{out} is the duration of system outage, X_n is an indicator variable for load n where $X=0$ means to shed the load and $X=1$ means to serve the load, W_{op} and P_{rated} are the available kWh capacity and rated kW power of the storage resource, respectively, and P_n is the kW demand of load n during the outage.

Each term in the summation in the objective function is the expected cost of an outage for a particular load. The input to the customer damage function is the duration of the outage as experienced by the customer, which is the duration of the system outage minus the duration that storage is serving the load, assuming it is active (i.e. $X_n = 1$). If storage is not active, the load experiences an outage of duration equal to that of the system outage. The duration that storage is available is the ratio of the available storage capacity (kWh) and the aggregate kW demand of all served loads.

The second constraint states that net demand on the system must not exceed rated demand, a formulation which neglects additional demand due to network losses as a first approximation.

Finally, due to the complexity of the power system constraints, the formulation used here treats them as a black-box. At each iteration of the numerical solution algorithm, all of the network, load and operating data are passed to a power flow program to determine whether or not the solution is feasible, i.e. if any current or voltage limit violations occur. With modern day computing systems, power flow software can solve a network of approximately 1000 nodes in less than a second. Consequently, from a computing time-cost perspective, this feasibility constraint is relatively “cheap” to compute when adopted for small scale optimization problems.

5.5. Prioritized Ride-through Solution Algorithms

The optimization problem formulated above is a non-linear, non-convex binary integer program with non-linear constraints. Problems of this form are notoriously intractable and require solution techniques that are specialized for the individual application [55]. For this reason, this thesis presents a number of different algorithms and analyzes their relative merits in solving this problem.

5.5.1. Simulated Annealing

Simulated annealing is a probabilistic meta-heuristic modeled after a metallurgical process. It controls the issues of cycling and local minimum termination by accepting non-improving moves according to probabilities tested with computer generated random numbers. In addition to problem data, simulated annealing algorithms use additional input parameters and stopping criteria to tune algorithm performance and configure running time. These parameters and the algorithm outline are shown below.

- **Algorithm Parameters**
    - Initial Configuration, $X_{init} = \{X_1, X_2, \dots X_n\}$
    - Temperature, T: Constant used in determining the probability of accepting non-improving moves
    - Annealing Rate, ρ: Factor by which to reduce temperature
    - Inner Loop Size, L: Number of iterations to run before reducing temperature
- **Stopping Criteria**

After every inner loop, L, check to see if a better solution has been found. If improvement has been made, continue. Otherwise, return the best solution to date.

- **Algorithm Outline**

1. Starting with initial configuration X_{init}, get initial solution, S
2. While best solution has improved:
   2.1. Loop L times
      2.1.1. Pick a random feasible neighbor S’ of S
      2.1.2. Let $\Delta = f(S') - f(S)$
         2.1.2.1. If $\Delta \le 0$, set S = S’ and save solution as best to date
         2.1.2.2. If $\Delta \ge 0$, set S = S’ with probability $\exp(-\Delta/T)$
      2.1.3. Set $T = \rho T$ (i.e. reduce the temperature)
3. Return the best solution found and associated configuration, X

5.5.2. Local Search Heuristic

Simulated Annealing relies on computer-generated random numbers to select neighboring solutions and test them for feasibility and, as a result, spends a considerable amount of time selecting “poor” solutions. Greedy algorithms, on the other hand, will attempt to move in the direction of steepest descent and quickly arrive at a minimum and terminate without trying non-improving moves [56]. The following local search algorithm takes into account the structure of the problem by making two observations. First, while the customer damage function is non-linear and non-convex, the outage-cost order of nodes tends to remain the same regardless of outage duration. Second, the customer damage functions have a non-zero cost at outage duration, $\varepsilon > 0$. That is, there is a significant cost associated with experiencing an outage, even if it only occurs for a short duration. Consequently, the optimal solution will typically occur when discharge time for a given configuration is greater than the duration of the outage, i.e. no loads are shed mid-outage.

- **Algorithm Outline**
  1. Starting with initial configuration X= {0 … 0}
  2. While $t_{storage} < t_{outage}$

2.1. For all disconnected loads $X_i = 0$

2.1.1. If feasible, add the next highest cost-of-outage load, get solution S', else continue

2.1.2. Let $\Delta = f(S') - f(S)$

2.1.2.1. If $\Delta \leq 0$, go to 2

3. Return the last solution and associated configuration, X

5.5.3. Combined Approach

As previously discussed, the local search algorithm will quickly terminate at a local minimum with an associated load-shed configuration, *X.* As we will see in the simulations, this solution is frequently not at a global minimum. However, this configuration can then be fed into the Simulated Annealing algorithm to accept non-improving moves and continue looking for better solutions outside of the local minimum. As we will see, this combined approach offers an improved solution quality to performance ratio than either of the two algorithms alone.

5.6. Prioritized Ride-Through Simulations

A two hour outage on the bulk transmission power system is simulated on the 123 node system and a BESS located in the distribution substation (node 150) is used to serve a subset of customers in the system.

5.6.1. Outage Cost Comparison

Without emergency backup, all customers experience the full duration of the outage and the total cost of the outage is $155,060. After a 1500 kWh BESS is implemented, if all loads are connected throughout the outage, the net demand on the BESS will be over 1700 kW, which exceeds the rated power of all of our candidate storage systems and would trip the system offline. In the hypothetical case that rated power had been sufficient, the outage cost would have been reduced to $100,890 and loads would have served for 9.5 minutes before the

BESS expended its capacity. Implementing the local search method, an optimal subset of 26 high-priority commercial and industrial customers at 17 load points is selected to ride through the entire outage, thereby reducing aggregate outage costs to $57,783. Results are summarized in the following table and figure.

Table 16: Outage Cost Comparison

Customer Outage Costs	Large C&I	Small C&I	Res.	Total	Loads Served
No Storage	$ 70,822	$ 82,027	$ 2,215	$155,060	0
With Storage - All Loads	$ 46,114	$ 53,067	$ 1,708	$ 100,890	85
With Storage - Selective Service	$ 0	$ 55,567	$ 2,215	$ 57,783	17

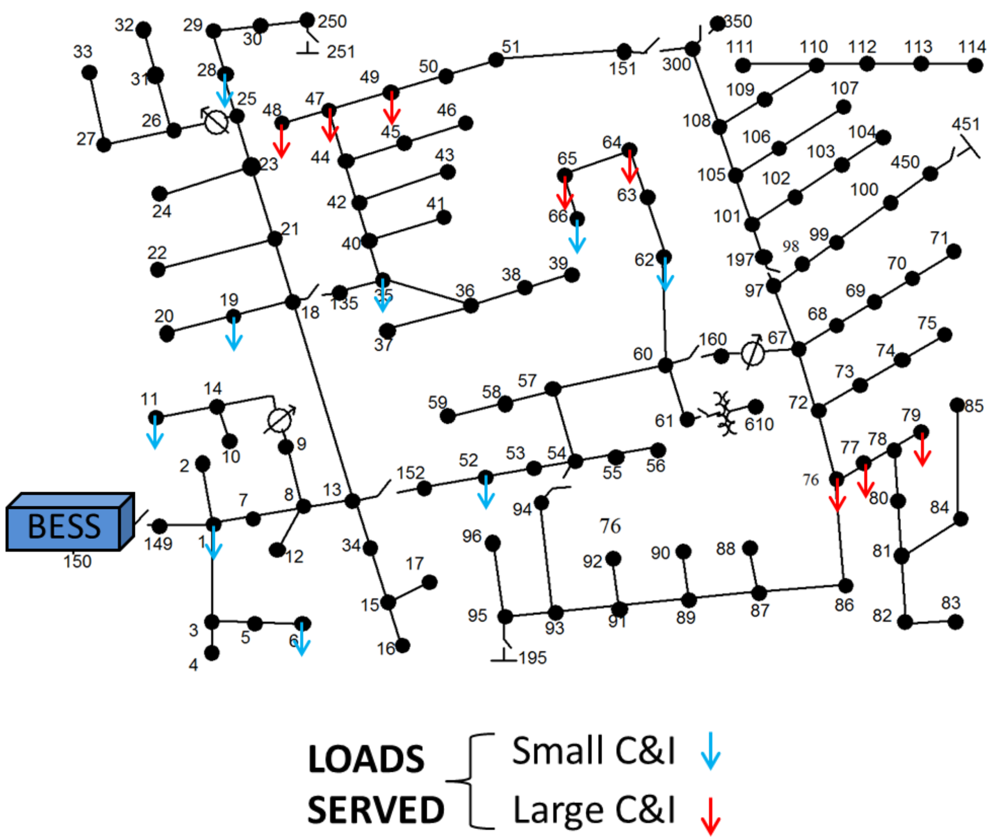

Figure 39: 123 Node Test Feeder with Priority Ride-through Service

5.6.2. Algorithm Comparison

For this simulation, a Zinc-Bromine 2 BESS was chosen with 2500 kWh capacity and a 500kW power rating. In running the simulation, the following three sets of input parameters are used for the Simulated Annealing algorithm:

Table 17: Simulated Annealing Parameter Sets

Name	Temperature	Annealing Rate	Loop Size	Xinit
SA1	70000	0.95	15	{0,…,0}
SA2	200000	0.99	35	{0,…,0}
SA2_Xinit	200000	0.99	35	Local Search best solution

Since the Simulated Annealing algorithm contains a probabilistic component, it is run (sampled) ten times to get a best solution, a solution mean and standard deviation. The following table summarizes results.

Table 18: Priority Ride-through Solution Results

	Best Min Cost	Mean Min Cost	σ	Mean Iterations	σ
Local	$92,448	NA	NA	113	NA
SA1	$95,383	$101,969	$5,269	146	45
SA2	$87,300	$91,760	$4,786	827	133
SA2_Xinit	$86,815	$90,267	$2,112	897	110

The results show that the local search heuristic terminates at a local minimum after a relatively few number of iterations. SA1 also solves in few iterations, but the solution quality is poor. On average, the SA2 simulation achieves a lower objective function value than the local search method, but at the expense of additional iterations. Using the final configuration of the local search method as the initial solution to the SA2 consistently provides the best solution quality, since the worst solution is at least as good as the local search heuristic.

5.6.3. Power System Considerations

To determine the effect of priority ride-through on distribution network operation, a three-phase unbalanced power flow was run on the final load configuration in the system using OpenDSS, an EPRI-developed distribution system simulator [57]. As it turns out, no voltage or current limits are violated as a result of selectively serving a subset of loads. The following considerations should be noted however:

- **Reactive Flow**: The capacitor banks in the 123 node circuit greatly influence the reactive power flow during priority ride-through operation. During normal operation with all cap banks switched in, the feeder head power flow at the substation is 0.997 lagging and the reactive power flow is only 109 kVar. During priority ride-through the reactive power flow jumps to 488kVar in the other direction with a 0.7 leading power factor.
- **Current**: Line currents are drastically reduced. During normal operation, the substation phase A current is 271A. During priority ride-through operation it is reduced to 100A.
- **Voltage**: Due to reduced currents, resistive voltage drops along the lines are also reduced and no limits are violated. However, voltage regulator settings do not take into account this selective service case and artificially keep bus voltages high despite the fact that few customers are being served. This phenomenon is illustrated below for both normal and priority-ride through operation through the use of voltage drop plots. The x-axis represents distance from the substation and the y-axis is voltage in per unit.

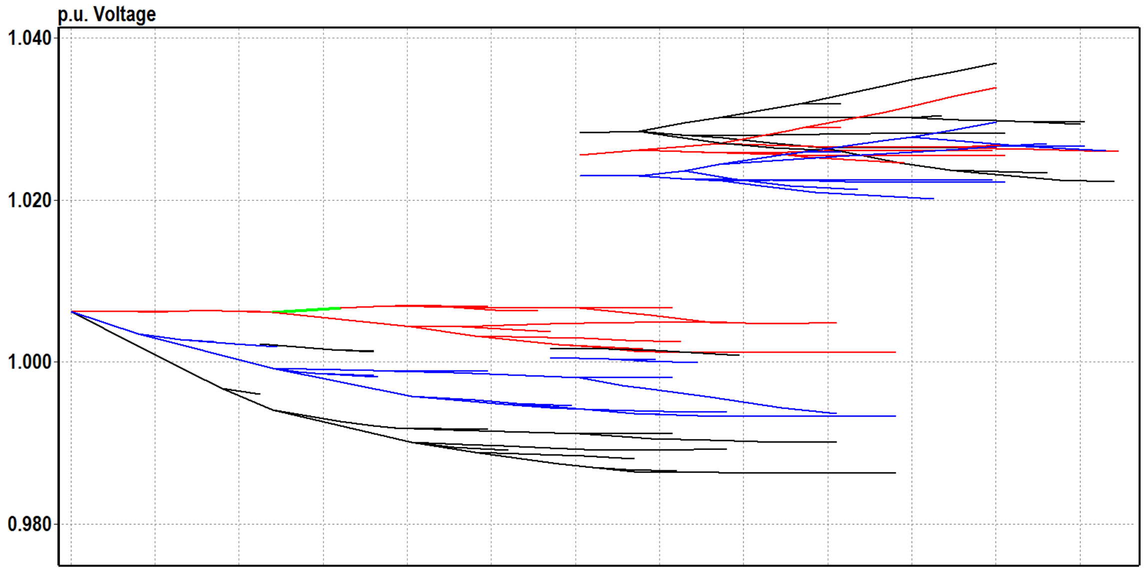

Figure 40: Voltage Drop Diagram – Normal Operation

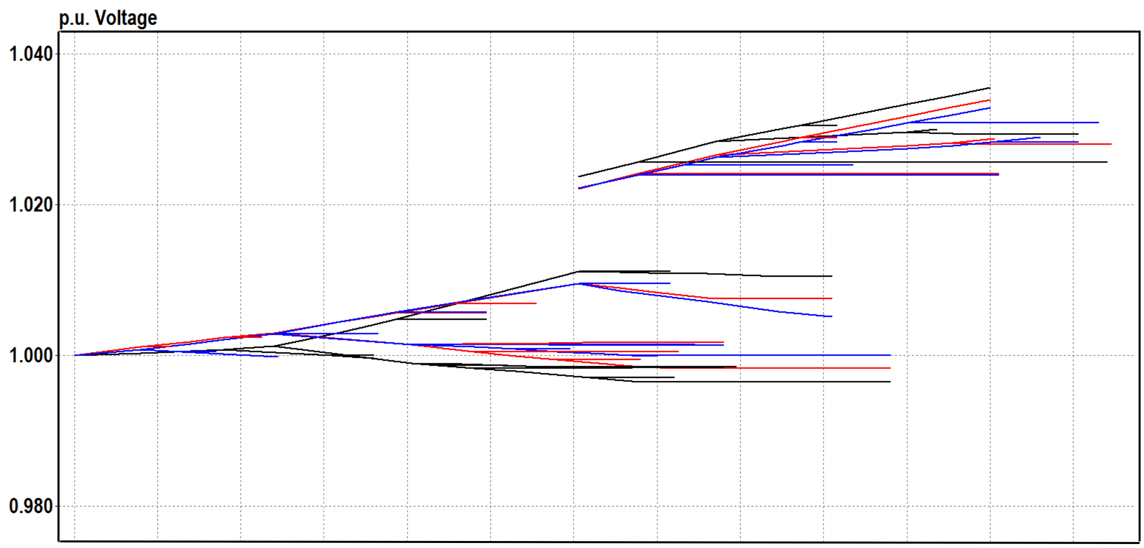

Figure 41: Voltage Drop Diagram – Priority Ride-Through

Here, we see that during normal operation the voltage regulators compensate for line drop and keep service voltages close to 1.0 per unit. In the case of priority ride-through the leading power factor and kVar flow actually causes a downstream voltage increase, which is exacerbated by the regulator settings.

This effect is particularly evident at the mid-point of the diagram, which represents the mid-feeder regulator at node 67.

5.6.4. Capacity and Power Rating Sweeps

For this simulation, a number of battery storage capacities and power ratings were tested to determine their relative effect on outage cost savings using the SA2_Xinit algorithm. The results are shown below with BESS power rating plotted along one horizontal axis, BESS capacity plotted along another horizontal axis and aggregate outage cost plotted along the vertical axis.

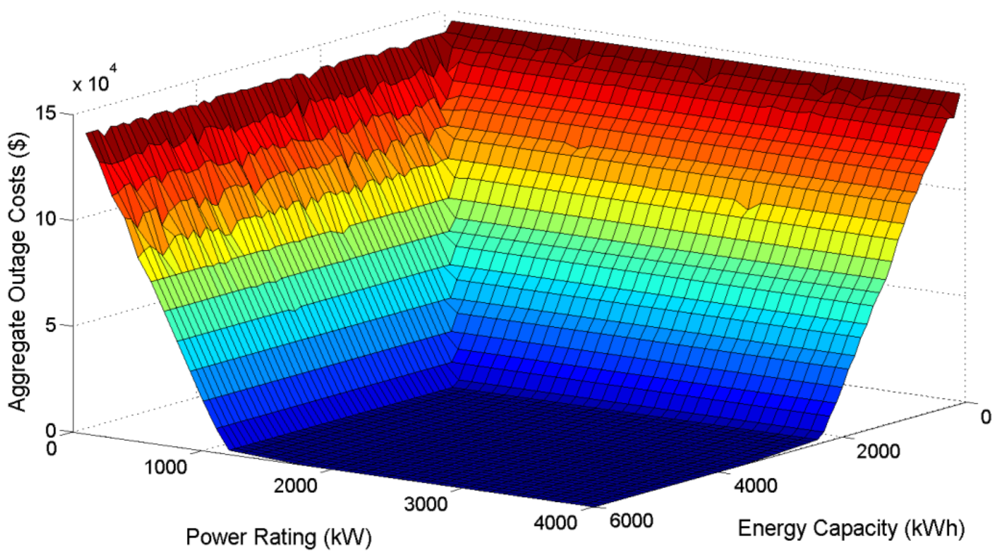

Figure 42: Effect of BESS Energy Capacity and Power Rating on Aggregate Outage Cost – Priority Ride-Through Service

5.7. Optimal Mix and Placement Optimization Model

The implementation of distributed storage resources for emergency backup purposes implies that, during a system event, certain disconnected but non-faulted sub-networks will begin to operate in islanded mode with customers being served by a local BESS. For sub-networks that contain multiple BESS units, it is assumed that they can be electrically paralleled to provide additional power capacity and total available energy.

Since the optimal mix and placement problem is a capital planning problem that of a 15 to 20 year time horizon, the outage duration values for each sub-network are chosen to be equal to the unavailability (average hours interrupted/year), *U*, of the sub-network, which is calculated using classical distribution reliability analysis techniques discussed in section 3.3.2. Similar approaches [58] have been used to determine optimal gas turbine sizing for emergency backup.

Given the average outage duration per sub-section, the optimization problem can be stated as follows: *Given a set of I candidate storage systems capacities W_i, power rating P_i and cost C_i, respectively, determine the optimal mix and placement of resources to minimize aggregate outage costs subject to a global budget constraint.* Mathematically, this can be stated as follows:

$$\underset{X}{\text{minimize}} \sum_{n=1}^{N} AOC_n\left(\sum_{i=1}^{I} X_{n,i}W_i, \sum_{i=1}^{I} X_{n,i}P_i\,, t_{out,n}\right) \qquad s.t.$$

$$(1) \qquad X_{n,i} \in +\mathbb{Z}^n \qquad (43)$$

$$(2) \qquad \textstyle\sum_n^N \sum_i^I X_{n,i}\, C_i < Budget$$

(3) *Power System Operating Constraints*

Where n is the sub-network index with $n \in \{1 \ldots N\}$, $X_{n,i}$ is a positive integer selection variable representing the number of unit *i* storage systems to be placed at location *n*. The budget constraint is the maximum amount to be invested in

BESS for the entire distribution system and the power system operating constraints are the same as previously discussed.

5.8. Optimal Mix and Placement Solution Methodology

The problem formulated above is again a non-linear, non-convex constrained integer program where the decision variables are now open to the set of all integers. Again, this type of problem is highly intractable and can only be solved using heuristic methods except for problems with small feasible sets. For small budget constraints, the number of possible storage system combinations will not be large and all solutions can be enumerated explicitly. For larger feasible sets, the proposed solution technique is to implement a local search heuristic, where one storage unit is chosen at a time until the budget limit is met. The local search algorithm can be summarized is as follows:

- **Algorithm Outline**
  1. While budget is not exhausted
     - 1.1. Calculate aggregate outage savings for each candidate system at each node
     - 1.2. Choose the system and location that achieves the greatest Return on Investment (savings/capital cost) and fix at that location
     - 1.3. Update available budget
  2. Return the systems and locations and minimum aggregate outage cost

The local search heuristic has the added advantage of building up a “priority list” of chosen BESS that doesn’t rely on the budget constraint to restrict the feasible set.

5.9. Optimal Mix and Placement Simulations

The 123 node test feeder system was again used for simulations. All five feeder sections are potential locations for one or more BESS. Applying the local search heuristic, a priority list of BESS system is developed for systems where priority ride through service is provided.

Table 19: Local Search BESS Priority List – Priority Ride-Through

Units Selected	BESS Selected	Location	Capital Cost	Annual Outage Costs	Payback Period
0	None	--	$ 0	$ 1,435,814	--
1	ZB1	M4	$ 303,125	$ 1,150,038	***1.06 yrs***
2	ZB1	M4	$ 606,250	$ 942,289	***1.23 yrs***
3	ZB1	M4	$ 909,375	$ 717,531	***1.27 yrs***
4	ZB1	M4	$ 1,212,500	$ 492,136	***1.29 yrs***
5	ZB1	M3	$ 1,515,625	$ 388,687	***1.45 yrs***

Table 20: Local Search Priority Ride-Through Reliability Improvements

Index	M1	M2	M3	M4	M5
Total Cust.	200	85	44	72	112
Cust. Served	0	0	4	35	0
SAIDI: 3.93 (down 0.44)		***SAIFI: 5.90 (down 0.66)***		***CAIDI: 1.5 (same)***	

The results show that, from a collective standpoint, pooled energy storage resources can be very valuable. Deploying five zinc bromine BESS into the system reduces overall outage costs to 27% their original value and has a payback period of only a year and a half. And, despite the fact that only 39 out of 513 customers are allowed to remain online during outages, system-wide reliability indices also show marked improvement.

6. Conclusions and Future Work

Electric energy storage is a transformative technology that opens up a wide-range of utility and end-use applications by shifting energy in time. Energy storage technology also has the potential to be highly disruptive. The traditional regulated natural monopoly model of the utility industry may become less relevant if electricity can be efficiently stored at different points in the supply chain. As storage system costs continue to decline and Smart Grid technologies take foothold, third-party companies may begin to supply to power and energy products and services directly to consumers, acting as an intermediate party between grid-owners and their present day customers. The customer-perspective modeling presented in this thesis give us the ability to quantitatively assess non-utility capital investments in customer premise and distributed energy storage systems and to determine the break-even point for a variety of technologies. It also opens up a wide-range of potential research opportunities, a few of which are discussed below.

A complete analysis of multi-application customer premise energy storage would include power quality and utility service applications as well as energy, demand and emergency backup services. The inclusion of fast response applications such as power quality would in turn necessitate detailed modeling of storage and conversion system dynamics and control schemes. Furthermore, in addition to investigating these applications issues on a planning horizon, much research needs to be done at the operational level for energy storage systems to become practical. This would include developing multi-objective control strategies for various operating scenarios, investigating centralized and distributed control and communications architectures for local and multi-unit operation, and researching existing and future policies and standards that would enable interaction of utility and customer resources.

In the area of distributed energy storage, work needs to be done to extend the optimal mix and placement modeling presented in this thesis to smaller scale community energy storage systems of 25-200kW rating that are placed closer to customer premises. DESS implementation at this level may be more practical as there would be less control and communications infrastructure overhead and utilities wouldn't need to overhaul legacy protection schemes. While investigating small-scale DESS would cause the number of optimization variables to increase precipitously, a more detailed reliability assessment could be performed that better aligns with common utility practices. In addition, as we have seen with customer-premise applications, operating an energy storage system according to multiple control objectives simultaneously can provide additional benefit and merits investigation for DESS as well.

Lastly, quantifying and comparing both the utility and customer value of distributed energy storage would shed light on each party's economic incentives and true stake in reliability improvements. Doing so would potentially make a renewed case for "performance-based rated", where utilities are compensated based on the reliability and quality of electric power service as opposed to revenues earned from electricity sales. In the absence of such a regulatory transformation, this same research may also be used to hasten disintermediation and the adoption of retail-level deregulation.

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Appendix A: Battery Energy Storage Systems

Battery Energy Storage Systems (BESS) are electrochemical energy storage and conversion systems that charge and discharge banks of batteries. In addition to the generic energy storage system parameters discussed in section 2.1, the following parameters are also used to characterize the operational state of the system:

- **State of Charge, SoC:** The amount of energy currently stored, given as a percentage of storage capacity. The *SoC* can be determined by summing the history of instantaneous power:

$$SoC = \frac{1}{W_{st}}\left(\int_{t_o}^{t} P(t)\,dt + P(t_o)\right) \tag{44}$$

- **Depth of Discharge, DoD:** Analogous to SoC, the depth of discharge is the percentage of storage capacity that has been discharged. Many storage batteries have rated depths of discharge, representing the limit of available energy capacity.

BESS utilize a variety of cell chemistries and consist of a set of low voltage battery modules connected in series and parallel to achieve the desired electrical characteristics. Since battery bank voltages and currents are DC, power electronic inverters are required to generate AC currents and voltages that are synchronized with the grid frequency at the point of interconnection.

Despite the complexity of the supporting apparatus, the operating characteristics of BESS depend primarily on cell electrochemistry and battery module interconnection. The most common chemistries for grid-scale battery storage applications are lead acid, lithium ion, sodium sulfur and flow batteries.

- **Lead-Acid**

Lead-acid batteries are the single most-used battery system worldwide. They are used for a wide range of applications, ranging from portable electronics to telecommunications, and more recently for commercial UPS, remote power and industrial and utility controls power. Today, lead-acid batteries are the most popular choice for most large-scale energy storage applications due to their low cost, ready availability and technological maturity. At the same time, lead acid batteries have lower energy, shorter cycle life and high maintenance requirements, although continuous improvements in chemistry, design and manufacturing techniques have helped mitigate these shortcomings [59]. Newer generations of lead-acid battery technology include valve-regulated lead acid (VRLA) are often described as “advanced lead-acid”.

- **Lithium Ion**

Lithium ion batteries are commonly used in consumer electronics, such as laptop batteries, and are actively being developed for hybrid electric vehicles. The 2012 Chevy Volt® electric vehicle, for instance, contains a lithium ion battery pack that is rated at 16kWh and consists of 288 individual cells. Despite cost reductions from economies of scale in transportation and consumer products manufacturing, lithium ion batteries are still among the most expensive options for utility-scale applications. Development of lower energy density lithium ion chemistries, such as lithium iron phosphate, has helped bring down cost by utilizing raw materials that are more abundant.

The battery electrochemistry is relatively simple and utilizes non-aqueous electrolytes, allowing the cell to be hermitically sealed. As a result, no routine maintenance is required and higher cell voltages of 3-4V are practical, which contributes to higher energy density. Another advantage of Lithium Ion BESS is their shallow cycling capability, which allows the battery to maintain relatively high efficiency over a wider range of state of charge [60].

- **Sodium Sulfur**

Sodium sulfur, or molten salt, batteries have been researched and developed for over 40 years, most notably by Tokyo Electric Power Company (TEPCO) and its industry partner, NGK, which is the world's sole supplier for utility applications. Characterized by its high energy density, high round trip efficiency and long cycle life, sodium sulfur batteries are made from inexpensive materials and are typically designed for several hours discharge and mega-watt scale applications. The largest BESS installations in the world are NaS batteries, including a 34MW / 204 MWh installation at the Rokkasho Wind Farm in Japan [61], shown below:

Figure 43: 34MW NaS Installation at Rokkosho Wind Farm, Japan [61]

In contrast to most batteries, sodium sulfur cells consist of a solid electrolyte membrane and liquid sodium anode, which requires the battery to operate at 300 to 350°C. In addition, sodium polysulfides are highly corrosive and can spontaneously explode in contact with air. Consequently, sodium sulfur battery design and operation is often restricted by environmental and safety considerations.

- **Flow Batteries**

An electrochemical cell's power and energy are dictated by the nature of the chemical reaction and the volume of electrolyte, respectively. In traditional batteries, the electroactive components in the aqueous electrolyte inside the cell are not externally accessible and energy capacity is constrained by cell geometry, electrode placement, etc. Flow batteries differ from traditional batteries in that are characterized by having external tanks of electrolytes that are pumped through a stationary electrode stack, where the reaction takes place. In theory, the available power is determined by the size of the electrode stack and the energy capacity is dictated by the volume of the electrolyte tanks. To this extent, flow batteries are essentially rechargeable fuel cells, where electrolytic fuels are externally supplied.

The term flow battery refers to a variety of cell chemistries. Vanadium redox, zinc-bromine and sodium bromide - sodium polysulfide are the most common for utility scale applications. In some flow batteries, electrodes merely supply a means of transferring ions and there is no solid-solid phase change, hence cycle life is greatly increased and electrodes are unaffected by deep discharges [60]. Other flow battery characteristics are lower energy density and round-trip efficiency, higher operational complexity due to pumps, sensors and control units, and flexible battery layout.

Appendix B: 123 Node Test System Customer Data

Spot Loads **Load Factor (LF): 0.45** **Type1: Large C&I** **Type 2: Small C&I** **Type 3: Residential**

Node			Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3	3Ph	3Ph			
	FeederSeg	Model	kW	kVAr	kW	kVAr	kW	kVAr	kVa	kVA*LF	# Cust	Type	kVA*LF/Cust
1	**1**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
2	**1**	Y-PQ	0	0	20	10	0	0	22.4	10.1	7	3	1.44
4	**1**	Y-PR	0	0	0	0	40	20	44.7	20.1	14	3	1.44
5	**1**	Y-I	0	0	0	0	20	10	22.4	10.1	7	3	1.44
6	**1**	Y-Z	0	0	0	0	40	20	44.7	20.1	2	2	10.06
7	**1**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
9	**1**	Y-PQ	40	20	0	0	0	0	44.7	20.1	14	3	1.44
10	**1**	Y-I	20	10	0	0	0	0	22.4	10.1	7	3	1.44
11	**1**	Y-Z	40	20	0	0	0	0	44.7	20.1	2	2	10.06
12	**1**	Y-PQ	0	0	20	10	0	0	22.4	10.1	7	3	1.44
16	**1**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44
17	**1**	Y-PQ	0	0	0	0	20	10	22.4	10.1	7	3	1.44
19	**1**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
20	**1**	Y-I	40	20	0	0	0	0	44.7	20.1	14	3	1.44
22	**1**	Y-Z	0	0	40	20	0	0	44.7	20.1	14	3	1.44
24	**1**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44
28	**1**	Y-I	40	20	0	0	0	0	44.7	20.1	2	2	10.06
29	**1**	Y-Z	40	20	0	0	0	0	44.7	20.1	14	3	1.44
30	**1**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44

31	**1**	Y-PQ	0	0	0	0	20	10	22.4	10.1	7	3	1.44
32	**1**	Y-PQ	0	0	0	0	20	10	22.4	10.1	1	2	10.06
33	**1**	Y-I	40	20	0	0	0	0	44.7	20.1	14	3	1.44
34	**1**	Y-Z	0	0	0	0	40	20	44.7	20.1	14	3	1.44
35	**2**	D-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
37	**2**	Y-Z	40	20	0	0	0	0	44.7	20.1	14	3	1.44
38	**2**	Y-I	0	0	20	10	0	0	22.4	10.1	7	3	1.44
39	**2**	Y-PQ	0	0	20	10	0	0	22.4	10.1	7	3	1.44
41	**2**	Y-PQ	0	0	0	0	20	10	22.4	10.1	1	2	10.06
42	**2**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
43	**2**	Y-Z	0	0	40	20	0	0	44.7	20.1	14	3	1.44
45	**2**	Y-I	20	10	0	0	0	0	22.4	10.1	1	2	10.06
46	**2**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
47	**2**	Y-I	35	25	35	25	35	25	129.0	58.1	1	1	58.07
48	**2**	Y-Z	70	50	70	50	70	50	258.1	116.1	2	1	58.07
49	**2**	Y-PQ	35	25	70	50	35	20	169.2	76.1	1	1	76.14
50	**2**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44
51	**2**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
52	**3**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
53	**3**	Y-PQ	40	20	0	0	0	0	44.7	20.1	14	3	1.44
55	**3**	Y-Z	20	10	0	0	0	0	22.4	10.1	7	3	1.44
56	**3**	Y-PQ	0	0	20	10	0	0	22.4	10.1	7	3	1.44
58	**3**	Y-I	0	0	20	10	0	0	22.4	10.1	2	2	5.03
59	**3**	Y-PQ	0	0	20	10	0	0	22.4	10.1	1	2	10.06
60	**3**	Y-PQ	20	10	0	0	0	0	22.4	10.1	1	2	10.06
62	**3**	Y-Z	0	0	0	0	40	20	44.7	20.1	2	2	10.06
63	**3**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
64	**3**	Y-I	0	0	75	35	0	0	82.8	37.2	1	1	37.24
65	**3**	D-Z	35	25	35	25	70	50	172.0	77.4	1	1	77.42

66	**3**	Y-PQ	0	0	0	0	75	35	82.8	37.2	4	2	9.31
68	**4**	Y-PQ	20	10	0	0	0	0	22.4	10.1	1	2	10.06
69	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
70	**4**	Y-PQ	20	10	0	0	0	0	22.4	10.1	1	2	10.06
71	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
73	**4**	Y-PQ	0	0	0	0	40	20	44.7	20.1	2	2	10.06
74	**4**	Y-Z	0	0	0	0	40	20	44.7	20.1	2	2	10.06
75	**4**	Y-PQ	0	0	0	0	40	20	44.7	20.1	2	2	10.06
76	**4**	D-I	105	80	70	50	70	50	304.0	136.8	2	1	68.40
77	**4**	Y-PQ	0	0	40	20	0	0	44.7	20.1	1	1	20.12
79	**4**	Y-Z	40	20	0	0	0	0	44.7	20.1	1	1	20.12
80	**4**	Y-PQ	0	0	40	20	0	0	44.7	20.1	2	2	10.06
82	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
83	**4**	Y-PQ	0	0	0	0	20	10	22.4	10.1	1	2	10.06
84	**4**	Y-PQ	0	0	0	0	20	10	22.4	10.1	1	2	10.06
85	**4**	Y-PQ	0	0	0	0	40	20	44.7	20.1	1	2	20.12
86	**4**	Y-PQ	0	0	20	10	0	0	22.4	10.1	1	2	10.06
87	**4**	Y-PQ	0	0	40	20	0	0	44.7	20.1	2	2	10.06
88	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
90	**4**	Y-I	0	0	40	20	0	0	44.7	20.1	2	2	10.06
92	**4**	Y-PQ	0	0	0	0	40	20	44.7	20.1	2	2	10.06
94	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	2	2	10.06
95	**4**	Y-PQ	0	0	20	10	0	0	22.4	10.1	1	2	10.06
96	**4**	Y-PQ	0	0	20	10	0	0	22.4	10.1	7	3	1.44
98	**4**	Y-PQ	40	20	0	0	0	0	44.7	20.1	14	3	1.44
99	**4**	Y-PQ	0	0	40	20	0	0	44.7	20.1	14	3	1.44
100	**4**	Y-Z	0	0	0	0	40	20	44.7	20.1	2	2	10.06
102	**5**	Y-PQ	0	0	0	0	20	10	22.4	10.1	7	3	1.44
103	**5**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44

104	**5**	Y-PQ	0	0	0	0	40	20	44.7	20.1	14	3	1.44
106	**5**	Y-PQ	0	0	40	20	0	0	44.7	20.1	14	3	1.44
107	**5**	Y-PQ	0	0	40	20	0	0	44.7	20.1	14	3	1.44
109	**5**	Y-PQ	40	20	0	0	0	0	44.7	20.1	14	3	1.44
111	**5**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
112	**5**	Y-I	20	10	0	0	0	0	22.4	10.1	7	3	1.44
113	**5**	Y-Z	40	20	0	0	0	0	44.7	20.1	14	3	1.44
114	**5**	Y-PQ	20	10	0	0	0	0	22.4	10.1	7	3	1.44
Total			**1420**	**775**	**915**	**515**	**1155**	**630**	**3993**	**1797**	**513**		**841.04**