EVALUATING ENERGY STORAGE OPTIONS:

A CASE STUDY AT LOS ANGELES HARBOR COLLEGE

A Group Project submitted in partial satisfaction of the requirements for the degree
of
Master's in Environmental Science and Management for the
Bren School of Environmental Science & Management

Group Members
Rebecca Hausheer
Kurt Heinze
Sheena Katai
Karly Kaufman
Jefferson Litten
Gomati Madaiah

Faculty Advisor
Sangwon Suh

March 23, 2012

As authors of this Group Project report, we are proud to archive this report on the Bren School's website such that the results of our research are available for all to read. Our signatures on the document signify our joint responsibility to fulfill the archiving standards set by the Bren School of Environmental Science & Management.

REBECCA HAUSHEER	KURT HEINZE
KARLY KAUFMAN	JEFFERSON LITTEN
GOMATI MADAIAH	SHEENA KATAI

The mission of the Bren School of Environmental Science & Management is to produce professionals with unrivaled training in environmental science and management who will devote their unique skills to the diagnosis, assessment, mitigation, prevention, and remedy of the environmental problems of today and the future. A guiding principal of the School is that the analysis of environmental problems requires quantitative training in more than one discipline and an awareness of the physical, biological, social, political, and economic consequences that arise from scientific or technological decisions.

The Group Project is required of all students in the Masters of Environmental Science and Management (MESM) Program. It is a three-quarter activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Final Group Project Report is authored by MESM students and has been reviewed and approved by

SANGWON SUH

Acknowledgements

We would like to acknowledge and thank those who have assisted us during this year-long project, and whose support and guidance have been of great assistance to our group. We would first like to thank our advisor, Sangwon Suh, for his time, continuous support and valuable feedback as our project evolved. We would also like to acknowledge our client, AECOM, for their project proposal and guidance. In particular, we would like to thank Michael Conrardy, Rob Larkin, and Todd Haurin for their time and assistance throughout this process.

We would also like to thank the Los Angeles Community College District, and in particular, Blair Doane and Tony Fairclough for meeting with us and providing data for our case study of Los Angeles Harbor College.

Additionally, we would like to thank all those who volunteered their time to give us valuable feedback on our project, including: Melvyn Manalis, Tam Hunt, Jeff Dozier, James Frew, and Jordan Sager.

Finally, the project team gratefully acknowledges the support of the Yardi Systems Group.

Table of Contents

List of Tables

List of Figures

Acronyms and Abbreviations

AC alternating current
AEP American Electric Power
CAES compressed air energy storage
CEC California Energy Commission
DC direct current
DOE U.S. Department of Energy
ELM Energy Load Monitoring
EPA Environmental Protection Agency
EPRI Electric Power Research Institute
FERC Federal Energy Regulatory Commission
GHG Greenhouse gases
kW kilowatt
kWh kilowatt-hour
IOU investor-owned utility
ISO independent system operator
LADWP Los Angeles Department of Water and Power
LAHC Los Angeles Harbor College
Li-ion lithium-ion
MW megawatt
MWh megawatt-hour
Na-S sodium/sulfur
NiCad nickel-cadmium
NiMH nickel-metal hydride
NPV net present value
O&M operation and maintenance
PCU power conditioning unit
PCS power conversion system
PV photovoltaic
PW present worth (factor)
Rpm Revolutions per minute
SMES superconducting magnetic energy storage
SNL Sandia National Laboratories
T&D transmission and distribution
TOU time-of-use (energy pricing)
UPS uninterruptible power supply
VRLA valve-regulated lead-acid
ZnBr zinc bromine

Abstract

The problem of climate change is inextricably linked to society's increasing demand for energy. In the United States, almost 70 percent of all electricity is generated from greenhouse gas-emitting fossil fuels. Fortunately, renewable energy resources, such as solar and wind power, can help meet future electricity demand with negligible emissions. However, widespread adoption of renewable energy solutions has been limited by intermittency and variability of solar and wind resources – for example, electrical generation can only occur when the wind blows or the sun shines. Energy storage addresses this limitation by allowing electricity to be stored for later use, when generation is unavailable. This practice, in turn, can reduce energy demand from the electrical grid and thereby offer economic benefits to electricity end users that possess renewable generation systems. Unfortunately, quantifying the economic benefits of energy storage technologies is difficult because of system complexities and limited information. To address this difficulty, this project created a comprehensive tool for evaluating the lifetime costs and benefits of energy storage coupled with renewable generation systems. This tool, RESET (Renewable Energy Storage Engagement Tool), calculates the maximum economic value of excess renewable generation by optimally sizing energy storage systems. RESET allows users to compare and evaluate the economic profitability of multiple energy storage technologies at their site. Los Angeles Harbor College (LAHC), which currently has 2.1 megawatts of solar generation, was analyzed as a case study for the RESET tool. Based on LAHC's solar generation, demand, and current electricity rates, RESET calculated that an investment in energy storage would not be recouped though future energy savings. Thus, at present, energy storage at LAHC is not financially profitable. Despite the result obtained for LAHC, our analysis illustrated the utility and feasibility of energy storage systems for end-users. Energy storage technologies can make clean, emission-free energy available at any hour and therefore should be considered in any efforts to increase the global penetration of renewable technologies.

Executive Summary

Introduction

The problem of climate change is inextricably linked to society's increasing demand for energy. In the United States, almost 70 percent of all electricity is generated from greenhouse gas-emitting fossil fuels. Fortunately, renewable energy resources, such as solar and wind power, can help meet future electricity demand with negligible emissions. However, these resources suffer from limitations including intermittency and variability. Energy storage offers a potential solution to these limitations and may improve the economics of renewable generation systems.

Energy storage involves the conversion of electrical energy into another form such as chemical, kinetic or potential energy. This energy can then be stored for a period of time and converted back to electrical energy, as the electricity is needed. At present, due to a number of economic and technical issues, energy storage technologies are not widely employed. Despite its limited adoption, energy storage can provide a range of benefits. Storage can reduce the need for building power plants to meet peak demand, or enable end users with renewable generation to capture excess electricity and use it on site, negating the need to send it back to the grid.

Unfortunately, quantifying the economic benefits of energy storage technologies is difficult because of system complexities and limited information. If there is excess electricity, the options for using that electricity is either to sell it to the grid or store it. Giving power back to the grid incurs no additional cost, but there will only be savings if the generator can be paid for that electricity. Energy storage may have potential savings of avoided electricity purchase or avoided cost of carbon emissions. However, there are capital, operations and maintenance, replacement, and insurance costs. The complexity here is the fact that that all of these potential costs and savings depend on a variety of factors, from the price of electricity to the type of storage device used and the actual size of the device. Our objective was to create a model that would determine optimal size, if any, of the energy storage system that maximizes benefits and minimizes costs.

The Renewable Energy Storage Engagement Tool

To address system and pricing complexities, this project created a comprehensive tool – the Renewable Energy Storage Engagement Tool (RESET) – for evaluating the lifetime costs and benefits of energy storage technologies coupled with renewable generation systems. First, a comprehensive literature review was conducted to determine the costs and characteristics of numerous energy storage technologies including various battery types, flywheels, compressed air, supercapacitors, pumped hydro, hydrogen fuel cells, and superconducting magnetic energy storage. RESET maximizes the net present value of an energy storage investment by determining the optimal capacity for fourteen different storage technologies. Further, RESET allows end-users of electricity to compare the economic profitability of the various energy storage technologies and run multiple scenarios with ease. Key inputs to RESET include electricity demand and solar generation profiles, discount rate, electricity prices, and annual growth rates.

Applying RESET - A Case Study at Los Angeles Harbor College

With the creation of RESET complete, we wanted to demonstrate its functionality by applying it to a real world case study – Los Angeles Harbor College. Harbor College is one of nine community colleges within the Los Angeles Community College District. Harbor College currently has a 2.1-megawatt (MW) solar photovoltaic system, with plans for expansion to 2.8 MW. Harbor College has two problems. First, the campus lacks metering equipment to measure excess electricity generation and thus Harbor's energy manager does not know if there is any excess electricity available to store. Second, since Harbor College's solar generation capacity exceeds a 1 MW threshold, Harbor College is not eligible to receive credits, through its utility, for energy sent back to the grid. Therefore, Harbor can either transfer excess electricity to the grid without compensation, or find a way to capture and use the electricity. Using RESET, we aimed to discover how Harbor College can maximize the economic value of its solar generation. Multiple scenarios were run to analyze the conditions under which energy storage would be a profitable investment.

Our analysis revealed that energy storage is not economically profitable under any realistic conditions at this time. However, through our scenario analysis, we found that an increase in solar generation or a decrease in demand – yielding more excess generation to store – would make energy storage more attractive.

Conclusion

RESET calculated that energy storage is not currently economically profitable for Harbor College. This is a reflection of the high and often prohibitive upfront capital costs of energy storage technologies. Though in this example, storage was not profitable, the numerous benefits of energy storage should not be overlooked. These benefits include reduced electricity bills and the increased penetration of renewable energy. Moreover, determining the costs and potential savings is complicated due to complex billing rate structures, information gaps and the lack of easy-to-use decision tools. Although, energy storage is at present not cost-effective in many applications, energy storage addresses many of the limitations currently preventing the penetration of renewable energy technologies. Thus, any path towards a clean energy future should consider energy storage. It is our hope that the RESET tool will allow all users to better understand the benefits of energy storage and aid in the path towards a clean energy future.

Structure of the Report

Part I of this report contains background information on the benefits and barriers to renewable energy and energy storage technologies, as well as explaining the objective and significance of our project. An extensive literature review on storage technologies and existing analytical tools is also presented. Lastly, the development of our portable modeling tool, RESET, is described in detail.

Part II of this report presents our project case study, the Los Angeles Harbor College (LAHC), and demonstrates how RESET can be employed to address a real-life problem. Our methods and scenario analysis results for LAHC are discussed in detail, including data limitations.

Part III of this report is a discussion of conclusions drawn from both Parts I & II. Specific recommendations for LAHC are provided, in addition to general recommendations for further research.

PART I: EVALUATING ENERGY STORAGE TECHNOLOGIES

1 Introduction

Fossil fuels have been a fundamental building block to industrialization and have become the dominant source of energy in both the United States and the world (IEA, 2012). However, in the last few decades, the drawbacks of fossil fuel dependency have become increasingly prominent. These drawbacks – global climate change, unequal resource accessibility, energy security, and price volatility – have caused societies to explore alternative sources of energy.

1.1 Renewable Energy

An attractive solution to the problem of fossil fuel dependency is harnessing the earth's renewable energy sources and turning them into usable electricity. Renewable energy technologies including: solar photovoltaics (solar PV), wind, solar thermal, geothermal, small-hydro, biogas, wave and tidal technologies, offer inexhaustible energy sources with negligible greenhouse gas (GHG) emissions that enhance energy security and fuel diversity.

Currently, renewable energy makes up less than ten percent of total U.S. energy consumption. Between 2000 and 2009, renewable energy sources (including hydropower) has increased from 5.3% to 8.2% of total domestic energy consumption (Gelman, 2010). Wind and solar PV are the fastest growing renewable energy sectors. In 2009, solar PV installations grew by 52% and wind energy installations increased by 39% from 2008 (Gelman, 2010).

As of December 2009, the U.S. had a cumulative installed wind generating capacity of 35.2 gigawatts (GW), up from only 2.5 GW in 2000 (NREL, 2010b). While wind capacity has grown tremendously over the last decade, wind power still only accounts for about 2% of our nation's electricity (NREL, 2010b; Gelman, 2010). U.S. Solar PV capacity as of 2009 was approximately 1.7 GW and accounted for only 0.1% of U.S. net electricity generation (Gelman, 2010). California PV installations accounted for about 46% of the U.S. market, with cumulative installations of 768 megawatts (MW) in 2009 (Gelman, 2010).

Various policy decisions and market mechanisms have spurred the recent growth in renewable energy production. Thirteen billion dollars in tax credits and $6 billion in federal grants from the American Recovery and Reinvestment Act of 2009 drove a 14.4% increase in renewable capacity between 2009 and 2010 (British Petroleum, 2011). Aggressive state renewable portfolio standards such as California's 33%

renewable generation requirement have also helped to stimulate renewable energy production in over thirty states.

Despite favorable regulatory policies and the numerous environmental and energy security benefits of renewable energy, penetration of renewables remains hampered by the inherent limitations of the resources. The most fundamental limitation is that solar and wind energy resources are intermittent – generation can only occur when the sun is shining or when the wind is blowing (Ibrahim, 2008). Further, the timing of renewable energy production does not always align with the timing of consumer demand for energy. Insufficient renewable generation during times of peak demand necessitates generation from easily dispatched sources of energy, such as GHG-emitting natural gas fired plants. Conversely, renewable generation during non-peak demand hours may be wasted or curtailed – causing an economic loss to the producer. Further limitations of solar PV and wind include issues of power quality and difficulties with forecasting generation.

Energy storage technologies offer solutions to many of the aforementioned limitations.

1.2 Energy Storage

Energy storage involves the conversion of electrical energy into another form such as chemical, kinetic or potential energy. This energy can then be stored for a period of time and converted back to electrical energy, as the electricity is needed. At present, due to a number of economic and technical issues, energy storage technologies are not widely employed. In 2007, worldwide energy storage capacity was just ninety GW, representing only 2.6% of the world wide electrical production capacity of 3,400 GW (Ibrahim, 2008).

Benefits of Energy Storage

Despite its limited adoption, energy storage can provide a range of benefits. Currently, electricity distribution systems are operated for one-way transmission from power plants to consumers with no storage. This existing distribution system requires that electricity must be supplied (i.e. generated) as it is demanded. However, demand fluctuates rapidly over a day – thus, matching generation with demand becomes a complex problem. Grid operators must constantly balance electricity flow while ensuring adequate power quality and avoiding grid congestion (see Figure 1.1). During peaks in demand, rapidly dispatchable power generation must come online. These “peaker” plants typically burn fossil fuels such as natural gas. Used in both grid-scale and end-use applications, energy storage technologies can reduce the need for peaker plants and avoid the associated emissions. Energy storage helps decouple electrical supply from demand, allowing system planners to meet average demand rather than peak demand.

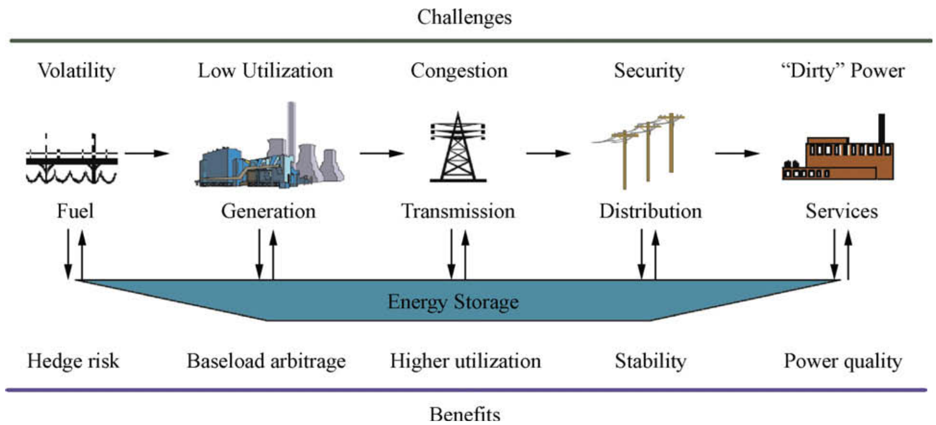


Figure 1.1 - Challenges of electricity systems and benefits of energy storage. Source: Chen et al. 2008.

Research indicates that energy storage has the potential to save millions in dollars in energy costs and provide millions of dollars in non-market benefits. For example, the CEC and DOE estimate that time-of-use energy management can provide over $4 billion in benefits over ten years (Eckroad, 2002). The following is a description of several of the potential benefits of energy storage:

Matching supply and demand

Electricity demand varies throughout the day and seasonally. When there is high demand, most conventional power plants are not able to rapidly increase output to accommodate peaks in demand. Maintaining or constructing new power plants purely for the purpose of meeting peak demand is costly. When demand is low, energy often must be diverted or dumped to avoid overloading the grid. Energy storage can help meet peak demand needs and provide a reservoir for dumping excess energy when demand is low.

Providing back-up power to prevent outages

Electricity outages have been estimated to cost the U.S. approximately $79 billion annually, and two-thirds of those costs were from outages lasting less than five minutes (LaCommare & Eto, 2004). Energy storage devices can provide short-term solutions for power outages to minimize the costly impact of outages.

Peak Shaving/Load-shifting

In peak shaving or load-shifting applications, energy can be stored during low demand periods and then used during peak demand. This helps avoid the costs to end-users of purchasing electricity during peak demand when it is most expensive. Energy storage offers the most financial savings in the case when peak demand is substantially higher than the average load (EPRI-DOE, 2003). Economic benefits can also be realized for energy consumers by reducing peak demand charges as peak shaving decreases power loads. By employing energy storage, electricity providers realize economic savings through lower generation capacity requirements. Figure 1.2 demonstrates the economic benefits of peak shaving with energy storage. Energy is stored during nighttime hours (represented by the pink area in the graphic to the right). This stored energy is then discharged during peak-demand, daytime hours. The end consumer lowers peak demand (represented in blue) during the hours when electricity is most expensive. Generators see less demand for energy and can operate with less capacity online (as indicated on the y-axis).

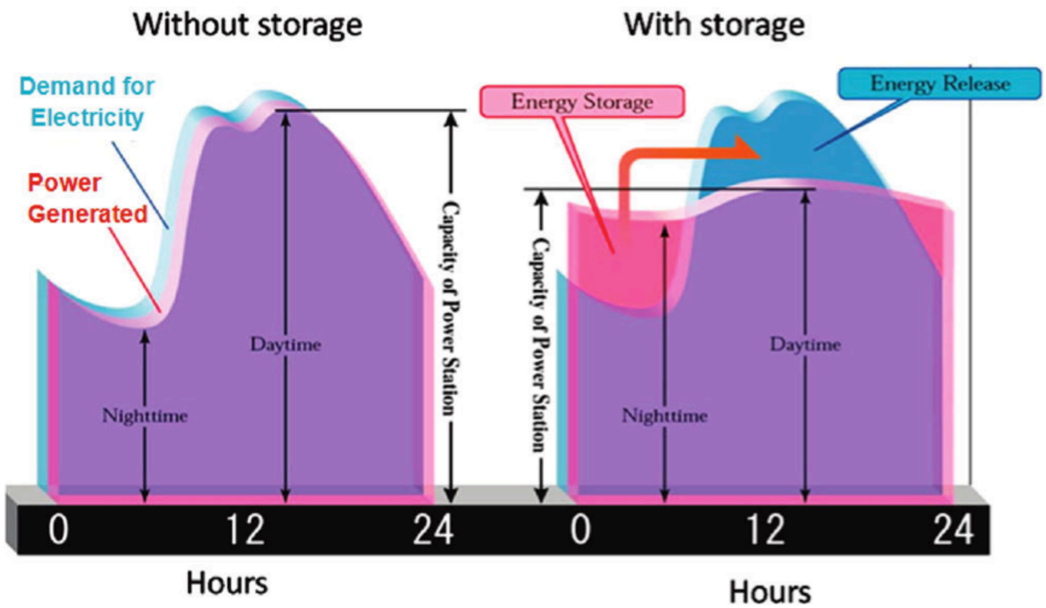


Figure 1.2 - Peak load shaving. Peak load demand is shaved in the figure on the right through energy storage utilization. (Source: Yang et al., 2010)

Power Quality and Reliability

Power quality anomalies include: variations in voltage magnitude, variations in the frequency at which power is delivered or short service interruptions. In the United States, poor power quality anomalies can cost over $100 billion dollars in annual losses (EPRI-DOE, 2003). Power quality applications of energy storage can protect power loads against these anomalies and spikes.

Electricity Arbitrage

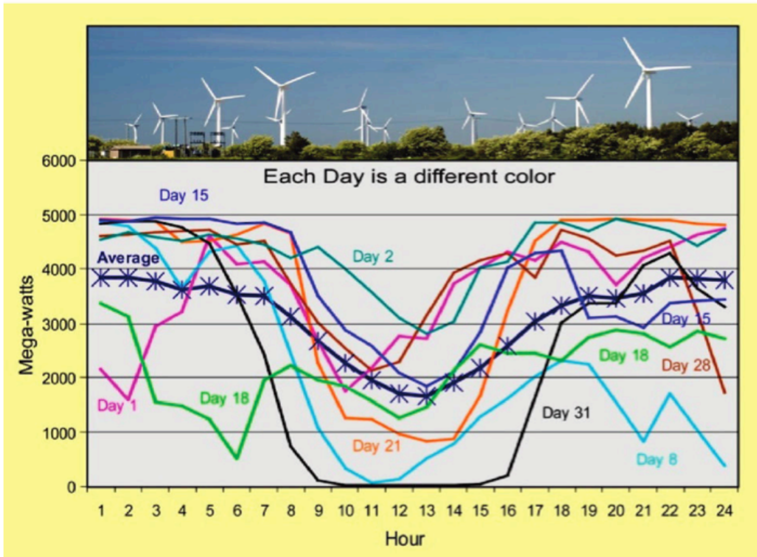
Arbitrage is the practice of purchasing electricity during off-peak hours when rates are low, and selling it during peak hours when rates are high. In arbitrage applications, storage systems charge from the grid when both demand and electricity rates are low and discharge during peak rate hours. Used effectively, arbitrage can significantly lower energy costs for storage users.

Enabling Integration of Renewable Technologies

The widespread penetration of renewable energy technologies and the corresponding replacement of conventional energy technologies can be enhanced with energy storage systems. By increasing the integration of storage technologies with renewable generation systems, many of the limitations of renewables, including intermittency and power quality can be ameliorated.

- **Intermittency**: The chief advantage of coupling energy storage with solar and wind generation is the ability to deal with intermittency (see Figure 1.3). In grids with a significant amount of input from renewables, intermittency and variability can create significant imbalances between generation and load, causing transmission issues for grid operators. Energy storage can assist in responding to these imbalances without emissions associated with "peaker" plants. Energy storage can also "smooth" the intermittent generation by avoiding spikes of electricity onto the grid.
- **Curtailment**: Another benefit of coupling renewables with energy storage is to reduce curtailment. In the curtailment process, some wind generators are asked by utilities to shut down or slow down their turbines because there is no demand for the electricity at the time it is generated. Thus, potential "clean" electricity production gets wasted or unused. Some researchers have even noted that in absence of storage options, increased penetration and grid integration of solar or wind generation actually requires the addition of gas-powered generators to meet peak energy demands (Benitez, 2008).

(a)



(b)

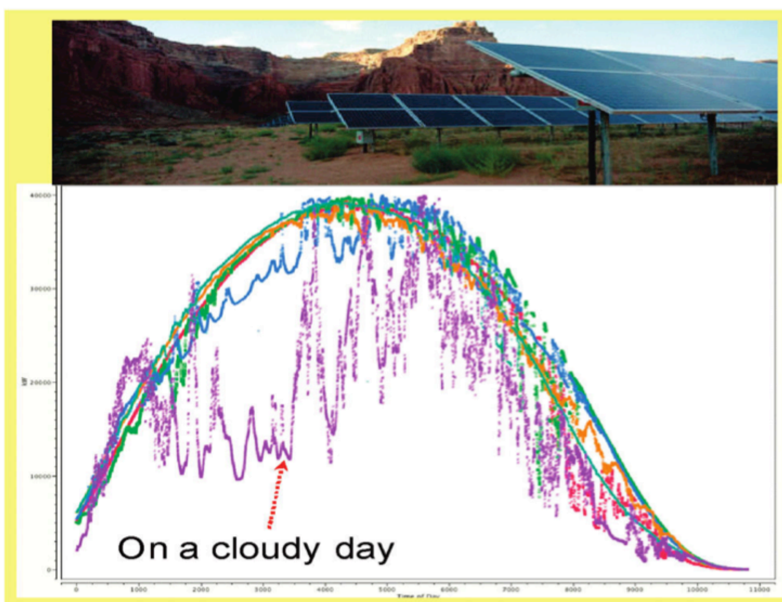


Figure 1.3 - Intermittent wind and solar generation example: a) Wind power profile sample in Tehachapi, California b) Solar power generation over 6 days in Spain; (Source: Yang et al., 2010)

Lowering GHG Emissions

Energy storage can reduce GHG emissions by providing electricity in lieu of high-emissions sources of electricity. This however, depends on the electrical generation mix in question. In California for example, baseload power has a lower emissions profile than peak power. This is because baseload power comes mostly from low-emissions sources (such as nuclear and hydropower), whereas peaking power (power used during peak demand) is from higher emissions sources (such as natural gas). Using stored energy that is generated from low emissions sources during off-peak demand can help lower overall GHG emissions from electricity generation (Deal et al. 2010).

Barriers to Energy Storage

Though energy storage offers a range of benefits to utilities and consumers, there are many barriers standing in the way of proliferation. A few of the barriers to energy storage—high cost, lack of regulatory structure, and uncertainty and risk—are discussed in this section.

High Cost

The high cost, difficulty in estimating costs, and lack of cost-recovery mechanisms for energy storage, are all barriers to deployment. Though costs are decreasing, energy storage systems remain costly because of materials expense and the absence of large-scale manufacturing. Furthermore, though there are many existing technologies that provide energy storage services, few are mature or have been proven at the commercial-scale (see Section 2). These factors make it difficult for energy storage to compete with fossil fuels to supply electricity (Elkind, 2010).

Another complicating factor is that it is difficult to create detailed cost estimates. The cost of energy storage systems is highly dependent on the size of the system and its purpose. Costs also depend on the system efficiency and how frequently and deeply the system is charged and discharged (Deal et al., 2010).

Contributing to this problem is the lack of cost-recovery mechanisms. Energy storage has many benefits, but the benefits often spillover to those not directly involved or dispersed to many stakeholders. Also, utilities lack methodologies to quantify savings and benefits (Elkind, 2010). For investors who must prove a return on investment, this spillover effect prevents the range of benefits from being fully considered in cost calculations. This may deter investment in energy storage (Sioshansi et al., 2012).

Lack of Adequate Regulatory Structure

Policy-makers and energy regulators are tasked with determining how to define, treat, and integrate energy storage into electrical systems and markets. But so far, there are few specific laws and regulations that directly address energy storage (see Section 1.2.3). Investors may be hesitant to invest in storage without knowing what to expect from the regulatory structure.

Uncertainty and Risk

The lack of regulatory structure creates uncertainty and risks that deters investment in energy storage. Further, there are technological uncertainties that act as barriers to deployment. Though there are a number of technologies that seem to be viable, but there are few demonstration projects to prove their feasibility. Developers are reluctant to be the first mover due to this lack of proof (Sioshansi et al., 2012).

These barriers, as well as a lack of information, create high transaction costs for decision makers considering investments in energy storage. The implication of storage on economic profitability is complex; thus, a sophisticated framework to evaluate energy storage options is needed.

Energy Storage Policies

Capitol Hill, utilities, and federal regulators have begun to recognize the potential benefits of energy storage and attempt to resolve deployment barriers. There is a wide range of policy options available to encourage energy storage. For example, policies may involve providing tax credits or subsidies to lower costs, providing manufacturing incentives, investing in research and development, or removing regulatory barriers. The following is a discussion of recently adopted or proposed energy storage policies.

Federal Energy Regulatory Commission (FERC):

The mission of FERC is to "assist consumers in obtaining reliable, efficient and sustainable energy services at a reasonable cost through appropriate regulatory and market means" (FERC, 2012a). In an effort to encourage energy storage as a means to improve grid reliability, FERC has recently issued rulings related to storage.

- In 2007, FERC issued a ruling (Order No. 890, "Preventing Undue Discrimination and Preference in Transmission Service") designed to improve grid reliability and promote competition in electricity markets. The rule mandates grid regulators to allow non-generation resources (such as storage systems) to be able to bid and sell into electricity markets.
- In 2011, FERC issued another rule requiring grid operators to fairly compensate power sources that can provide fast and adequate frequency

regulation services (Order No. 755, "Frequency Regulation Compensation in the Organized Wholesale Power Markets"). The U.S. power grid is designed to operate at a frequency of 60 hertz, and frequency regulation is a necessary component of a stable grid. Commonly, when frequency adjustments are needed, power generators increase or decrease operations, which can be costly and take time. The new rule gives an advantage to energy storage operators that can respond quickly to frequently fluctuations.

Congress:

Several bills have been introduced in Congress to encourage and incentivize energy storage development. However, only one bill so far has become law.

- Section 48c of the American Recovery and Reinvestment Act of 2009 includes incentives for energy storage manufacturing facilities (ESA, 2011a).
- In July 2011, Senator Debbie Stabenow (D-MI) introduced the Battery Innovation Act (S. 1351). This bill includes a provision to boost research and development by creating an "Energy Innovation Hub for advanced batteries, which would bring together universities, businesses, and nonprofits to develop new battery technologies and make improvements to current technologies." The bill would also spur lithium production in the U.S. (Stabenow, 2011). This bill is still under consideration and has not been passed by the Senate.
- In August 2011, Senator Jeff Bingaman (D-NM) introduced the Clean Energy Financing Act of 2011 (S. 1510), a bill that would establish the Clean Energy Deployment Administration (CEDA) to finance the development of clean energy technologies. According to the Electricity Storage Association, the finance mechanisms provided in this bill would help "move energy storage technologies from pilot demonstration to scale manufacturing" by lowering the financial involved with building the first plant (ESA, 2011b). This bill is still under consideration and has not been passed by the Senate.
- In November 2011, Senators Ron Wyden (D-OR), Jeff Bingaman (D-NM), and Susan Collins (R-ME) introduced the Storage Technology for Renewable and Green Energy (STORAGE) Act of 2011 (S.1845). Congressmen Christopher Gibson (R-NY) and Mike Thompson (D-CA) introduced a House version of the bill (H.R. 4096) in March 2012. These bills include investment tax credits for energy storage systems connected to the grid and for businesses and homeowners who install on-site renewable energy or energy storage. These bills are still under consideration and have not been passed in either the House or Senate (ESA, 2011).

U.S. Department of Energy (DOE):

The DOE has had a long history of researching and funding energy storage technologies. The DOE began researching energy storage options during the oil crisis in the mid-1970s. Since then, DOE and the DOE national laboratories had numerous energy storage research and grant programs.

- The DOE Energy Storage Systems (ESS) Program was established in the 1990s and is managed by Sandia National Laboratories. The goal of the program is to "develop advanced energy storage technologies and systems, in collaboration with industry, academia, and government institutions that will increase the reliability, performance, and competitiveness of electricity generation and transmission in the electric grid and in standalone systems" (SNL, 2011).
- The Advanced Research Projects Agency-Energy (ARPA-E), created in 2007, provides funding to energy innovation projects. Since its creation, ARPA-E has provided millions of dollars to battery and grid storage research projects (ARPA-E, 2010).

States and Utilities:

Several states and utilities have adopted incentive programs for energy storage.

- The California Public Utility Commission's Self Generation Incentive Program (SGIP) offers a $2/W incentive payment for advanced energy storage technologies. At this time, only energy storage for flywheels and fuel cells are eligible for this incentive (SGIP, 2011).

1.3 Project Objective & Significance

The objective of this project was to develop a tool for electricity customers, specifically renewable energy generators, to analyze the profitability of energy storage systems.

To accomplish this goal, we first synthesized available literature about potential costs, benefits, and environmental impacts of energy storage technologies. Second, a portable optimization tool was created to determine the storage capacity that maximizes the net present value (NPV) of an investment in energy storage.

By filling the numerous information gaps surrounding energy storage technologies and allowing decision makers to quickly evaluate the costs and benefits of storage technologies, this project seeks to remove uncertainty surrounding the implementation of storage technologies.

It is our hope that the research and methodology presented in this report will promote the integration of energy storage allowing for greater penetration of renewable electricity generation. In doing so, the country and the world will enjoy reduced emissions, greater energy security and an inexhaustible supply of energy resources into the future.

2 Literature Review

The following literature review covers the advantages and disadvantages of energy storage technologies in development and those commercially available today. The energy technologies discussed include batteries, pumped hydro, compressed air energy storage, ultracapacitors, supercapacitors, lead carbon asymmetric capacitors, superconducting magnetic energy storage, flywheels, and hydrogen. Each technology is evaluated on development status (i.e., commercially available or not), storage capacity, cycle life, voltage range, energy density, conversion efficiency, cycle efficiency, cost and environmental impacts. The literature review also presents a background on currently available energy storage analysis tools.

2.1 Batteries

Lead Acid Batteries

2.1.1.1 Flooded-Stationary Lead-Acid Batteries

Background

The traditional flooded-stationary lead-acid battery, invented in 1860, is the most commonly available and commercially mature rechargeable battery technology in the world (EPRI, 2010). They are used in a variety of mobile and stationary applications including automobiles, distributed energy resource devices, telephone systems, and emergency lighting.

The traditional flooded-stationary lead-acid battery is made up of two electrodes - one lead (negative plate) and one lead-oxide (positive plate) immersed in a solution consisting of sulfuric acid and water (see Figure 2.1). This solution, called an "electrolyte" causes a chemical reaction that produces electrons (NREL, 2011). During discharge, the positive plate and negative plate react to create lead sulfate, water, and energy. During charging, the cycle is reversed.

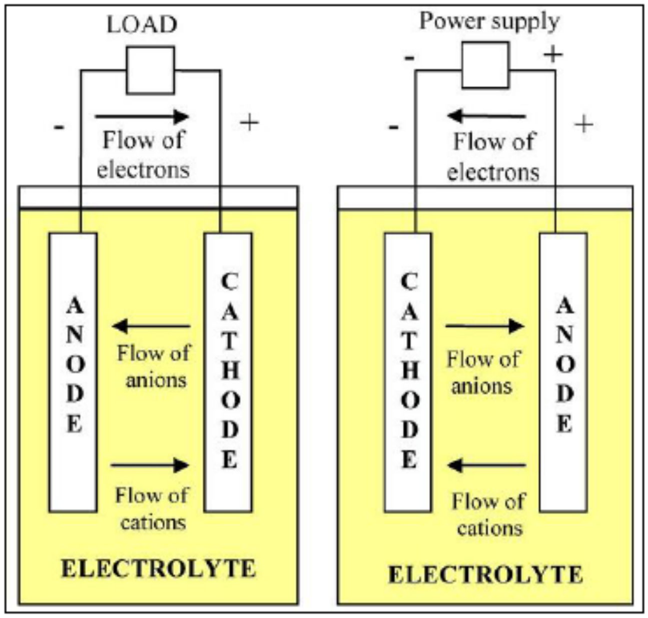


Figure 2.1 - Diagram of a lead-acid battery. Discharge (left) and charge (right) (Source: Mosher, 2006)

Advantages

Main advantages of traditional lead-acid batteries are that they are cheap, readily available, and easy to integrate. There are no specific siting restrictions. These batteries are well suited for applications that require large amounts of energy storage to be discharged over a long period of time. They have a high power capacity. The reaction in a lead-acid battery is reversible, so the battery can be reused. These batteries are also tolerant to overcharging, can deliver high currents, and come in a wide range of sizes and capacities. Lead-acid batteries are also the world's most recycled product.

Disadvantages

However, negating lead-acid batteries' low-cost advantage is its short life cycle and low efficiency. Because of a short life cycle, lead-acid batteries need to be replaced often. Another disadvantage that occurs primarily in flooded stationary batteries is the loss of electrolytes during the charging process. During charging, hydrogen and oxygen gases enter into the electrolyte solution as a result of electrolysis of water inside the battery. This water is consumed and must be replaced, requiring frequent maintenance. Gases entering into solution may also present an explosion hazard. Valve-regulated lead-acid batteries, discussed below have been designed to address this concern. Overtime, the performance of lead-acid batteries is also reduced because a layer of lead sulfate tends to build up at the electrodes during cycling. This problem becomes more significant if the battery is left discharged for long periods of time.

Applications

Flooded-stationary lead-acid batteries have numerous applications including peak load shaving, frequency regulation and control, and black start. The largest existing installation is a 10-MW/40-MWh system in Chino, California that is used for load leveling by the Southern California Edison utility (Yang et al., 2010). From 1994-1999, the Puerto Rico Electric Power Authority utilized a 14 MWh lead-acid battery for frequency control.

Companies

Some of the companies that produce flooded-stationary lead-acid batteries include: Storage Battery Systems, Inc. GNB Industrial Power/Exide, C&D Battery, and Hagen OCSM.

Environmental Impacts

There is the potential for lead pollution if these batteries are carelessly disposed of (Makaraov et al., 2008).

2.1.1.2 Valve-Regulated Lead-acid

Advantages

In contrast to other lead-acid batteries, the valve-regulated lead-acid (VRLA) types offer several advantages. The VRLAs are considered low maintenance because they are designed to allow oxygen and hydrogen to recombine preventing water loss. Therefore, regular maintenance to replace lost water that other types of lead-acid batteries require is unnecessary with VRLAs. The "valve" term refers to the pressure-release valve that manages oxygen pressure inside the battery.

VRLA batteries can further be classified as either an *absorbed glass mat battery* which has the electrolyte absorbed in a fiber-glass mat separator or as a *gel cell*, in which the electrolyte is mixed with silica dust to form an immobilized gel. VRLAs are also called "sealed" lead-acid batteries because unlike the flooded type, they will not spill electrolyte fluid if turned upside down. This advantage allows them to be mounted in any position.

Disadvantages

Despite the aforementioned advantages over flooded lead-acid batteries, VRLAs similarly suffer from short lifetimes. They also have higher costs and are more susceptible to open circuit failures, rendering the batteries inoperable (Frost & Sullivan, 2004). VRLAs are also less reliable than the flooded type (Clark, 2009). There are, however, clear advantages for the use of one type of lead-acid battery over the other depending on intended use.

Applications

VRLA batteries can be used in several applications including frequency regulation, peak shaving and load shifting. Existing installations include a 15 MWh facility in Hawaii built in 1993 that is used for all three of the aforementioned applications. Metlakatla Power and Light in Alaska utilizes a 1.4MWh VRLA for voltage regulation and displacing diesel generation.

Environmental Impacts

Similar to conventional lead-acid batteries, there is the potential for lead pollution from VRLAs (Makarov et al., 2008). However, the environmental risks associated with the use of VRLA batteries are less than those of the flooded lead-acid batteries. VRLAs are sealed so there is little threat of an acid spill if the battery is inverted. Also, the improved design over flooded lead-acid reduces the need to add water to the cells, thereby reducing water consumption. Finally, the design of VRLAs leads to fewer emissions of hazardous gases than those from flooded-stationary lead-acid batteries.

Companies

Storage Battery Systems, Inc. supplies VRLA batteries in both the absorbent glass mat and gelled electrolyte types for a variety of applications. GNB Industrial Battery/Exide Technologies and General Electric also produce VRLA batteries.

Lithium-Ion Batteries

Background

Compared to lead-acid batteries, lithium-ion battery technology is relatively new. Still, lithium-ion batteries are considered a mature technology and are widely available commercially. Lithium-ion batteries are replacing many battery technologies such as lead-acid types because of their superior performance. Lithium-ion batteries are commonly found in consumer electronic products such as cell phones and notebook computers. Additionally, lithium ion batteries are well positioned to be the battery technology used in plug-in hybrid electric vehicles and all-electric vehicles.

Lithium-ion batteries are made of three primary components including the anode, cathode, and electrolyte. The anode is made from graphitic carbon, the cathode is a lithiated metal oxide and the electrolyte is made up of lithium salts dissolved in a non-aqueous organic solvent. Both the anode and cathode are materials lithium can migrate into and out of. During discharge, lithium ions carry the current from the negative to the positive electrode through the non-aqueous electrolyte (see Figure 2.2 below). During charging, an external power source applies a higher voltage than that produced by the battery, forcing the current to pass in the reverse direction. Migrating from the positive to negative electrode, lithium ions become embedded into a porous electrode material in a process called intercalation.

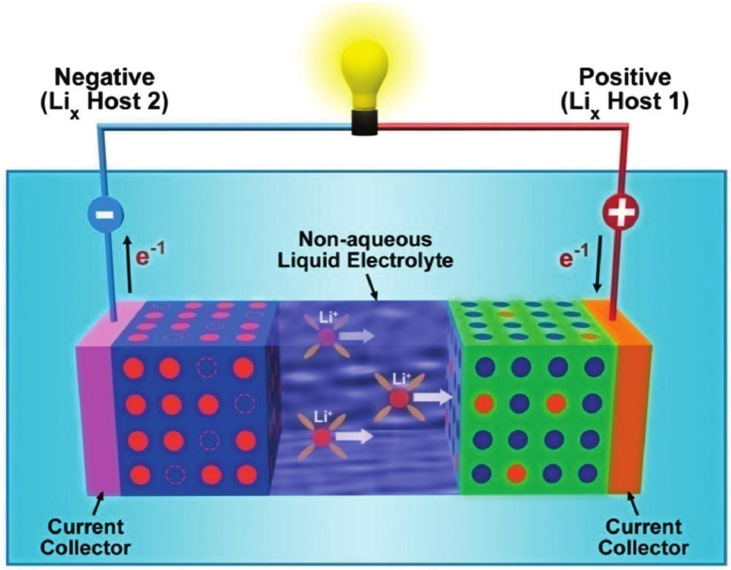


Figure 2.2 - Diagram of a traditional lithium-ion battery cell in which during discharge Li$^+$-ions migrate through the electrolyte carrying current from the negative to positive electrode. (Source: Yang et al., 2010)

Advantages

Lithium-ion batteries have several advantages including a high energy and power density as well as a high-energy efficiency (95%) (Kaldellis et al., 2009). Lithium-ions also have a long life cycle relative to other battery technologies.

Disadvantages

Although there are large-scale applications utilizing the advantageous qualities of lithium-ion batteries, there are several disadvantages limiting greater commercialization. Over time, batteries lose the ability to hold as much charge. The internal resistance of the batteries is high compared to other rechargeable battery types and increases with cycling and age. Increasing resistance means that the battery will no longer be able to operate for an adequate period of time. Also, due to special packaging, overcharge protection circuits, and heat management, lithium-ion batteries are expensive. Correspondingly, there are safety concerns if these batteries are overheated or overcharged. When in a fully charged state, the battery is sensitive to over-temperature, over-charge, and internal pressure buildup necessitating advanced monitoring equipment and safety precautions (Makarov et al., 2008). Finally, analysis of lithium's geological resource base reveals that there is an insufficient supply available in the earth's crust to sustain to support the electric vehicle demand for lithium, let alone demand for electrical energy storage (Tahil, 2006). Moreover, the supply is lithium geographically concentrated, potentially creating future new geopolitical tensions.

Applications

A123 Systems installed a 12MW lithium ion battery system in Chile for grid stabilization services and has plans for an additional 20 MW system in Chile A123 Systems recently announced an order for a 20 MW project in Northern Chile (A123 Systems, 2011). A123 Systems is currently evaluating the performance of an 8 MW/32 MWh lithium-ion battery system to improve grid performance and integration with large-scale wind-powered electricity generation in Tehachapi, California (Recovery Act Smart Grid Programs, 2012). Another company, ABB, is designing a distributed energy, lithium-ion storage system for a Swedish utility provider. This system will provide a storage capacity of 87 kWh and offer the ability to balance peak loads, improve grid stability, and support the integration of renewable energy for current and future smart grid applications.

Figure 2.3 - A123 Systems 12MW battery in Chile. (Source: A123 Systems, 2011)

Environmental Impacts

Lithium-ion batteries are made of toxic materials and require recycling and safety control.

Companies

ABB and A123 Systems are the primary manufactures of large lithium-ion batteries for grid integration.

Flow Batteries

Flow batteries are a type of stationary battery storage system. Like conventional batteries, flow batteries contain electrodes (an anode and a cathode), an electrolyte and a separator. However, flow batteries differ in that the electrolyte does not take part in the reaction. Instead, the electrodes receive the material that is either dissolved into or precipitated from the electrolyte solution during charge and discharge. The electrolytes are stored in tanks and are pumped through an electrochemical cell to convert chemical energy to electrical energy. Another feature of flow batteries is that there is no loss of performance from repeated cycling. This is because in most batteries, the repeated charge and discharge causes the electrodes to deteriorate. But in flow batteries, the electrodes do not take part in the reactions but just act as substrates for the reactions (Electropaedia, 2012). In reduction-oxidation flow batteries (redox), all of the electroactive components are dissolved in the electrolyte. Otherwise, one or more electroactive component can be a solid layer. This is known as a hybrid flow battery (Leonardo Energy, 2007). There are four leading flow battery technologies, each of which are discussed further below: Vanadium Redox, Zinc Bromine, Hydrogen Bromine, and Polysulfide Bromide.

A major advantage of flow batteries is that they are easily scaled, increasing or decreasing the volume of electrolyte solution stored in the system. A disadvantage of flow batteries is that they contain a series of pumps and plumbing, which can be prone to leaks and add complexity and cost to the battery system (EPRI-DOE, 2003).

2.1.1.3 Vanadium Redox Flow Batteries

Background

Vanadium Redox flow batteries (VRB) were developed in the 1980's at Australia's University of New South Wales. A VRB battery consists of two electrolyte tanks containing vanadium ions dissolved in mild sulfuric acid solutions in different oxidation states. One tank contains positively charged V^{5+} ions and the other tank holds V^{2+} ions. When energy is needed, pumps move the electrolytes with the ions from tanks into the stack where an oxidation-reduction reaction chemical reaction occurs, causing the ions to change their charge and releasing chemical energy to create electricity. This reaction is reversible, allowing the batteries to be charged and discharged (see Figure 2-4).

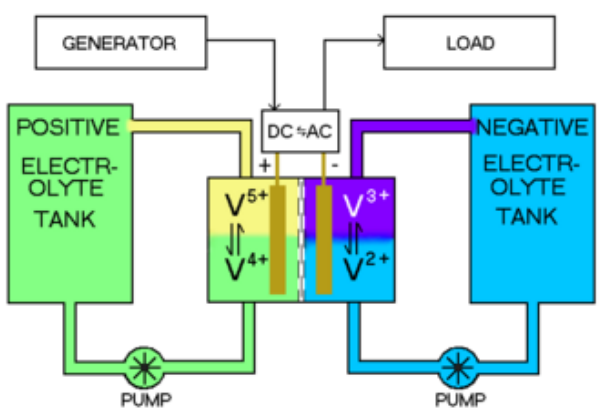


Figure 2.4 - Diagram of a vanadium redox flow battery (Source: Joos et al., 2011)

Advantages

The advantages of VRB batteries are that they have a high efficiency (up to 85%) and a long life. They are used for large stationary applications such as load leveling or peak shaving, and can be used for 1 kWh to 10 MWh of storage (Electricity Storage Association). VRB batteries are emerging as a promising technology to couple energy storage with renewable generation, though only a few demonstration-scale projects have been built.

Disadvantages

The primary problems with VRB batteries are that they are expensive and can only operate in a limited temperature range. However, new research shows that modifying the electrolyte solution can improve performance. By simply adding hydrochloric acid to the acid solution, the storage capacity can be increased by 70% and the temperature range expands (Li et al., 2011). VRB's low energy density of 16-33 Wh/L is another disadvantage (Leonardo Energy 2004). Furthermore, market prices of vanadium compounds are currently high.

Applications

So far, there are few VRB installations. The first large-scale commercial installation in North America was in Castle Valley, Utah. This 2 MW unit is used for load leveling for peak power in a remote location in southeast Utah (Frasier, 2006).

Environmental Impacts

VRB systems are often promoted as an environmentally friendly storage system for many reasons. Firstly, VRB cell stacks and tanks are frequently made out of recyclable plastics. Secondly, the electrolyte (provided it does not get exposed to oxygen) has a very long life span (Beck, 2012). Lastly, there are no toxic chemicals in VRBs that would special disposal procedures. According to an EPRI and DOE report,

> "The only chemical in the VRB system is the vanadium electrolyte, which is ionic vanadium in sulfuric acid at approximately the same concentration found in flooded lead-acid batteries. Its handling and safety requirements are the same as sulfuric acid. The electrolyte is internally contained within industrial-grade HDPE tanks and pressure-rated PVC pipe and fittings. The VRB is placed within a spill containment area compliant with local regulations" (EPRI-DOE 2003).

Lastly, a life cycle assessment comparing lead-acid batteries and VRBs found that VRBs have a lower environmental impact because of a long lifespan and potential for vanadium recycling. Furthermore, VRBs require less energy during the manufacturing and recycling processes than lead-acid batteries (Rydh, 1999).

Companies

Companies that currently manufacture VRBs include: VRB Power Systems, Sumitomo Electric, Reliable Power, SEI, Pinnacle, Celleniu, and Prudent Energy.

2.1.1.4 Zinc-Bromine Flow Battery

Background

The Zinc-Bromine (ZnBr) flow battery is a hybrid flow battery developed by Exxon in the 1970's. A ZnBr battery cell contains a negative zinc electrode and a positive bromine electrode separated by a microporous membrane (see Figure 2.5 below). A zinc and bromine aqueous solution flows between the two compartments of the cell (Electricity Storage Association, 2011). At the point of complete discharge, all of the zinc in the negative electrode is dissolved in the electrolyte, and at the point of complete charge all of the zinc is deposited on the cathode and all of the bromine is concentrated at the anode. All battery parts are made from inert bromine plastic (CEC/DOE, 2011).

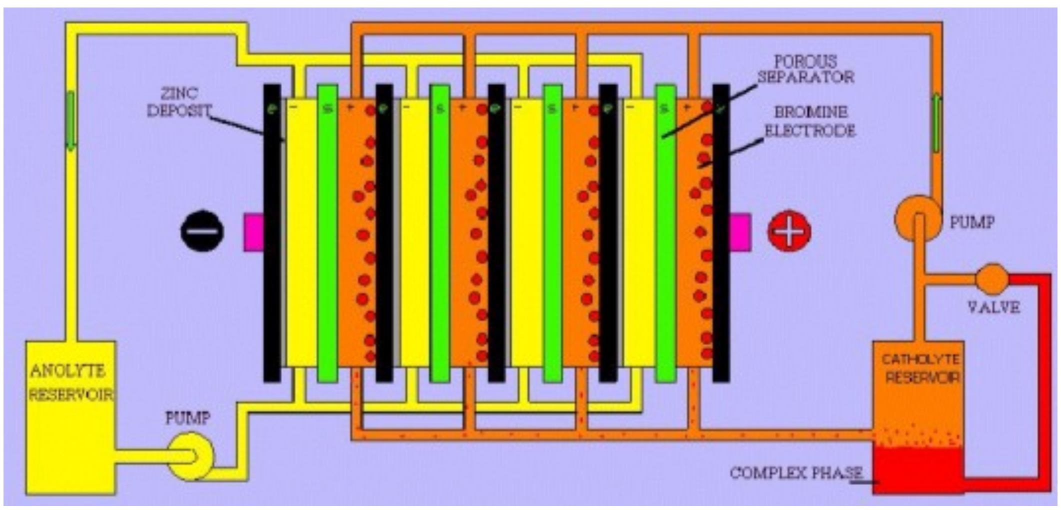


Figure 2.5 - Diagram of a Zinc Bromine battery (Source: CEC/DOE, 2011)

Advantages

There are many advantages to ZnBr batteries. First, they have a long life. Estimates of lifespan range from 5 to 30 years and 1,500 to 10,000 cycles (EPRI, 2010; Mosher, 2010; Leonardo Energy, 2007). Furthermore, they are relatively low cost ($250-400/kwh) relative to VRBs ($380-740/kwh). Though ZnBr batteries are a bit less efficient than VRB batteries, they still have an efficiency of up to 75% (Mosher, 2010). Advantages of ZnBr batteries over VRBs is that they can operate at close to ambient temperature and they have a much higher energy density of 60 to 90 Wh/L (Butler et al., 2004; Leonardo Energy, 2004).

According to the ZBB energy corporation, a leading manufacturer of ZnBr batteries, ZnBr systems operate quietly and are easily transportable. Moreover, they are "modular and configurable to meet power requirements for a wide variety of on-grid and off-grid market applications throughout the world" (ZBB Energy Corporation).

Disadvantages

Although flow batteries generally do not lose performance from repeated cycling, the performance capacity of ZnBr batteries can be degraded if the battery is not regularly and completely discharged (Leonardo Energy, 2007). However, ZnBr batteries can be completely discharged without degrading the battery (Butler et al, 2004). ZnBr batteries can only operate between 20 and 50 degrees Celsius (Sandia, 2011).

Applications

In 2001, ZBB installed two test systems in Michigan to assess ZnBr batteries' ability to conduct peak shaving. At one site, the ZBB system was installed near a grain drying facility whose activities spiked or disrupted the grid several times a day. The other system was installed at a site where a transformer was near capacity and was expected to exceed capacity during peak summer use. According to ZBB, these batteries took approximately 2-10 hours to discharge, operated at around 30 degrees Celsius, and, most importantly, were able to help with peak shaving and other issues (ZBB, 2001).

The California Energy Commission and U.S. Department of Energy are currently sponsoring a demonstration project for Pacific Gas & Electric. This installation will consist of four 500 kW modules in parallel, for a total of 2MWh of storage and will include real-time data monitoring. The system will be installed at a substation used for peak shaving, but the exactly location has not yet been chosen (CEC/DOE Project Overview, 2008).

Environmental Impacts

In general, ZnBr batteries are considered to have low environmental impacts because they are made of components that can be reused and recycled (Butler et al., 2004). However, ZnBr batteries do contain corrosive (zinc-bromine) and toxic (bromine) materials that can become environmental contaminants should they escape. Furthermore, liquid bromine can be hazardous if inhaled (EPRI-DOE, 2003).

Companies

The only company currently manufacturing ZnBr batteries is the ZBB Energy Corporation.

2.1.1.5 Hydrogen Bromine Flow Batteries

Background

Hydrogen-bromine (H_2-Br_2) flow batteries consist of two reversible electrodes and use H_2 and Br_2 for discharge and HBr for charge. Though hydrogen-bromine batteries were initially researched and developed several decades ago, research was largely abandoned due to high costs and safety concerns. However, Lawrence Berkeley National Laboratory has recently teamed with DuPont, Bosch, 3M, and Proton Energy to investigate the potential of H_2-Br_2 for grid-scale applications (LBNL, 2011).

Advantages

Hydrogen-bromine flow batteries have the potential to show high round-trip efficiency (>80%), be scalable to grid-scale applications, have high power capabilities (>1 W/cm2), and to cost under $100/kWh (LBNL, 2011).

Disadvantages

Hydrogen bromine flow batteries are still an emerging technology, thus there are no current demonstration projects to analyze or information about environmental impacts.

2.1.1.6 Polysulfide Bromide Flow Batteries

Background

Polysulfide-bromine flow batteries, sometimes referred to as regenerative fuel cells, have been developed under the brand name Regenesys since the 1990s (EPRI-DOE, 2003). In these batteries, a polysulfide bromide (PSB) cell uses two salt solutions, sodium bromide (NaBr) and sodium polysulfide as electrolytes. They are separated by a polymer membrane, which only allows positive sodium ions (Na^+) to pass through (Schaber et al., 2004). During charging or discharging, Na^+ pass through the membrane and the bromide and sodium components emit and accept electrons (see Figure 2.6).

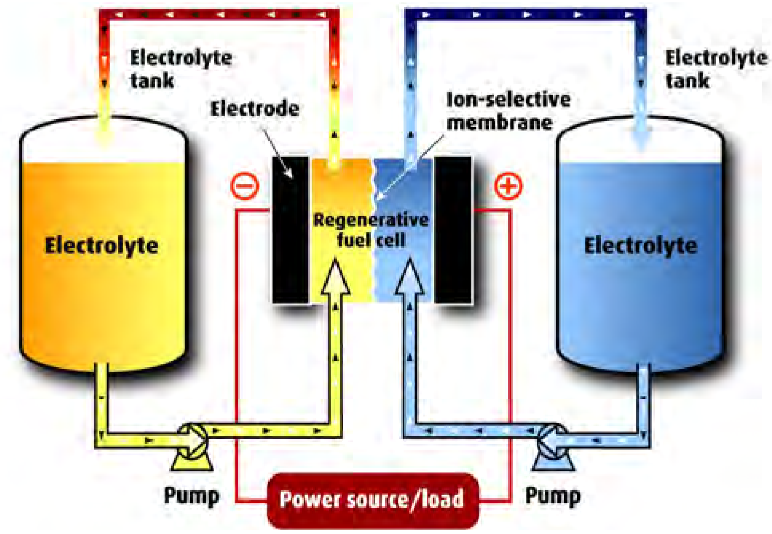


Figure 2.6 - Diagram of PSB storage system (Source: EPRI-DOE, 2003)

Advantages

PSB batteries are expected to have a long lifespan, up to 15 years.

Disadvantages

PSB are still an emerging technology and have not been fully demonstrated, and have a lower efficiency rating (60-65%) than other flow batteries.

Applications

Regenesys Technologies Ltd. has been developing PSB for large-scale applications. Regenesys was planning on building two demonstration energy storage plants using PSB batteries for load leveling: a 15 MW plant in the UK and a 12 MW plant in Columbus, Mississippi (Chen et al., 2009). However, both projects were canceled and no new demonstration projects have been announced (Leonardo Energy, 2007).

Environmental Impacts

PSB systems are considered to be environmentally benign (EPRI-DOE 2003), but if one of the tanks should fail, hazardous bromine gas could be released.

Companies

Regenesys Technologies, a subsidiary company of RWE npower plc, is currently the only company that manufactures these battery systems.

Nickel Cadmium Batteries

Background

Invented in 1899, Nickel-Cadmium (NiCd) batteries are alkaline batteries, which use nickel oxide as the anode and cadmium as the cathode, all in an aqueous potassium-hydroxide electrolyte (NETL). NiCd batteries gained popularity because of their use in the space program (Sandia, 1981).

Advantages

NiCd batteries are a mature technology, well known for their durability. They have a higher density and longer lifespan than lead-acid batteries and require less maintenance (Sandia, 2003). The upfront costs of NiCd batteries are higher than lead-acid batteries, but because NiCd batteries can be fully discharged, there is no need to oversize the battery. Assuming proper maintenance, NiCd batteries are durable, have a high number of charge/discharge cycles and can be fully discharged without damage to the battery. This quality is advantageous for solar PV applications because NiCd batteries can be fully discharged each night. Another advantage is that if the size of the power system is increased, additional batteries can be added to the bank, which cannot be done with lead-acid batteries.

Disadvantages

A disadvantage of NiCd batteries is the so-called "memory effect." Some NiCd batteries require occasional full discharge to prevent the battery from being able to discharge below the level it has been discharged to in the past, though this does not often occur with industrial NiCd batteries (Sandia, 2003).

Applications

NiCd batteries are widely used. Small NiCd batteries are used in electronics, such as digital cameras, and flashlights. Large NiCd batteries are used in airplane starters, and in backup generators. NiCd batteries have also been used in electric vehicles (Henault et al, 2008).

An example of a NiCd battery storage system is the Golden Valley Electric Association BESS (battery energy storage system) project in Alaska. Batteries manufactured by Saft provide 26 MW for 15 minutes or 40 MW for 7 minutes (Makarov et al., 2008).

Environmental Impacts

Hydrogen and oxygen are produced during charging and depending on the battery type, and may be vented into the atmosphere. Cadmium is a toxic metal to all forms of life, so careful monitoring and special disposal efforts are needed (Sandia, 2003).

However, because cadmium is toxic, it is often collected and recycled. Nickel cells are also highly recyclable and markets to recycle nickel exist in most countries (EPRI-DOE, 2003).

Companies

Companies that manufacture NiCd batteries include: Alcad, Hoppecke, and Saft.

Sodium Sulfur Batteries

Background

Sodium Sulfur (NaS) batteries were first developed in the 1960's, in part by Ford Motor Company to power electric vehicles. However, the development of NaS batteries, for electric grid applications, are currently being driven by the Japanese firms Tokyo Electric Power Company and NGK Insulator, Ltd (Virkar, 2010).

A NaS cell consists of a molten sulfur positive electrode and a molten sodium negative electrode that are separated by a solid electrolyte of sodium beta-alumina. The entire batteries are hermetically sealed (to reduce heat loss) in an aluminum or steel casing with an interior lining of molybdenum (to prevent corrosion). To maintain both sulfur and sodium in a molten state, NaS batteries must be operated at a minimum of 290° C.

During discharge, sodium is oxidized and sodium ions flow from the negative electrode through the electrolyte to combine with sulfur that is being reduced to form sodium polysulfide at the positive electrode ($2Na + 4S = Na_2S_4$). The electrons flow though a circuit that generates a voltage of 2 V per single cell (Toledo et al, 2010). The process is reversed during the charging process. Both processes are displayed in a graphic below.

Because this process is completely reversible, NaS batteries can be used continuously, making them well suited for energy grid applications such as peak shaving and load leveling (Bito, 2005).

A commercial NaS battery has an expected lifetime of 15 years with the number of cycles and depth of discharge (DOD) – a measure of the percentage of stored energy that you can discharge – represented in Table 2.1.

Depth of Discharge (%)	Number of Cycles (charge and discharge)
100%	2500
90%	4500
65%	6500

Table 2.1 - Depth of Discharge and Number of Cycles for a Sodium-Sulfur Battery (Source: Toledo et al 2007)

Advantages

Sodium sulfur batteries have a number of advantages for in peak shaving applications. First, they have a long lifetime of approximately 15 years. Second, they have a prompt response, and can completely discharge in less than one second. Third, they have a high energy density, about three to five times greater than lead-acid batteries. Fourth, they are capably of fully discharging. Lastly, they are modular and mobile.

Disadvantages

A major disadvantage of NaS batteries is their high operating temperatures. They need to maintain an operating temperature of at least 290 degrees Celsius and maintaining this temperature affects their overall efficiency rating. Further, Na-S batteries have been linked to fires (NGK Insulators, Inc., 2011).

Applications

To date, no NaS system has been coupled with Solar PV generation in the United States. However, The American Electric Power (AEP) utility installed a 1.2 MW distributed energy storage system in 2006 in West Virginia to store cheap off-peak power from the grid for use during peak demand. Though this system cost more to install than a similarly sized coal-fired plant, AEP has determined that the benefits of this system justify the added expense because: 1) this storage system operates essentially like a mini-generation plant that does not require a fuel source, 2) the NaS storage system precludes the need for a $10 million sub-station and 3) the system can be moved to another location (Toledo et al., 2005).

In 2008, XCEL Energy connected a NaS battery capable of storing 7.2 MWh of electricity with an 11 MW wind farm in Minnesota. The system can store enough energy to power 500 homes for seven hours and is about the size of two semi-trailers. According to XCEL the system has successfully compensated for the intermittency of wind and helped couple energy supply with demand (LaMonica, 2010). Based on the success of this system XCEL plans to add a NaS battery to Solar PV system near the Denver airport.

Environmental Impacts

Almost all of the materials in Na-S batteries can be recycled. In fact, NGK estimates that 98% of the materials can be recycled. The only material that requires special recycling as a hazardous material is sodium. However, questions remain about whether processes and markets to recycle these battery components actually exist (Sullivan and Gaines, 2010).

Companies

The only company manufacturing NaS batteries currently is NGK Insulators.

Sodium-metal chloride batteries

Background

Though the technical name for these batteries are for sodium-metal chloride ($NaNiCl_2$) battery, they are known as ZEBRA batteries because they were invented in 1985 by the Zeolite Battery Research Africa Project (ZEBRA) group. Sodium-metal chloride batteries evolved from NaS batteries, but use different materials and are mechanically different. Zebra batteries have the cathode in the center and the anode around it. The anode and cathode are separated by the electrolyte. ZEBRA batteries contain a molten sodium anode, nickel (nickel in the discharged state and nickel chloride in the charged state) as the cathode, and molten sodium aluminum chloride as the electrolyte. Similar to the NaS battery, sodium ions move from the anode to the cathode generating an excess of ions at the cathode. Excess ions move outside the battery, creating an electric current (Makarov et al., 2008).

Advantages

ZEBRA batteries have a high efficiency (up to 90%), high energy density, are capable of hours of discharge, and are made of low cost materials (PNNL, 2011)

Disadvantages

ZEBRA batteries operate at very high temperatures, between 200-400 degrees Celsius (Trickett, 1998).

Applications

ZEBRA batteries have been used in electric vehicles, but have yet to be used for solar PV systems.

Environmental Impacts

No information found.

Companies

MES SA, a Swiss company, manufactures ZEBRA batteries for automotive applications.

Nickel-Metal Hydride Batteries

Background

Development of nickel-metal hydride (NiMH) cells began in the 1970s (EPRI-DOE, 2003). Portable nickel-metal hydride cells were introduced in the late 1980s and by the mid-1990s had largely supplanted nickel cadmium batteries in many portable applications, before themselves losing market share to lithium-ion batteries (EPRI-DOE, 2003). The NiMH battery has a wealth of applications from portable consumer products such as digital cameras, cell phones, etc. to electric and hybrid vehicle applications and industrial standby applications for Telecom, UPS, and Distributed Generation applications (Kopera, 2005).

Nickel-metal hydride battery technology is an outgrowth of Nickel Hydrogen technology, also using hydrogen as the negative electrode (EPRI-DOE, 2003). The positive electrode of the NiMH battery is a nickel substrate in the form of nickel foam, felt, perforated sheet or other constructions with the active material nickel hydroxide pasted or sintered onto the substrate (Kopera, 2005). In NiMH batteries, the hydrogen is absorbed in a metal alloy, allowing a higher volumetric energy density at the cost of specific energy (EPRI-DOE, 2003). The battery must be sealed to prevent the hydrogen from escaping and the metal alloy is usually a complex mix of a number of elements, and can vary to a significant degree from design to design (EPRI-DOE, 2003).

The electrolyte is an aqueous solution of potassium hydroxide that has a very high conductivity and does not enter into the overall cell reaction to any significant extent. The electrolyte concentration remains fairly constant over the entire range of state of charge or discharge. These factors lead to a battery with high power performance and long cycle life.

NiMH batteries are sensitive to overcharge and to high-rate discharge and therefore have replaced NiCd in relatively low-current applications, including portable computers, cellular phones, and camcorders, but not in high-rate applications such as power tools (EPRI-DOE, 2003).

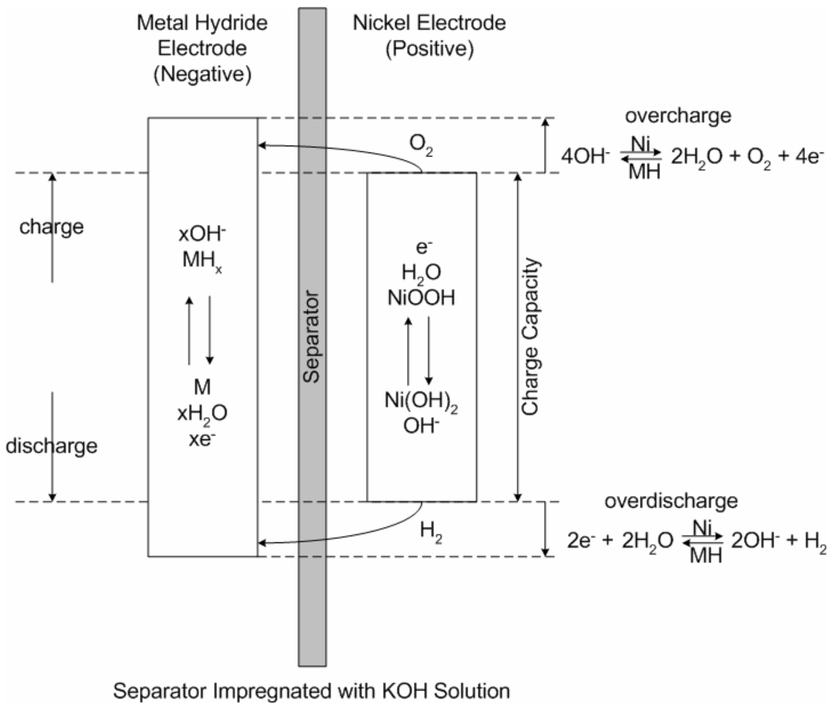


Figure 2.7 - Schematic representation of a NiMH cell (Source: Cobasys, n.d.)

Advantages

Some advantages of NiMH batteries include good energy density, excellent power delivery, a long shelf life and low need for maintenance (Solar Energy Grid Integration Systems, 2008).

Disadvantages

The main challenges with nickel-metal hydride batteries are their high cost, high self-discharge and heat generation at high temperatures, the need to control losses of hydrogen, and their low cell efficiency (Energy Storage-NREL, 2009).

Environmental Impact

NiMH batteries are composed of relatively environmentally benign materials (Considerations for the Utilization of NiMH Battery Technology in Stationary Applications, n.d). The absence of cadmium makes them a more environmentally friendly option than NiCd batteries.

Applications

NiMH batteries have been used in several different implementations of electric vehicles including the DaimlerChrysler EPIC, the GM EV-1 and electric S10, and the Toyota RAV4EV (Considerations for the Utilization of NiMH Battery Technology in

Stationary Applications, n.d.). Today's leading application for NiMH batteries in the automotive community is the hybrid electric vehicle with examples such as the Toyota Prius, Honda Insight, and the Ford Escape hybrids (NREL, 2009a).

Companies

Cobasys, Eagle-Picher technologies, ElectroEnergy Inc., Johnson Controls Inc., Varta and Panasonic are some companies dealing with NiMH batteries (EPRI-DOE, 2003).

Other batteries

These batteries are still emerging and lack significant information, thus they will not be elaborated on: iron-air rechargeable batteries, metal-air batteries, Na-ion batteries including Na-halide chemistries, New types of NaS cells (e.g., flat, bipolar, low-temperature, high-power), New Li-ion chemistries that improve performance and safety characteristics, Advanced lead-carbon batteries, Ultra-batteries (a hybrid energy storage device that combines a VRLA battery with an electrochemical capacitor), New flow battery couples including iron-chrome and zinc/chlorine (Zn/Cl).

2.2 Pumped Hydro

Pumped hydro energy storage is a mature technology that was first used in the 1890's in Italy and Switzerland and is the only commercially proven large-scale (>100 MW) energy storage technology (Deane et al., 2010). These storage systems are quite simple: electric energy is stored in the form of hydraulic potential energy. Pumped hydro involves the pumping of water to an elevated reservoir when electricity prices are low (i.e., off-peak or low demand periods). When electricity demand is high, potential energy of the water stored in the dam is converted to kinetic energy as it is released and forced through a hydroelectric turbine generating electricity. In the 1930's, reversible hydroelectric turbines that could operate as either a turbine or pump, depending on the flow direction, were developed. While pumped hydro is a relatively mature technology, innovations and improvements in design continue to be developed. New plants are employing variable speed pump/turbine units, with the advantage of allowing regulation of the amount of energy utilized while pumping. This technology allows plants to operate closer to their optimal efficiency points.

Pumped Hydro plants were originally developed to supplement base-load electricity generation. However, there has been a renewed interest in pumped hydro for energy storage as renewable energy generation has increased. Some researchers view it as the most promising technology to increase renewable energy penetration levels in power systems (Papaefthymiou et al., 2010). Figure 2.8 provides a visual of a pumped hydro system that utilizes wind energy.

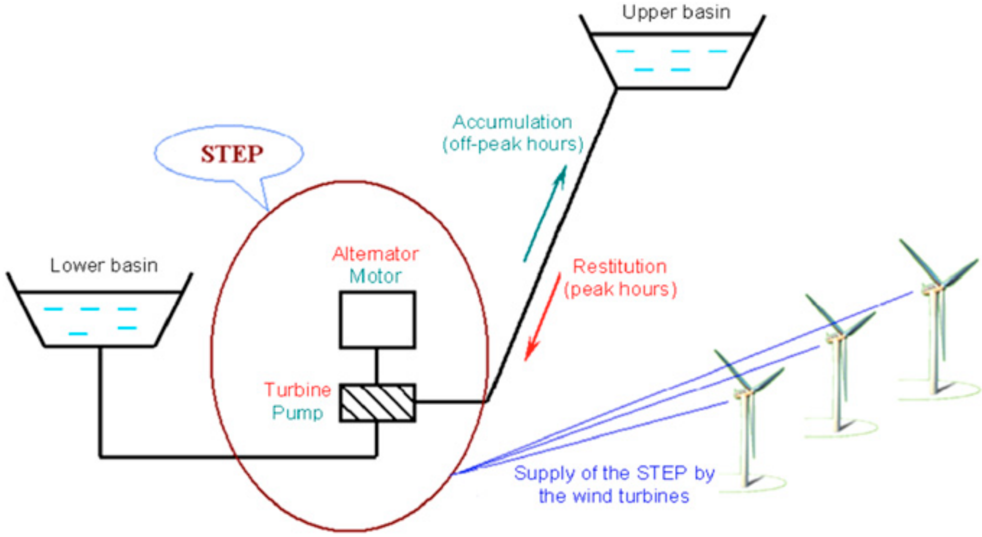


Figure 2.8 - Illustration of pumped hydro storage with the pumping energy supplied by wind turbines. (Source: Ibrahim et al., 2008)

Advantages

Pumped hydro has a huge energy and power capacity potential; the world's largest pumped hydro plant has a capacity of 2862 MW (Deane et al., 2010). Pumped hydro can accommodate energy spikes associated with generation from intermittent renewable energy sources. Pumped hydro has a cycle efficiency of approximately 75%, a long lifespan, and no life cycle limitations, given a continuous supply of water (Ibrahim et al., 2008). Another important advantage to consider is the fact that enhancement of existing project can yield large savings on capital expenditures while reducing environmental and planning issues at the same time.

Disadvantages

There are several disadvantages associated with pumped hydro storage facilities. First, pumped hydro facilities have highly variable costs and therefore, they can be quite expensive to build. Second, finding suitable sites with significant elevation difference necessary for efficient energy storage is difficult. Lastly, acquiring permits for dam and reservoir construction can be time consuming and challenging.

Applications

Pumped hydro technology has been used all over the world, predominantly for frequency control and electricity generation reserve (Makarov, 2008). There are over 300 plants installed worldwide, with a total capacity of over 127 GW (Yang and Jackson, 2011). The United States has over 39 plants with an installed capacity of 21.8 GW. The largest plant is the Virginia Electric & Power Co. owned Bath Plant with a capacity of 2862 MW, which was built in 1985 (Deane et al., 2010). Despite the high number of installations, none integrating renewable energy are currently online. However, one such project is under construction at the Hybrid Power Station on Ikaria Island, in Greece. This project will be one of the first wind-hydro-pumped-storage hybrid stations in the world (Papaefthymiou.et al., 2010).

Environmental Impacts

Hydro power plants have numerous environmental impacts. Environmental concerns arise mainly over impacts on water quality and aquatic ecosystems downstream from reservoirs. These issues are often the reason pumped hydro projects are abandoned or delayed. However, recently proposed projects differ with design plans to mitigate the environmental impacts associated with conventional pumped hydro facilities. For example, many new projects are closed-loop/off-stream design using abandoned quarries or mine pits as reservoirs, reducing the impacts on existing water bodies and aquatic ecosystems. One proposed project, Mulqueeney Ranch, in California, proposes to use recycled wastewater as the water resource. This has several potential positive environmental impacts, where the plant can actually improve the water quality of the resource it uses through aeration and aerobic biological treatment (Yang and Jackson, 2011).

Companies

Pumped hydro power plants are often utility company investments. LADWP constructed and operates the Castaic Power Plant with a capacity exceeding 1200 MW. This project was a cooperative venture between LADWP and California Department of Water Resources.

2.3 Compressed Air Energy Storage

Background

Compressed air energy storage (CAES) uses off-peak or low demand periods (i.e., when electricity is cheap) to power the pumping compressed air into underground caverns or above ground storage tanks (Figure 2.9). Electrical energy of pumping and compressing air is converted to potential energy stored until needed (i.e., during times of high demand). When the compressed air is released, the potential energy is converted into kinetic energy and heated in an expansion chamber, typically with natural gas. The heated air is used to drive AC turbines to generate electricity during the discharge cycle.

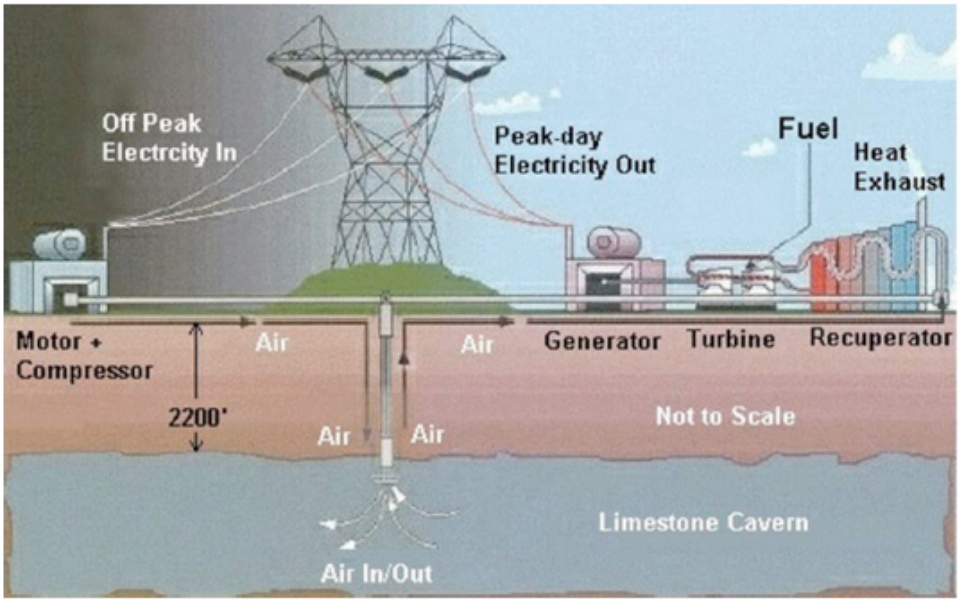


Figure 2.9 - Illustration of compressed-air energy storage (Source: Ibrahim et al., 2008)

Advantages

There are several advantages to CAES. First, similar to pumped hydro, CAES has a high-energy storage potential; nearly all CAES facilities are at least 100 MW in size. Second, using existing geological structures for storage reduces environmental impacts and footprints of CAES facilities. Lastly, CAES may be viable energy storage option for over 80% of the United States (Mosher, 2010).

Disadvantages

There are several disadvantages to CAES. First, as was the case with pumped hydro, CAES requires a suitable site that must satisfy specific underground geological characteristics. Large subterranean caverns of suitable geologic strata, ancient salt mines, or underground natural gas storage caves are ideal for CAES as they can contain maintain high geostatic pressures with minimal loss (Ibrahim et al., 2008). Second, given economies of scale and the costs of facilities, underground caverns must be large to make CAES cost effective (Gardner, 2007). Third, the round trip conversion (i.e., converting electric energy to compressed air and back) efficiency is low, between 70–75%. Fourth, each kilowatt-hour of compressed air stored would require 4500 kJ of fuel (usually natural gas) for heating. Lastly, CAES systems generally have a long construction time.

Applications

Common uses of CAES are for shaving peak electricity loads, load leveling, and frequency voltage control. In Huntorf Germany, a 290 MW installation has been in operation since 1978. In McIntosh, Alabama, a 110 MW CAES facility has been in operation since 1991, storing compressed air at 40–70 times atmospheric pressure in a 2,555,000 cubic meter (i.e., 2.555 billion liter) cavern 700 meters below ground. There are currently no CAES applications that have been coupled with renewable energy generation, though numerous studies cite the benefits of such applications in enabling integration of renewable energy generation (Denholm, 2006; Cavallo, 2006; Raugei, 2009).

Environmental Impacts

There are several environmental impacts associated with CAES. First, there are the greenhouse gas emissions associated with the burning of natural gas required to operate the turbines that generate electricity. Some studies suggest that this can be mitigated through the use of biofuels in place of natural gas (Denholm, 2006). Second, water consumption and discharge can be another important environmental issue. Relatively large volumes of water are consumed during various phases of plant construction and operation (Beckwith & Associates, 1983). Lastly, adverse subsurface and surface environmental impacts may occur if a CAES facility is constructed in geologically unsuitable mediums; however, these impacts can be avoided through geological characterization of subsurface conditions and utilizing appropriate sites (Beckwith & Associates, 1983).

Companies

Some companies developing CAES technologies are the CAES Development Company, Ridge Energy Storage, and Dresser-Rand Company.

2.4 Ultracapacitors/ Supercapacitors/ Electric double layer capacitors

Background

Electrochemical capacitors are energy-storage devices exhibiting characteristics of both electrostatic capacitors and conventional batteries (Long, 2009). The most common and mature electric capacitor is the electric double layer capacitor (EDLC – a.k.a. ultracapacitors or supercapacitors). The Standard Oil Company of Ohio developed the current form of EDLCs in 1966 (Long, 2009).

The term “supercapacitor” refers to the advances in direct current (DC) capacitors that were made possible by including state-of-the-art electrode materials in their design (Schoenung, 2001). Even though no chemical reactions occur within the device, supercapacitors store energy electrostatically using a polarized electrolytic solution (NREL, 2009b). This mechanism is highly reversible, allowing the device to be charged and discharged frequently and up to hundreds of thousands of times (NREL, 2009b).

A supercapacitor consists of two nonreactive porous plates, or collectors, suspended in an electrolyte, with a voltage potential applied across the collectors (NREL, 2009b). In an individual supercapacitor cell, the applied potential on the positive electrode attracts the negative ions in the electrolyte, while the potential on the negative electrode attracts the positive ions (NREL, 2009b). Energy is discharged when the voltage direction is reversed (Schoenung, 2001). A dielectric separator between the two electrodes prevents the charge from moving between them (NREL, 2009b).

Supercapacitors resemble regular capacitors except that they offer very high capacitance in a small package (Wagner, 2007). The factors that determine the capacitance are the size of the plates, the separation of the plates and the type of material used for the dielectric (Schoenung, 2001).

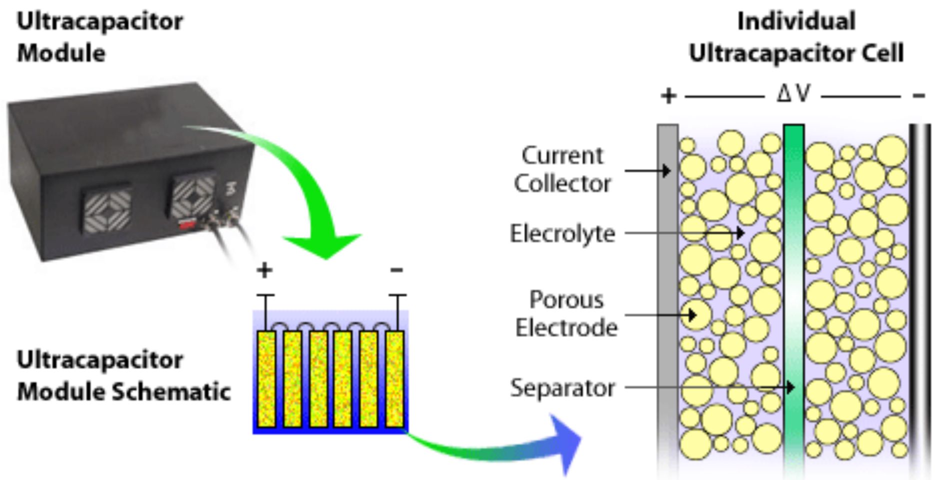


Figure 2.10 - An ultracapacitor, its modules, and an ultracapacitor cell (Source: NREL, 2009)

Supercapacitors have and long shelf life and offer a great potential for applications that have a high power demands, and require short charging time and high cycling stability (Halper & Ellenbogen, 2006). Some common applications of Supercapacitors include starting diesel trucks and railroad locomotives, and in electric/hybrid-electric vehicles for transient load leveling and capturing the energy used in braking (NREL, 2009b).

Advantages

There are a couple of advantages to supercapacitors. First, the lifetime of supercapacitors is virtually indefinite with their energy efficiency rarely falling below 90%, as long as they are kept within their design limits (Wagner, 2007). Second, supercapacitors have extremely long cycle life, a high power density, and the ability to charge and discharge quickly (Makarov et al., 2008). The latter benefit occurs since there is no chemical reaction occurring within the device, which is a stark contrast to most, if not all other energy storage devices.

Disadvantages

Supercapacitors have a few disadvantages including low energy density and few power systems applications (Makarov et al., 2008).

Environmental Impacts

Supercapacitors are considered to be environmentally benign as there are no or little environmental impacts associated with this technology (Bradbury, 2010; Makarov et al., 2008).

Applications

Honda has developed a high-performance ultracapacitor to serve as a supplementary power source to the FCX hydrogen fuel cell (Wagner, 2007).

Companies

Some companies involved in the distribution of supercapacitors include ELIT, ESMA, NESS, PowerCache (Maxwell), PowerSystem Company and SAFT (EPRI-DOE, 2003).

2.5 Lead Carbon Asymmetric Capacitors

Background

Lead Carbon Asymmetric Capacitors (LCAC) are based on lead-acid battery components for the positive electrode and carbon-based capacitive component for the negative electrode (Schoenung & Hassenzahl, 2007). Asymmetric capacitor technology is projected to have two valuable attributes. First, a cycle life that may exceed 5000 daily charge and discharge cycles and second, a relatively lower cost, with respect to other capacitor storage devices; the potentially lower cost is related to the utilization of some lead-acid battery components utilized during manufacturing (Schoenung & Hassenzahl, 2007). These two attributes have formed the rationale for continued development of this technology. It has also been suggested that asymmetric capacitor's life cycle costs may be competitive with other electricity storage technologies (Schoenung & Hassenzahl, 2007).

Advantages

Lead carbon asymmetric capacitors LCAC's have several advantages including rapid recharge rates, a deep discharge and high power delivery rates, a long cycle life and low maintenance (Ton et al., 2008).

Disadvantages

The two biggest disadvantages of LCACs are their lower energy density than batteries and a lower power density than other electrochemical capacitors (Ton et al., 2008).

Applications

The most common applications of LCAC are for peak shaving and grid buffering (Ton et al., 2008). If a storage system is designed for peak shaving when customer's rates are determined from peak demand, the system must have adequate storage above a predetermined threshold otherwise severe economic consequences for the customer can occur. The relatively lower cost of LCAC allows systems to be designed to ensure peak shaving does occur avoiding excessive energy charges.

Environmental Impacts

Lead carbon asymmetric capacitors are classified as electrochemical capacitors, which generally have a low environmental impact. The exception to this rule of thumb is when organic electrolytes are used in its design and manufacture (Chae et al., 2010).

Companies

A number of companies are developing and working toward commercially producing these types of devices, including ESMA/Universal Supercapacitors, Axion Power, and Furukawa (Walmet, 2009).

2.6 Superconducting Magnetic Energy Storage

Background

The technological basis for Superconductive Magnetic Energy Storage (SMES) systems had its beginnings in 1911 when Kammerlingh Onnes was investigating normal conductors at low temperature, discovered superconductivity (Polk et al., 1993). Several U.S, Japanese, and European groups initiated the groundwork for SMES R&D in the 1960's. In 1971, Peterson and Boom invented the SMES system used today (Polk et al., 1993).

Superconducting magnetic energy storage systems consist of a coil with many windings of superconducting wire storing and releasing energy as electric current flowing through the wire increases or decreases (Berkeley Law, 2010). Energy is stored in a magnetic field, which is produced by the current circulating in the superconducting coil (Schoenung, 2001). Today's SMES units use conventional metallic superconductor material (Niobium Titanium or Niobium Tin) cooled by liquid helium for the coil windings (Schoenung, 2001).

SMES systems are quite efficient since they store the electrical energy directly in a magnetic field with essentially no losses due to the superconducting coils aside from the parasitic losses due to their refrigeration systems (e.g., liquid nitrogen or helium), which are required to maintain their superconducting properties (Bradbury, 2010). Similar to batteries, SMES systems provide rapid responses to both charge and discharge (Schoenung, 2001). However, unlike batteries, the energy available is independent of the discharge rate (Schoenung, 2001).

Several MW-capacity SMES demonstration projects are in operation around the United States and the world to provide power quality services, especially at manufacturing plants requiring reliable electricity such as microchip fabrication facilities (EES, 2011).

Advantages

There are several advantages to SMES systems. First, power can be discharged almost instantaneously, seconds or less, with high power output for a brief period of time and less power loss than other technologies (APS, 2007). Second, SMES systems have a long lifetime. Lastly, SMES systems have a high power capacity (Makarov et al., 2008).

Disadvantages

There are a few disadvantages associated with SMES systems. The overall cost of the system is relatively high due its reliance on low temperature superconductors, requiring expensive cryogenics (APS, 2007). Also, there are high production costs associated and SMES systems. Finally, SMES systems suffer from low energy density (Makarov et al., 2008).

Environmental Impact

There are a couple of environmental impacts associated with SMES systems. For one, the strong magnetic field, especially ones aligned with large-scale facilities, and prolonged exposure to the magnetic field causes some concern. Secondly, the non-ionizing radiation field associated with SMES systems and its impact on human physiology is unknown (Bradbury, 2010; Makarov et al., 2008).

Applications

The DOE/BPA currently has a 10 MVA (Megavolt-amperes) SMES demonstration project to stabilize the 900-mile, alternating current connection between the Bonneville Power Administration (BPA) and Southern California (APS, 2007).

Companies

Bruker Energy & Supercon Technologies manufactures SMES systems.

2.7 Flywheels

Background

Flywheels have been around for hundreds of years in various forms from spindles to continuously variable transmissions (Meeker & Walker, 2010). New advances in materials, bearings, seals, and other components assist flywheels to boast near immediate response times, long life under constant cycling, and efficiencies of 85% and higher have been reported (Meeker and Walker, 2010).

Flywheels are made of advanced high strength materials and operate by storing kinetic energy in a spinning rotor that is charged and discharged through a generator (EPRI, 2010). Flywheels include a cylinder with a shaft that can spin rapidly within a robust enclosure (Eyer & Corey, 2010). The cylinder is levitated by a magnet eliminating friction-related losses and wear (Eyer & Corey, 2010). The shaft is connected to a motor/generator converting electric energy to kinetic energy which is then stored by increasing the flywheel's rotational speed and eventually converted back to electric energy via the motor/generator, slowing the flywheel's rotational speed (Eyer & Corey, 2010).

Typical flywheel applications include power quality and uninterruptible power supply (UPS) uses (EPRI, 2010). Flywheel energy storage systems available today are usually categorized as either low-speed or high-speed (NREL, 2003).

- Low Speed: Most low-speed flywheels are designed for 10,000 revolutions per minute (rpm) or less, and are typically made of extremely heavy steel discs (Bradbury, 2010). The shaft is either vertical or horizontal, and may have mechanical or magnetic bearings (Bradbury, 2010).
- High Speed: High-speed designs operate above 10,000 rpm, some upwards of 100,000 rpm (Bradbury, 2010). Because of the speeds and associated fatigue failure risks, stronger materials are required, including composites of graphite or fiberglass, requiring magnetic bearings and a vertical shaft (Bradbury, 2010).

Figure 2.11 - Flywheel Applications: Right, 1-MW/15-min Beacon Power flywheel in an ISO ancillary service application, Left: Pentadyne GTX flywheel (Source: EPRI, 2010)

Advantages

There are several advantages of flywheels including the maturity of the technology, high power capacity, short access time, long lifetime, low maintenance and high efficiency (Makarov et al., 2008).

Disadvantages

Flywheels have several disadvantages including its low energy and power density, large standby losses, and potentially dangerous failure modes (Walawalkar & Apt, 2008).

Environmental Impact

Flywheels are considered a green technology having no to little environmental impacts due to the benign materials flywheels are constructed of and their rather compact design (Bradbury 2010, Makarov et al., 2008).

Applications

The JY-60 Fusion Test Facility in Japan, a 200 MW system is composed of six flywheels, each with a 6.6 m diameter (APS, 2007). Each flywheel has a mass of 1,100 tons, reaching rotation speeds of 420-600 rpm with a velocity of 65.7 meters per second at the rim (APS, 2007).

The Pentadyne ASD Voltage Support Solution from the Pentadyne Power Corporation offers 120 kW of power for 20 seconds of discharge (APS, 2007). The total system weight is half a ton, the rotation speed is 50,000 rpm, and the maximum tip speed is about 800 meters per second (APS, 2007).

Beacon Power Corporation has proposed a 20 MW flywheel energy storage system for frequency regulation applications at the transmission level (Walawalkar & Apt, 2008). This application is being tested at a small-scale demonstration site, funded by the New York State Energy Research and Development Authority (NYSERDA), and the California Energy Commission (CEC) in New York and California respectively (Walawalkar & Apt, 2008).

Companies

Beacon Power, Active Power, Boeing, Pentadyne and Urenco Power Technologies are some companies involved in flywheel manufacture and distribution (EPRI-DOE, 2003).

2.8 Hydrogen

Background

Hydrogen storage involves using electricity to split water into hydrogen and oxygen via electrolysis (Berkeley Law, 2010). The elements of a hydrogen storage system include an electrolyzer to convert the electrical energy into chemical energy stored in the hydrogen, the hydrogen storage system itself, and a hydrogen energy conversion system to convert the stored chemical energy in the hydrogen back to electrical energy (EA Technology, 2004).

Power is generated from hydrogen either by conversion in a fuel cell, or by combustion in an internal combustion or turbine engine (Schoenung, 2001). Hydrogen can be stored as compressed gas, tiny microspheres, a (cryogenic) liquid, hydride compounds, or in other chemical forms (Schoenung, 2001). The various storage types each have different characteristics, some of the most important ones being energy density and cost (Schoenung, 2001).

Storing hydrogen gas in tanks is the most mature technology, but difficult because hydrogen is the lightest element and has very low density under normal conditions (DOE, 2002). Liquid hydrogen stored in cryogenic containers requires less volume than gas storage but consumes significantly more power on the input side due to the liquefaction of hydrogen, which is equivalent to about one-third the energy value of the hydrogen (DOE, 2002).

Alloys of metal hydrides can assist with hydrogen storage, optimizing both the system weight and temperature at which the hydrogen can be recovered (DOE, 2002). When the energy stored in the hydrogen is needed, the hydrogen is released from the metal hydride alloy under specific temperature and pressure conditions, and the alloy is restored to its previous state (DOE, 2002). In irreversible storage with metal hydrides, the material undergoes a chemical reaction with another substance, such as water, that releases the hydrogen from the hydride (DOE, 2002).

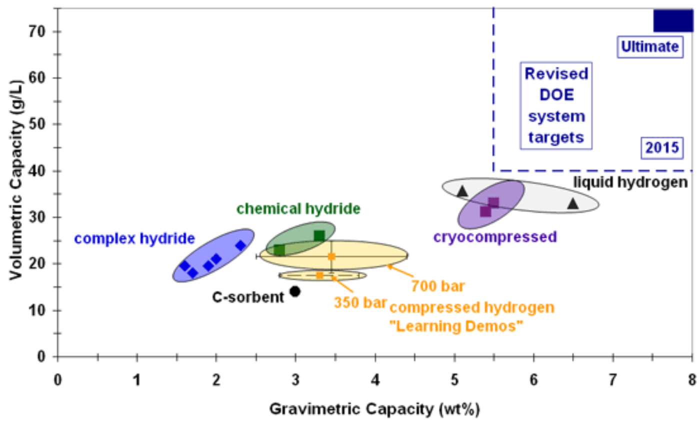


Figure 2.12 - Status of Hydrogen Storage Technologies (Source: DOE, 2002)

Advantages

There are several advantages to hydrogen energy storage. First, hydrogen possesses a high energy density. Second, hydrogen energy storage is easily scalable to the application (e.g., kilowatt to multi megawatt capacity). Third, hydrogen has a significant potential to provide an energy source for road transport applications. Lastly, hydrogen has a system charge and discharge rate and a storage capacity that are independent from the storage technology (EA Technology, 2004).

Disadvantages

There are several disadvantages to hydrogen storage systems. First, the storage cost of hydrogen is quite high given current technology. Second, the round trip efficiency of hydrogen as an energy storage medium is low. Third, materials and components of a hydrogen storage system that can provide 1500 cycles or more do not exist. Lastly, analyses of the full life cycle cost for hydrogen storage systems have not yet been performed (DOE, 2011).

Applications

Currently, only a few projects to demonstrate technical and economic feasibility of integrated hydrogen energy generation are being conducted (DOE, 2012). The feasibility studies are examining how hydrogen energy storage can address society's energy needs for transportation, infrastructure, and electricity generation under real world conditions. One potential use for hydrogen would be to generate electricity for power grid something similar to natural gas fired power plants (Kleijn & van der Voet, 2010). Plants that would use fuel cells in conjunction with electricity production for the grid would be smaller than current size gas fired electricity plants (Kleijn & van der Voet, 2010).

Environmental Impacts

Hydrogen based storage technologies are considered to have environmentally benign operating characteristics (EA Technology 2004). However, the environmental impacts of hydrogen as a storage medium are strongly dependent on the manner through which the hydrogen is produced (Lipman et al., 2005). If used with wind power, hydrogen production and reuse has low environmental impacts (Lipman et al., 2005). On the other hand, hydrogen produced through electrolysis using electricity generated from non-renewable resources, (e.g., coal or natural gas) can have considerable environmental impacts (Lipman et al., 2004; Milborrow & Harrison 2003; Lipman et al., 2005).

Companies

There are a few companies currently producing the first generation hydrogen based fuel cell power plants. Fuel Cell Energy of Danbury, CT manufactures 1.4 -2.8 MW fuel cells that can operate of biogases (FuelCell, 2012). Ballard from Burnaby, Canada will be manufacturing a small-scale test project for use in Pittsburg, CA that will power a small bleach manufacturing plant from by-product hydrogen gas (Ballard, 2012).

Figure 2.13 - 2.8 MW fuel cell power plant designated ultra clean by CARB (Source: FuelCell, 2012)

2.9 Cost Comparison Table

The following table shows the cost estimates for the energy storage technologies included in our analysis (SNL, 2003; SNL, 2011; EPRI-DOE 2003)

Storage Technology	Lifetime (years)	Cycle life (# cycles)	Power-related cost ($/kW)	Energy-related cost ($/kWh)	Fixed O&M cost ($/kW-yr)	Variable O&M cost ($/kWh)	Replacement Cost ($/kWh)
Flooded Lead-Acid Batteries	6	1,500	175	150	15	0.01	150
Valve Regulated Lead-Acid Batteries (VRLA)	5	2,000	175	200	5	0.01	200
Nickel Cadmium Batteries (NiCd)	10	2,000	175	600	25	0	600
Zinc Bromine Batteries (ZnBr)	8	3,000	400	400	20	0	100
Sodium Sulfur Batteries (NaS)	15	3,000	350	350	20	0.7	230
Lithium Ion Batteries (Li-Ion)	10	4,000	400	600	25	0.7	500
Vanadium Redox Batteries (VRB)	10	5,000	400	600	20	0	600
Nickel Metal Hydride Batteries (NiMH)	No Data	3,000	No Data	800	No Data	No Data	No Data
Flywheels	20	25,000	600	1,600	1000/yr	No Data	0
Superconducting Magnetic Energy Storage (SMES)	20	n.d.	200	50,000	10	No Data	0
Supercapacitors	20	25,000	500	10,000	5	No Data	0
Compressed Air Energy Storage (CAES)	30	25,000	700	5	2.5	0.12	0
Pumped Hydro	30	25,000	1,200	75	2.5	0.4	0
Hydrogen Fuel Cells	6	5,000	1500	15	3.8	No Data	100

Table 2.2 - Energy storage cost comparison table

2.10 Environmental Impact Comparison

The following table describes potential health, safety and environmental risks that may arise during the manufacturing, use, and disposal of energy storage devices (PNNL, 2008; NETL, 2008; Rydh, 1999; Rydh and Sanden, 2004; EPRI-DOE 2008; Butler et al, 2003).

Technology	Healthy & Safety Risk	Environmental Risk	Recycled Content	Recyclability	Manufacturing Energy Requirement (MJ/Wh)	Operating Temperature
Flooded Cell Lead-Acid Batteries	Contains lead and sulfuric acid	Potential lead pollution	Often use recycled lead	Recyclable	0.42	Designed for optimal performance at room temperature (25°C), very sensitive to temperature changes
Valve Regulated Lead-Acid Batteries (VRLA)	Contains lead and sulfuric acid	Potential lead pollution	Often use recycled lead	Recyclable	unknown	Designed for optimal performance at room temperature (25°C), very sensitive to temperature changes
Nickel Cadmium Batteries (NiCd)	Contains toxic metal which can be hazardous if spilled	Cadmium is a highly toxic metal Contain transition metals which can be ground water and soil contaminants	Often use recycled cadmium and nickel	Cadmium and nickel can be recycled	2.1	Prefer room temperature, self-discharge rate goes up with higher temperatures and lifetime goes down
Zinc Bromine Batteries (ZnBr)	Liquid bromine can be hazardous if it escapes or spills	Contains corrosive and toxic materials	Made of recycled plastic	Cell stacks are made of recyclable plastic, electrolyte can be reused but limited markets exist	0.6	Between 20°C and 50°C
Sodium Sulfur Batteries (NaS)	High operating temperature can pose safety risk	Contains corrosive materials	Unknown	Almost all of the materials can be recycled, but limited markets exist	0.6	300°C
Lithium-ion Batteries (Li-Ion)	Contains flammable materials	Contains toxic materials	None	No recycling programs available	1.2	Between -10°C and 50°C
Vanadium Redox Batteries (VRB)	Contains sulfuric acid at same concentration as lead-acid batteries	Contains no toxic materials	Made of recycled plastic	Cell stacks are made of recyclable plastic, electrolyte can be reused but limited markets exist	0.74	Between 10°C and 40°C
Nickel Metal Hydride Batteries (NiMH)	None	Contain transition metals which can be ground water and soil contaminants Less toxic than NiCd	Unknown	Materials can be recycled	2.1	Between -20°C and 50°C
Flywheels	Failure of flywheel rotor during rotation could pose safety hazard	None	Unknown	Unknown	Unknown	Between 0° to 40° C
Superconducting Magnetic Energy Storage (SMES)	Magnetic field can cause health impact	Unknown	Unknown	None, all materials are industrial wastes	Unknown	-269°C
Supercapacitors	Can have voltages at lethal levels, some fire hazards	Do not contain toxic or corrosive materials	None	No recycling programs available	Unknown	Unknown
Compressed Air Energy Storage (CAES)	None	Special site required Some NOx emissions can occur	None	None	Unknown	Unknown
Pumped Hydro	None	Special site required Land destruction to create reservoir	None	None	Unknown	Unknown
Hydrogen Fuel Cells	Significant fire and explosion hazard; Certain cell types operate at high temperatures (1000°C)	Impacts of mining and manufacturing of catalyst; Low roundtrip efficiency increases emissions impact of energy conversion losses	Water can be recycled	Catalyst can be reclaimed at end of life	unknown	Between 90°C and 1000°C

Table 2.3 - An environmental impact comparison of energy storage technologies

2.11 An Overview of Energy Storage Analysis Tools

Upon conducting a thorough literature review on energy storage analysis tools in use today, a 2010 report by Pacific Northwest National Laboratory (PNNL), *Analysis Tools for Sizing and Placement of Energy Storage in Grid Applications*, was found to be the most comprehensive source on current commercial and non-commercial energy tools with a focus on storage. The report reviews pertinent literature and studies carried out in the year 2000 and later to identify current models and analytical tools that optimize the siting, sizing, and economic value of energy storage in a smart grid infrastructure (Hoffman et al., 2010). The report reviewed storage technologies currently used by transmission planners that are supportive of the smart grid concept, which requires ease of installation. Therefore, management systems, which optimized the usage of pumped hydropower facilities, were not included (Hoffman et al., 2010).

Future implementation of smart grid infrastructure may, in part, depend on the availability of energy storage models that utilities can use to compare competing technologies and application benefits (Hoffman et al., 2010). Having successful energy storage models available to utilities can significantly change the rate at which the U.S. grid transitions to a modern infrastructure that will meet national energy security and climate goals (Hoffman et al., 2010).

The following is a description of non-commercial (free of cost) and commercial energy analysis tools widely in use today.

Non-Commercial Tools

The Hybrid Optimization model for Electric Renewables (HOMER) by the National Renewable Energy Laboratory (NREL) is a computer model that evaluates design options for both off-grid and grid-connected power systems for remote, stand-alone, and distributed generation (DG) applications (NREL-HOMER, n.d.). HOMER models the following power sources, storage technologies, and loads (NREL-HOMER, n.d.):

Power sources:
- Solar photovoltaic (PV)
- Wind turbine
- Run-of-river hydro power
- Generator: diesel, gasoline, biogas, alternative and custom fuels, co-fired
- Electric utility grid
- Microturbine
- Fuel cell

Storage:
- Battery bank
- Hydrogen
- Flow batteries
- Flywheels

Loads:
- Daily profiles with seasonal variation
- Deferrable (water pumping, refrigeration)
- Thermal (space heating, crop drying)
- Efficiency measures

HOMER finds the least-cost combination of components that meet electrical and thermal loads through simulating the operation of a system by making energy balance calculations for each of the 8,760 hours in a year and then displaying a list of feasible systems sorted by lifecycle cost (NREL-HOMER, 2004). HOMER also has the capability of performing a sensitivity analysis for various inputs (NREL-HOMER, 2004).

The National Energy Modeling System (NEMS) and Regional Energy Deployment System (ReEDS) are non-commercial energy modeling tools that utilize a linear programing approach in their methodology (Hoffman et al., 2010).

NEMS is a computer-based, energy-economy modeling system that was designed and implemented by the Energy Information Administration (EIA) of the DOE (DOE-EIA, 2009). NEMS consists of four supply modules, two conversion modules, four end-end demand modules, one model to simulate energy/economy interactions, one module to simulate international energy markets, and one module that provides the mechanism to achieve a general market equilibrium among all the other modules (EIA, 2009). The components of these modules are indicated in the figure below:

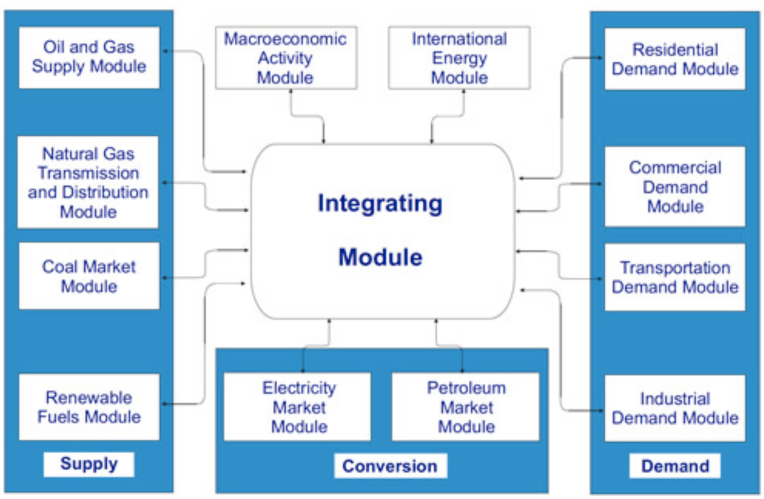


Figure 2.14 - National Energy Modeling System (Source: EIA, 2009)

NEMS determines the optimal power system characteristics, including the characteristics of various storage technologies to be used. The optimization is performed using an objective function that minimizes the total discounted present value costs (Hoffman et al., 2010).

ReEDS is a computer model developed by NREL's Strategic Energy Analysis center that optimizes the regional expansion of electric generation and transmission capacity in the continental United States over the next 50 years (NREL-ReEDS, n.d.). The ReEDS model minimizes the costs of the U.S. electric sector, including:

- The present value of the cost for both generation and transmission capacity installed in each period;
- The present value of the cost for operating that capacity during the next 20 years to meet load, (i.e., fixed and variable operation and maintenance (O&M) and fuel costs); and
- The cost of several categories of ancillary services and storage (NREL-ReEDS, n.d.).

ReEDS considers four storage technologies – pumped hydropower, compressed air, batteries, and thermal storage – for which projections can be made through 2050 (Hoffman et al., 2010). The model takes into account projected capital costs for installation, fixed O&M costs, and round trip efficiencies of the storage technologies (Hoffman et al., 2010). Figure 2.15 illustrates an example scenario estimated by ReEDS:

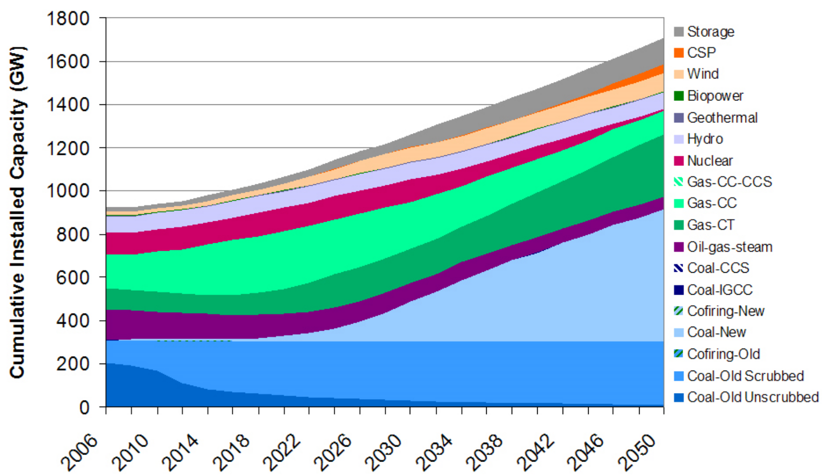


Figure 2.15 - ReEDS capacity estimates for the United States for different generation technologies over the 44-year evaluation period (Source: NREL-ReEDS, n.d.)

RETScreen (Renewable Energy Technology Screen) is a tool that has been developed by Natural Resources Canada (NRCan) CANMET Energy Technology Center for renewable energy technologies analysis (Stefula, 2007). RETScreen evaluates the energy production and savings, life-cycle costs, emission reductions, financial viability and risk for various types of energy efficient and renewable energy technologies (REEEP, n.d.). In order to determine financial viability and cost effectiveness of clean technologies relative to conventional technologies, RETScreen compares clean energy technologies to a conventional "base-case" specified by the user (Hoffman et al., 2010). New modules also estimate greenhouse gas emission savings relative to conventional systems (Stefula, 2007). RETScreen allows users to model energy storage, in the form of a battery, and also suggests values of battery size based on a formula involving the desired number of days of autonomy (Hoffman et al., 2010).

The KERMIT model is a tool by the KEMA Company and is configured for studying power system frequency behavior over a time horizon of 24 hours (Masiello et al., 2010). The figure below shows the inputs and outputs of KERMIT:

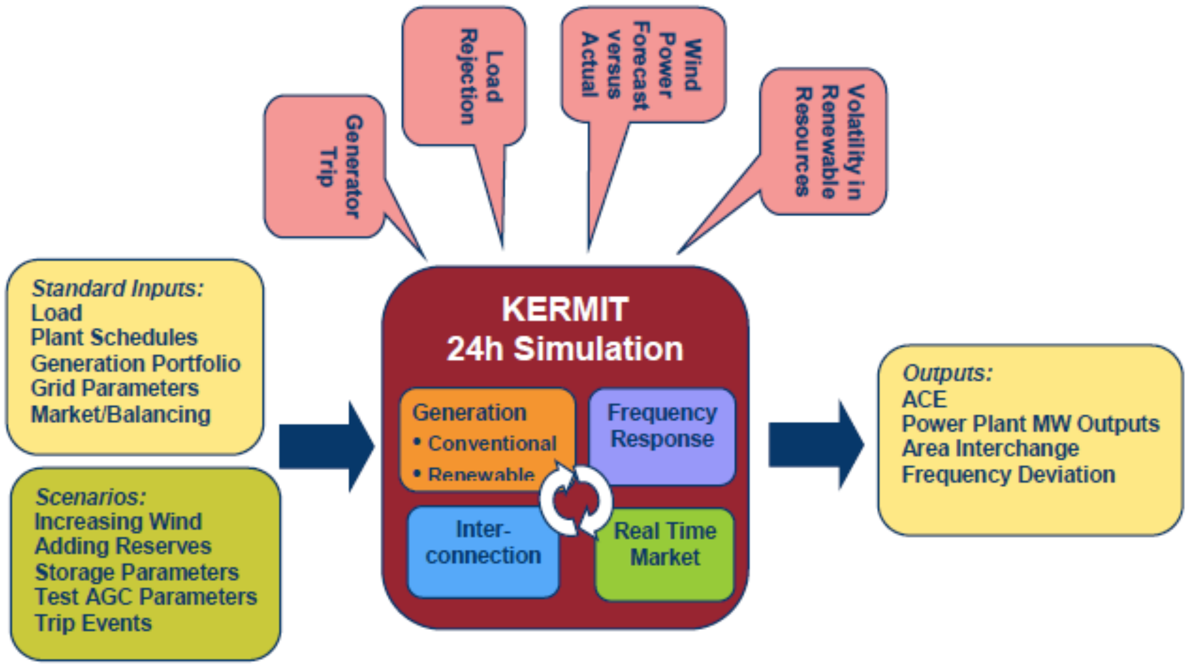


Figure 2.16 - KERMIT model overview by KEMA researchers (Source: Masiello et al., 2010)

As indicated above, the parameters for electricity storage in KERMIT are also inputs to the tool. These parameters include energy capacity, power ratings, efficiencies, and rate limits on the change of power levels (Masiello et al., 2010).

Other non-commercial tools include **GridLabD,** which was developed at PNNL, and **EnergyPlus**, a DOE energy analysis and thermal load simulation program that allows builders and architects to predict energy flows (building heating, cooling, lighting, ventilating, and other energy flows, as well as water) in residential and commercial buildings before construction (PNNL, n.d.; NREL-EnergyPlus, n.d.). While GridLabD does not include energy storage modeling capabilities, new versions of EnergyPlus incorporate storage capability, for example a new thermal storage module allows users to specify the size of thermal storage units (Hoffman et al., 2010).

Summary of Non-commercial Software Characteristics with Energy Storage Modeling Capabilities:

Characteristic /Component	Homer	ReEDS	NEMS	RETScreen	Energy Plus	Kermit	GridLabD
Locational Marginal Pricing[1]		X	X	X			
Energy Storage	X	X	X	X	X	X	X
Arbitrage	X	X				X	
Energy storage by Node	X			X	X		X
Round trip efficiency	X	X	X	X		X	X
Minimizes system efficiency	X	X	X				
Show single or multiple ancillary service[2] value streams	Yes	No	No	Yes	No	Yes	No
Aggregation of multiple ancillary services value streams?	No	No	No	No	No	No	No

Table 2.4 - Non-commercial tools (Source: Hoffman et al., 2010)

Commercial Tools

General Electric Multi-Area Production Simulation Software (GE MAPS) integrates highly detailed representations of a system's load, generation, and transmission into a single simulation (GE Energy, 2009). This enables calculation of hourly production costs in light of the constraints imposed by the transmission system on the economic dispatch of generation (GE Energy, 2009). GE offers MAPS databases for the three major interconnections within the United States: Western

[1] Locational Marginal pricing (often referred to as nodal pricing) determines an energy price for each electrical node on the grid as well as the transmission congestion price (if any) to serve that node (Western Area Power Administration, n.d).

[2] Ancillary Services: The Federal Energy Regulatory Commission defines ancillary services as those necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system (Kirby and Hirst, 1996).

Electricity Coordinating Council (WECC), Eastern Interconnection, and Electric Reliability Council of Texas (ERCOT) (GE Energy, 2009).

System Optimizer and ProMod are tools developed by the Ventyx company, a supplier of enterprise software and services for industries such as energy, mining, public infrastructure and transportation (Ventyx, n.d.). The System optimizer is a screening tool used with load curves to do system capacity analysis (Hoffman et al., 2010). System Optimizer develops long-term (20 to 30 year horizon) resource investment plans for reliability requirements, which include the technology type, fuel, size, location, and timing of capital projects (System Optimizer, n.d.). The optimal solution uses either Mixed Integer Programming (MIP) or Linear Programming (LP) algorithms to solve for the desired time period with the existing system as well as alternatives for future expansion plans (System Optimizer, n.d.).

ProMod is a detailed production costing system that uses detailed direct current (DC) power flow for analysis and is used to create detailed plans while the System Optimizer is used to screen possible futures (Hoffman et al., 2010).

The methodological development of the **Energy 2020 model** was done by George Backus of the Policy Assessment Corporation (Systematic Solutions Inc., n.d.). “The ENERGY 2020 model is an integrated multi-region energy model that provides complete and detailed, all-fuel demand and supply sector simulations” (Energy 2020 model overview, n.d). It is a policy-planning model that simulates the physical and economic flows of energy users and suppliers (Energy 2020 model overview, n.d). It consists of a number of “standard” policy options and variables and simulates how energy users and suppliers make decisions and how those decisions translate to energy use and emissions (Energy 2020 model overview, n.d). It is useful for agent-based analysis to aid policy decisions by regulators (Hoffman et al., 2010).

The Integrated Planning Model (IPM) tool is proprietary of ICF International and provides integration of wholesale power, system reliability, environmental constraints, fuel choice, transmission, capacity expansion, and all key operational elements of generators on the power grid in a linear optimization framework (ICF International, n.d.). It can only model energy storage in the form of pumped hydro (Hoffman et al., 2010).

Other commercial models in use include **Synergee-**a proprietary tool of the Germanischer Lloyd group, the PowerWord **Simulator**-a proprietary tool of Power World Corporation and **Dynastore**, a tool developed by the Electric Power Research Institute (GL group, n.d.; PowerWorld Corporation, n.d.; Hoffman et al., 2010). Synergee models electrical distribution systems and its current version in use does not consider energy storage or distributed generation (Hoffman et al., 2010). However, since software development is driven by requests from customers there is a high potential of incorporating distributed generation analysis in the future, as there is currently customer interst in adding this component into the model (Hoffman et al., 2010). "The PowerWorld Simulator presents depictions of the specified network topography based on loads, generation and line configurations in use at a particular point in time" (Hoffman et al., 2010). The model does not include energy storage arbitrage and locational marginal pricing of energy storage is possible but requires a detailed knowledge of how to use the product (Hoffman et al., 2010). Dynastore software only deals with energy storage and can model 12 weeks per year for up to 30 years (Hoffman et al., 2010). "It deals with ancillary services dispatch of energy storage for spinning reserve, load following, and frequency regulation" (Hoffman et al., 2010).

Summary of Commercial Software Characteristics with Energy Storage Modeling Capabilities

Characteristic /Component	GE Maps	Ventyx System Optimizer/ ProMod	Power World	Energy 2020	Integrated Planning Model (IPM)	Dynastore	SynerGee
Locational Marginal Pricing	X	X	X	X	Zonal basis (cut plane)		
Energy Storage	X pumped hydro is basic option	X ProMod	Possible	X including efficiency	X pumped hydro only	X	
Arbitrage		X ProMod including efficiency	Hard but possible	X			
Energy storage by Node	X	X ProMod		X		X	
Round trip efficiency	X	X ProMod		X			
Minimizes system efficiency		X Only optimizer			X		
Show single or multiple ancillary service value streams	Yes	Yes	Yes	Yes	No	Yes	No
Aggregation of multiple ancillary services value streams?	No	No	No	No	No	No	No

Table 2.5 - Commercial tools (Source: Hoffman et al., 2010)

In conclusion, none of the tools reviewed appear to be capable of choosing a preferred storage technology, its capacity and location for optimal placement and functionality on the electric grid (Hoffman et al., 2010). The PNNL report recommends the development of a software-based tool that can fill these gaps in order to help decision makers fully assess the technical and economic attributes of energy storage.

3 RESET Development

To meet our project objective, we developed an Excel-based tool – the ***Renewable Energy Storage Engagement Tool*** **(RESET) –** that determines the optimal energy storage technology and capacity given temporal demand load and on-site renewable energy generation. Microsoft® Excel was chosen as a software platform for our tool since it is fairly ubiquitous, inexpensive and user-friendly.

RESET is essentially an economic model that compares various storage technology options and calculates the optimal storage amount, or capacity needed, by maximizing the net present value (NPV) of the storage investment.[3] Optimization is performed in RESET by Excel's Solver add-in tool, where the objective function is to maximize NPV for each technology by changing the storage capacity values. Due to the complexity of the optimization problem (e.g. the fact that capacity, cost, and savings calculations are mutually dependent), our tool employs a generalized reduced gradient (GRG) nonlinear solving method due to the complexity of the problem. When optimization is not feasible or the desired amount of energy storage is known, RESET also allows the user to manually input capacity values to compare the calculated costs, benefits, and NPVs across various storage technologies.

The development of such a tool was crucial to our project – as it not only enabled us to run multiple scenarios and develop recommendations for our case study (see Part III) – but it also developed a framework for evaluating energy storage options in terms of economic profitability and optimal sizing.

3.1 RESET User Inputs

One notable feature of RESET is its intuitive user interface and the ease at which inputs can be entered. For example, many input fields include either a drop-down menu (see Figure 3.1) or an instruction prompt when the field is selected. An instructions tab is also located within the workbook to assist with user data entry. Fields are also color-coded, such that white cells are available for data entry and shaded cells contain protected formulas that cannot be altered unintentionally.

---

[3] Net Present Value (NPV) is the amount of cash flow (in present value terms) that a project generates after repaying the invested capital and required rate of return on that capital (Brigham & Houston, 2009).

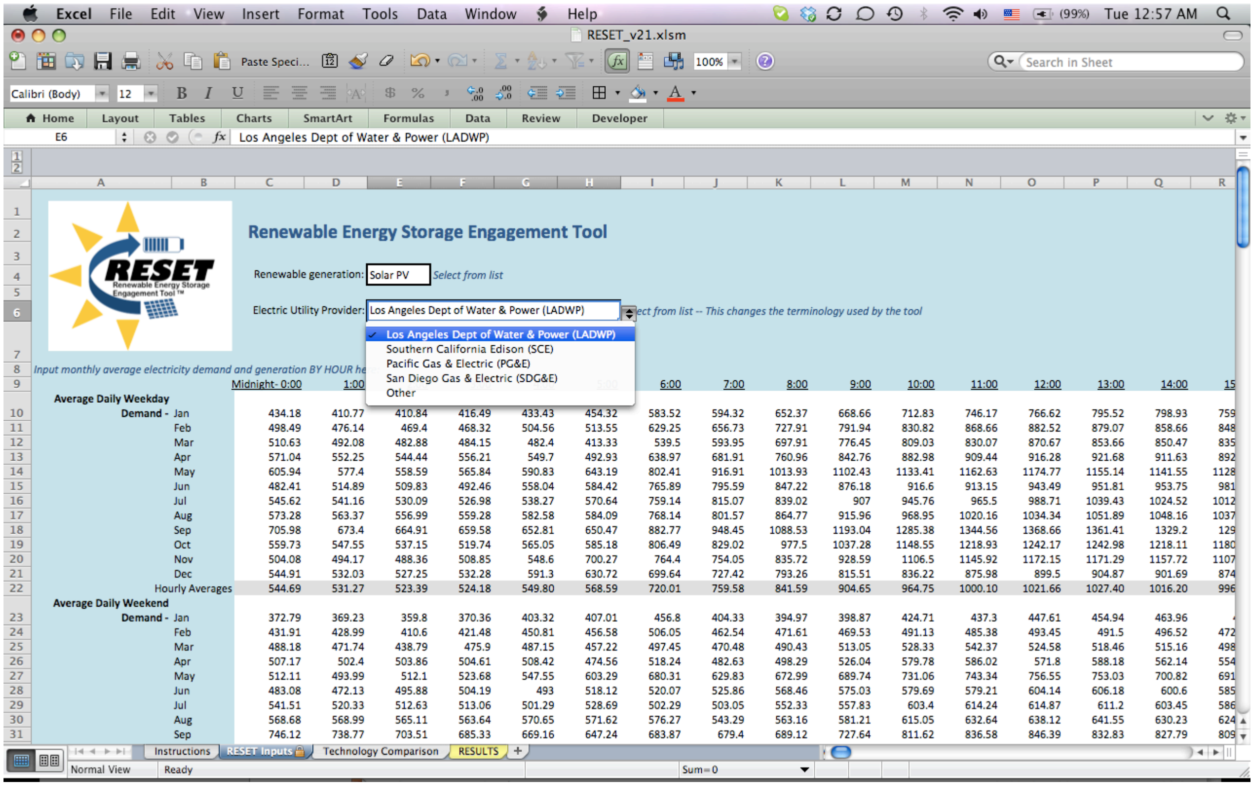


Figure 3.1 - Screenshot of RESET Inputs tab

User Inputs include:

1) **Renewable generation type (*optional*):** This drop-down menu allows the user to select the renewable energy technology used for electricity generation (e.g. solar, wind, etc.). This input is optional since it currently does not affect the results of the model. However, future model versions could incorporate this field to aid in the energy storage technology selection process, if it is later deemed that certain technologies work better together than others.
2) **Electric Utility Provider (*optional*):** This drop-down menu allows the user to select his or her electric utility provider. While technically optional, this useful feature tailors the terminology displayed by the tool based on the selected utility provider's current terminology. For example, the Los Angeles Department of Water & Power (LADWP) uses the terms "High-peak, Low-peak, and Base" in their rate structure, whereas Southern California Edison (SCE) uses the terms "On-peak, Mid-peak, and Off-peak."
3) **Average Daily Weekday / Weekend Demand Profiles:** The hourly electricity demand at each time of day (12AM – 11PM), averaged discretely for each month of the year (Jan.–Dec.) must be entered separately for weekdays (Mon.–Fri.) and weekends (Sat. & Sun.). This enables RESET to accurately calculate projected financial savings, since weekend electricity

rates differ from those during peak weekday hours, and demand on weekends may also differ greatly from demand on weekdays for many potential users.

4) **Average Daily Generation:** The hourly renewable energy generation at each time of day (12AM – 11PM), averaged discretely for each month of the year (Jan.–Dec.) must be entered as well. However, it is not necessary to segregate weekday and weekend generation, as it is assumed that generation does not vary based on day of the week (e.g. the sun does not necessarily shine more brightly on Saturdays than it does on Wednesdays, or vice versa).
5) **Electricity rates (in $/kWh):** Electricity prices must be entered during each rate period (e.g. High-peak, Low-peak, and Base) for both *High Season* (typically summer months) and *Low Season.*
6) **Energy credit rates (in $/kWh, *if applicable*):** For customers who are eligible for net-metering benefits, the electricity rate paid by the utility for each kWh of electricity returned to the grid, during each rate period, can be entered here. When these fields are populated, RESET uses the net electricity rates (electricity prices less energy credits) to determine projected financial savings. Thus, the option of selling electricity back to the grid rather than storing it is considered in the economic analysis.
7) **Stored energy usage (%) during each rate period:** For both *High Season* and *Low Season*, the electricity rate period during which stored energy is expected to be used must be approximated and entered in the form of a percentage. For example, in the LADWP rate structure, 5:00PM to 7:59PM corresponds with Low-peak period and 8:00PM to 9:59AM corresponds to Base period. If stored energy is expected to be used generally from 5:00PM to 9:00PM, then 75% of usage would occur during the Low-peak rate period and 25% would occur during the Base rate period. This input determines the proper electricity rate to apply for financial savings calculations.
8) **Storage operation parameters (Operating days, Operating time per day, and Duration of storage):** Planned storage operating days (either Weekdays only, Weekends only, or Weekdays & Weekends) and duration of storage are both selected by the user via drop-down menus. Operating time per day (in hours) is the expected number of hours that the storage device will be *providing* energy (i.e. discharge time in hours). These parameters help determine which storage devices are technically feasible for the intended application and also affect cost and savings calculations.
9) **Discount rate:** The user's desired annual discount rate must be entered, based either on personal preferences or a firm's required rate of return. The discount rate takes into account the *time value of money* (the idea that money available now is worth more than the same amount of money available in the future since it could be earning interest) and the risk or uncertainty of the anticipated future cash flows.

10) **Annual growth rates (%) for electricity demand and prices:** These fields allow the user to enter estimated annual growth rates that are then used by RESET to project demand and electricity prices for years 2 through 10. Both of these values affect savings calculations and can easily be changed to run "what-if" scenarios.

11) **Renewable generation factor (*Default* = *1*):** This field serves as a multiplier for the renewable generation profile and can also be easily changed to run "what-if" scenarios. For example, a factor of 1.25 would increase the entire generation profile by 25%, and a factor of 2 would double the current generation. A factor of 1 corresponds to the current renewable generation profile and should be used as the default.

12) **Carbon price ($/metric ton CO_2e, *optional*) and eGrid sub-region:** Both of these inputs are used in greenhouse gas (GHG) savings calculations. The carbon price field allows the user to enter an actual or expected price per metric ton of carbon dioxide-equivalents (CO_2e), or it can be omitted. The eGrid sub-region field allows the user to select his or her appropriate electric grid region from a drop-down menu, which then auto-populates the corresponding emissions factor obtained from U.S. EPA data (see Section 9.1.4.4. GHG Savings for a more in-depth explanation of EPA's eGrid.) A map of U.S. eGrid sub-regions is also provided in RESET's "Instructions" tab to assist users with their selection.

3.2 Other RESET Features

In addition to its user-friendly input sheet, RESET also enables the user to easily view results and compare storage technologies. A brief overview of features is given below in the form of illustrative screenshots from RESET.

Summary statistics for demand and generation data are displayed at bottom of the RESET Inputs sheet. Although the more detailed raw data are used for model calculations, this summary is intended to give users a better sense of their average daily energy consumption and generation, and in which electricity rate periods it typically occurs, as averaged over the entire year.

Summary Statistics

Average Daily Energy Consumption (in kWh) for each rate period:

Weekday

High-peak: 4,002 Low-peak: 5,671 Base: 9,476

Weekend

High-peak: 0 Low-peak: 0 Base: 13,557

Average Daily Renewable Energy Generation (in kWh) for each rate period:

Weekday

High-peak: 3,054 Low-peak: 2,999 Base: 877

Weekend

High-peak: 0 Low-peak: 0 Base: 6,931

Average Daily Excess generation (in kWh):

Weekday

High-peak: -948 Low-peak: -2,672 Base: -8,599

Weekend

High-peak: 0 Low-peak: 0 Base: 1,360

Maximum Average Daily Excess generation (kWh):

Weekday: 1,127 *Weekend:* 4,024

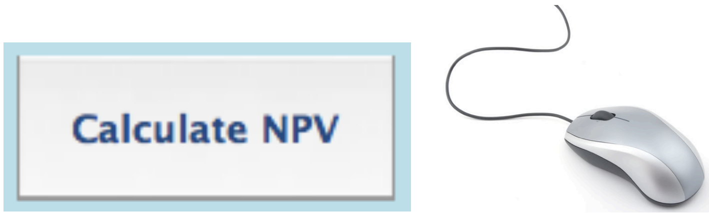
Figure 3.2 - Example of Summary Statistics displayed by RESET

Technology comparison allows users to view the operational characteristics (energy density, duration, round-trip efficiency, etc.) and costs of each energy storage option explored. These values can also be updated or changed by the user as necessary, and subsequent cost calculations performed by RESET will automatically be revised.

Technology	Energy Application	Power Application	Energy Density (Whr/kg)	Duration of discharge (hrs - upper range)	Roundtrip Efficiency	Energy-related cost ($/kWh)	Power-related cost $/kW	Fixed O&M ($/kW-yr)	Variable O&M ($/kWh)	Replacement Costs ($/kWh)	Replacement Year	Environmental/Health Impacts
Flooded Cell Lead-Acid Batteries	Feasible	Capable	40	4	0.75	150	175	15	0.01	150	6	*Potential lead pollution *Recyclable
Valve Regulated Lead-Acid Batteries (VRLA)	Feasible	Capable	40	4	0.75	200	175	5	0.01	200	5	*Potential lead pollution * Recyclable
Nickel Cadmium Batteries (NiCd)	Reasonable	Capable	65	8	0.65	750	125	25	0	600	10	*Cadmium is highly toxic *Cadmium and nickel are recyclable
Zinc Bromine Batteries (ZnBr)	Reasonable	Capable	40	10	0.7	400	400	20	0	100	8	*Contains some toxic and corrosive materials *Can be hazardous if materials escape *Made of recycled and recyclable materials
Sodium Sulfur Batteries (NaS)	Capable	Capable	195	10	0.75	350	350	20	0.7	230	15	*Contains little hazardous material *Operates at high temperatures, can be a safety hazard
Lithium-ion Batteries (Li-Ion)	Capable	Feasible	135	8	0.85	600	400	25	0.7	500	10	*Contains toxic materials
Vanadium Redox Batteries (VRB)	Reasonable	Capable	20	10	0.65	600	400	20	0	600	10	*Recyclable materials, but few markets exist *No toxic materials
Nickel Metal Hydride Batteries (NiMH)	N/D	N/D	40	N/D	0.66	800	N/D	N/D	N/D	N/D	N/D	*Nickel is recyclable *Non-toxic alternative to nickel cadmium batteries
Flywheels	Feasible	Capable	20	0.25	0.95	1600	600	20	N/D	0	20	*Low environmental impact
Superconducting Magnetic Energy Storage (SMES)	Capable	Feasible	2.5	0.01	0.95	50,000	200	N/D	N/D	0	20	*Magnetic field can cause health impact
Supercapacitors	Not Capable	Capable	10	0.01	0.95	10000	500	N/D	N/D	0	20	*Environmentally-friendly materials *No recycling programs *High voltages are safety concern
Compressed Air Energy Storage (CAES)	Capable	Not Capable	45	24	0.7	5	700	2.5	0.12	0	30	*Special site required *Emissions from natural gas
Pumped Hydro	Capable	Not Capable	1	24	0.85	75	1200	2.5	0.4	0	30	*Land destruction to create reservoir
"Dream" technology	Capable	Capable	Ideally high	Ideally high	0.95	100	100	5	0.01	0	30	*Ideally low

Table 3.1 - Screenshot of technology comparisons tab with relevant technological and cost data

Results calculated and displayed at the click of a button:



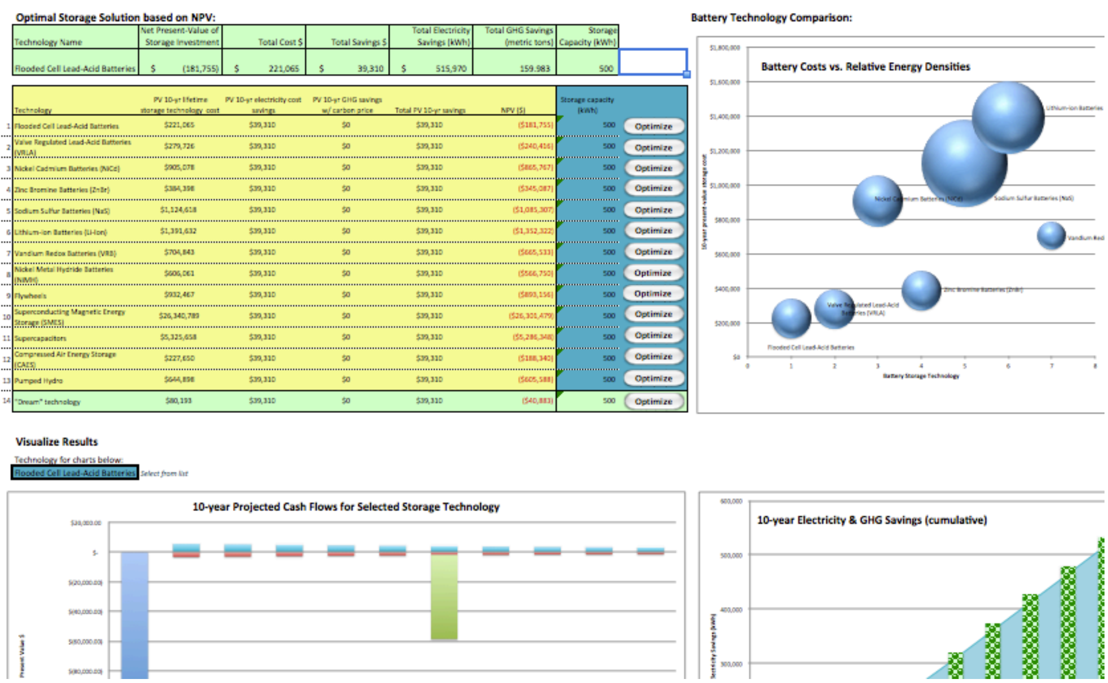


Figure 3.3 - Screenshot of RESET Results tab

By adjusting data input values and re-clicking the "Calculate" button, RESET enables multiple scenarios to be projected by any user. For example, the user can easily change the discount rate and/or projected growth rates for electricity demand and electricity price (see Figure 3.4 below) in order to test different projections about the future. The user can also optionally input a carbon price for CO_2e emissions based on future policy or pricing expectations.

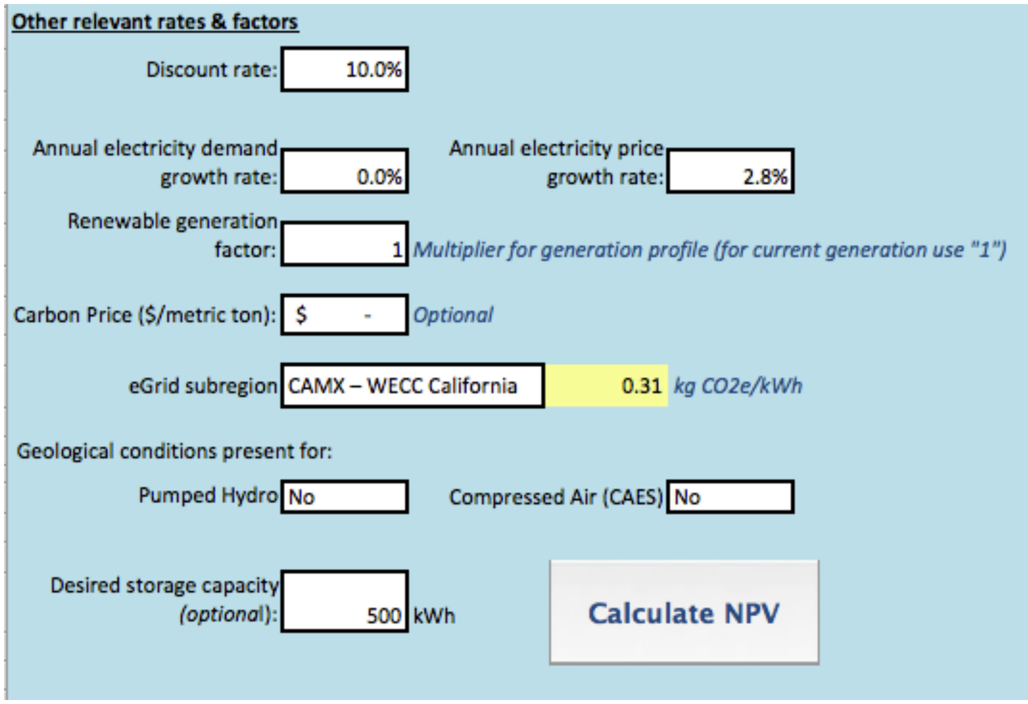


Figure 3.4 - RESET inputs screenshot for relevant rates and factors adjusted for scenario analysis

3.3 Net Present Value Calculations

Present value (PV) is the worth or value of a future sum of money given a specific rate of return on an investment. It reflects the discounted value of money into the future. The equation for the PV of a future sum is:

$$PV_n = \frac{Future\ Value}{(1+i)^n}$$

where i is the annual discount rate and n is the period.

In essence, the future value is the face value, or real value, at period n in the future.

All cost and savings calculations used in RESET reflect the present value of investments or payments for a ten-year period. RESET users have the ability to input their discount rate, as it is likely to vary across users and time.

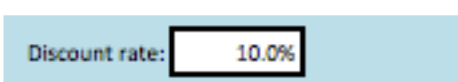


Figure 3.5 - RESET placeholder for user input of discount rate

For financial savings calculations, our PV calculation is as follows:

$$PV = \sum_{n=1}^{120} \frac{Monthly\ \ Savings}{\left(1 + \frac{i}{12}\right)^n}$$

Savings are being discounted monthly; hence, the annual discount rate is divided by twelve. PV was determined for each month through year ten to determine total savings over ten years.

The Net Present Value (NPV) was calculated by subtracting the ten-year present value costs from the projected ten-year present value savings.

3.4 Cost Calculations

The cost of storage systems can be characterized as either cost per unit power ($/kW) or the cost per unit energy ($/kWh). Power-related costs describe the cost of the power electronics and energy-related cost describes the cost of the storage medium (Makarov, 2010).

Capital Cost

The capital cost of energy storage systems is equal to the sum of the cost of the power conversion system (PCS), the cost of the storage device, and the balance of plant costs. For our calculations, we assume the balance of plant costs are accounted for in the cost of storage. Capital cost equations shown below were obtained from the Sandia National Laboratory's 2011 and 2003 reports (Schoenung, 2011; Schoenung & Hassenzahl, 2003).

$$Capital\ Cost\ =\ Cost\ of\ Power\ Equipment\ +\ Cost\ of\ Storage\ Device$$

$$Capital\ Cost\ (\$)\ =\ COST_{PCS}(\$)\ +\ COST_{Storage}(\$)$$

$$COSTStorage\ (\$)\ =\ UnitCostStorage\ (\$/kWh) \times E\ (kWh)$$

where E is the stored energy capacity and is what we optimize in RESET.

All energy conversion processes have some losses. Efficiency refers to the amount of energy that comes out of a process compared to the amount in ($E = E_{OUT} / E_{IN}$). The efficiency numbers were found during the literature review. In order to account for efficiency, the cost of storage equation was changed to the following:

$$COST_{Storage}(\$) \;=\; UnitCost_{Storage}\left(\frac{\$}{kWh}\right)\times\left(\frac{E}{\eta}\;kWh\right)$$

where η is the discharge efficiency,

$$COST_{PCS}(\$) \;=\; UnitCost_{PCS}\left(\frac{\$}{kW}\right)\,\cdot\,P\,(kW)$$

and where P is the power rating and

$$Power\;(kW) = \frac{E(kWh)}{operating\;time\;(hr)}$$

Therefore,

$$COST_{Total}\;(\$) =$$

$$[Power\;(kW)\times UnitCost_{PCS}\left(\frac{\$}{kW}\right)] \;+\; [UnitCost_{Storage}\left(\frac{\$}{kWh}\right) \cdot Energy\;(kWh)]$$

$$COST_{Total}\left(\frac{\$}{kW}\right) \;=\; COST_{PCS}\left(\frac{\$}{kW}\right) \;+\; COST_{Storage}\left(\frac{\$}{kWh}\right)$$

Total Costs

The total cost includes the initial capital cost, as well as operation and maintenance (O&M) costs and replacement costs. These were also discounted over a 10-year time frame to calculate the present value of total cost.

The following equation was used to calculate the present value of future costs.

$$PV = \frac{Yearly\ Costs}{(1+i)^n}$$

The following is a discussion of the assumptions in the total cost calculations:

Lifespan: Storage system life of ten years was assumed for cost calculations. Although this number is somewhat arbitrary, it is the amount of time most frequently used in reports and studies that also attempt to calculate life-cycle cost (SNL, 2011). According to the 2011 Sandia report, this is because "when accounting for the time value of money, a significant majority of benefits accrue in the first ten years." However, using a time period longer than ten years may not make sense because of market uncertainty-both for the cost of electricity and the costs of storage technologies (Eyer & Corey, 2010). Since each storage technology has a different lifespan, it is necessary to compare costs for each with the same time and to include replacement costs. It is important to note that the management of the system (proper maintenance and use) affects storage life, however it was not feasible to include all of those factors into our lifespan estimates.

Replacement Costs: It is expected that some storage systems will need to be replaced after a certain time period due to wear and tear and efficiency losses over time. The estimates for replacement costs, and when the costs are expected to occur (a function of the system's estimated lifespan) were found in the literature review. These replacement costs were added in to the total cost equation at the year the system is estimated to need a replacement.

O&M Costs: Fixed O&M costs (a function of the power rating), and variable O&M costs (a function of the energy capacity) were calculated for the ten-year time frame. O&M cost estimates were taken from the literature review.

Discount rate: All of the costs were discounted to account for the present value of money. The discount rate is a user input in RESET.

Therefore, the total cost equation is as follows:

$$Total\ Cost\ (\$) =$$

$$Total\ Capital\ Cost\ (\$)\ +\ O\&M\ Cost\ (\$)\ +\ Replacement\ Cost\ (\$)$$

3.5 Financial savings calculations

Electricity cost savings

RESET also allows the user to select (via a drop-down menu) whether storage will be used on weekdays only, weekends only, or both weekdays and weekends. This user input then flows through all the calculations to determine the appropriate electricity savings expected, as well as the number of operating days per year that is utilized by the energy storage cost calculations.

In order to determine electricity cost savings, RESET performs the following calculations for both weekday and weekend savings:

- RESET calculates the user's projected electricity demand for ten years based on the current demand profile and an annual demand growth rate, both entered as an input to the tool.
- Average daily excess electricity generation is determined for each month of the year through year ten. Specifically, the ten-year projected hourly demand profiles by month are subtracted from the electricity generation profiles. Average hourly excess generation are then summed across all hours of the day in which an excess occurred (i.e. Generation – Demand > 0) in order to obtain an average daily excess generation value for each month of the year. As mentioned previously, this is calculated separately for both weekdays and weekends, as RESET requires users to input distinct demand profiles for each.
- Average daily energy savings are then derived through a series of steps utilizing daily excess generation.
    - First, the average daily excess generation is multiplied by the user's planned times of use of stored energy during each rate period (high-peak, low-peak, and base) for high or low season, depending on the month of the year. This step is important, as it determines which electricity price rates will be used in subsequent savings calculations based on avoided electricity costs from the grid at those times. Users specify their planned time of stored electricity usage, on a percentage basis, in the RESET inputs tab. This input feature is illustrated in the figure below:

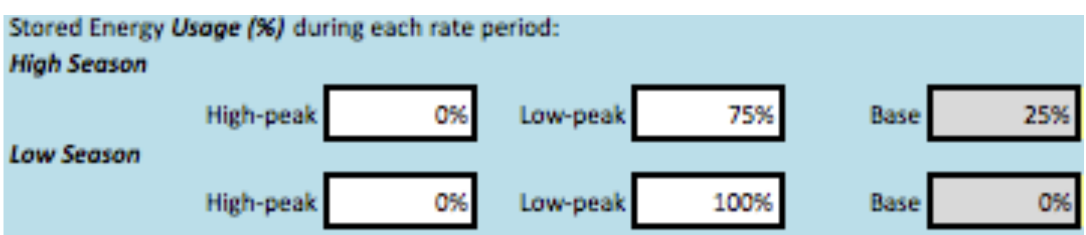


Figure 3.6 - User inputs for the amount of electricity they plan to utilize at different times of day. This is important because users may peak during different rate periods in different seasons.

- The resulting values during each rate period are then summed to determine the total average daily energy (in kWh) *available* to be stored for each month of the year. Since daily storage cannot exceed the storage technology's capacity, a logic function is employed to constrain *actual* daily energy stored (and thus daily electricity savings) by the optimal energy storage capacity derived from running RESET.
- Average daily cost savings from utilizing the energy stored for each time of day and season is then calculated by multiplying the corresponding electricity rates by the amount of stored energy used per rate period. Time of day savings are aggregated to reach a total average daily savings, and then multiplied by the number of days in each month to determine total savings each month for ten years (compartmentalized by weekday, weekend, and total savings).
- The ten-year present value of the monthly electricity cost savings is then determined using the formula described in the Present Value Calculations section above (again, compartmentalized by weekday, weekend, and total savings).

Greenhouse Gas Savings

RESET also calculates greenhouse gas (GHG) emissions savings in both: (1) metric tons of carbon dioxide-equivalent (CO_2e), and (2) avoided financial costs when there is a carbon price input entered by the user. It is important to note, however, that RESET only models the costs and benefits directly attributable to the use of energy storage. Therefore, the calculations do not include the additional GHG savings attained from renewable generation in general, as it would be improper to incorporate such benefits in the model without also including the costs of renewable energy generation. Instead, only GHG savings resulting from storing excess renewable generation for later use are considered.

GHG savings were calculated as follows:

- Average monthly electricity savings (in kWh) in each month for a ten-year period were calculated for both weekdays and weekends, following the same approach used for electricity cost savings (see above section).
- Electricity kWh savings were then multiplied by an appropriate emissions factor based on grid region, which was obtained from the U.S. Environmental Protection Agency's (EPA) eGrid data – eGRID2010 Version 1.1, Year 2007 GHG Annual Output Emission Rates (EPA, 2011).
    - eGrid is developed by the EPA and is used as the standard GHG database for all EPA projects. It distinguishes 26 grid regions and

gives unique GHG figures distinguishing CO_2, CH_4, and N_2O (Suh, 2010).

- For our purposes, CO_2, CH_4, and N_2O emissions were converted to CO2-equivalents using the 100-year global warming potential factors (GWP100) from the Intergovernmental Panel on Climate Change fourth assessment report (IPCC, 2007). Also, the pound (lb.) based data from eGrid was converted into kilograms (kg), and both MWh and GWh data were converted to kWh.
- This gave us an emissions factor (in kg CO_2e/kWh) that was then applied to kWh electricity savings.

• RESET enables users to select the appropriate grid sub-region from a drop-down menu, which then automatically determines the appropriate emissions factor. A map of U.S. grid sub-regions is shown in the figure below. For our analysis of LAHC, the “CAMX – WECC California” sub-region was used.

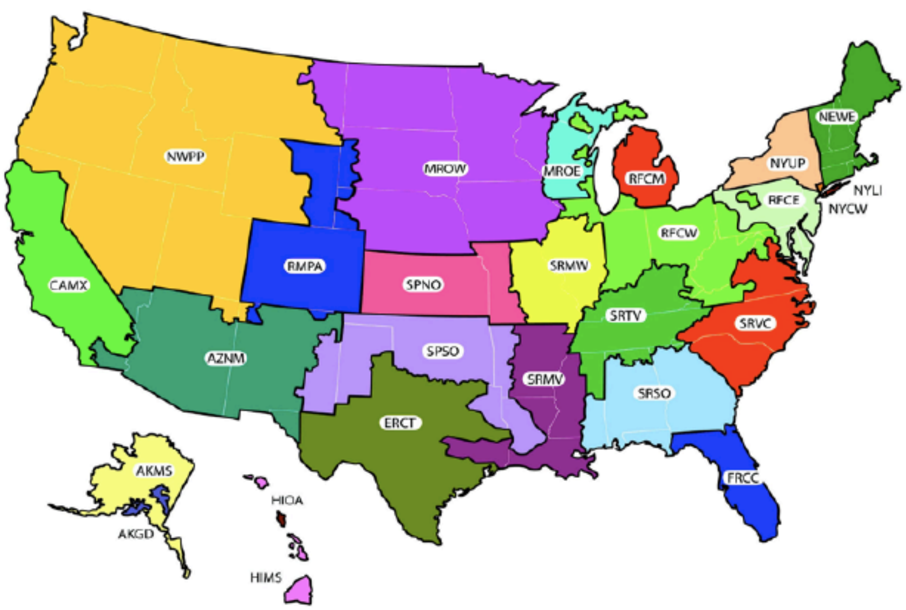


Figure 3.7 - U.S. Electric Sub-region Map (Source: EPA, 2011)

Results for GHG Savings are then displayed in metric tons of CO2e emissions avoided through the use of storage. If a carbon price per metric ton of CO2e was also input by the user, then the ten-year present value of the expected GHG cost savings is also given. As with the electricity cost savings, GHG cost savings are discounted monthly over ten years.

Part II: Applying RESET – A Case Study at Los Angeles Harbor College

4 Introduction

Los Angeles Harbor College (LAHC) served as a case study to demonstrate the applicability of RESET. This analysis was conducted to determine if integration of an energy storage system will enable LAHC to reduce energy and operating costs at its campus. If practical and economical, an energy storage system could reduce emissions associated with electricity LAHC would otherwise have purchased from the grid.

The following sections will provide further background information on the college district, the college itself, and their utility provider.

4.1 Los Angeles Community College District

Los Angeles Harbor College (LAHC) is one of nine, two-year community college campuses in the Los Angeles Community College District (LACCD). LACCD's nine campuses collectively serve 250,000 students annually within a geographic area of 882 square miles. LACCD's colleges offer low-cost education to a diverse population of students. More than 40% of all LACCD students are over the age of twenty-five and about 20% are thirty-five or older. About 65% of LACCD students are underserved minorities (LACCD, 2011).

LACCD is currently upgrading each of its nine campuses through LACCD Builds Green, a sustainable building program funded by three voter-approved bond measures. These three bonds, totaling $6 billion dollars, were allocated to retrofit and replace aging buildings as well as to construct new state-of-art buildings on each campus. Once construction is completed, LACCD will have eighty-five buildings that meet LEED (Leadership in Energy and Environmental Design) standards. Included in LACCD's sustainable building program is an energy program intended to encourage efficiency as well as renewable generation (primarily solar PV) on each campus.

4.2 Los Angeles Harbor College

Los Angeles Harbor College is located in Wilmington in the South Bay region of Los Angeles County. LAHC offers a broad spectrum of transfer, vocational, and community service oriented educational programs including a nursing program and a child development program in addition to traditional academic classes. As of 2010, LAHC's student population was 10,511 students (LACCD, 2011). LAHC's campus, along with other LACCD campuses, is currently being upgraded as part of LACCD's BuildGreen modernization program.

Figure 4.1 - Arial view of LAHC prior to solar array installation. (Source: LACCD website)

From the district-wide LACCD Builds Green $6 billion bond issue, LAHC has specifically been allocated $467 million dollars for upgrades. In 2010, the total square footage of LAHC's campus was 484,140 square feet. After all planned new construction and remodels through LACCD Builds Green are completed, the total square footage on campus will be 644,140 square feet. At that time, the campus will have a capacity for an enrollment of 12,000 students.

Through the BuildGreen program, LAHC has to date installed 2.11 megawatts (MW) of solar PV generation capacity and has approved budgets and construction for an additional 0.78 MW of capacity. With a system of this size, LAHC has on-site generation that exceeds the campus's energy demands during several hours of many days.

In many utility jurisdictions, utility customers can sell their excess generation back to the utility or receive energy credits that reduce their electricity bills – a process called net metering. However, due to LAHC's tax-exempt status and because LAHC's solar generation system exceeds a capacity threshold of one MW, LAHC is not eligible for net metering with their utility, the Los Angeles Department of Water and Power (LADWP). Further complicating LAHC's situation is that they do not have a two-directional electricity meter at their interconnection with the LADWP grid, thereby making it impossible to accurately measure LAHC's excess generation.

After an initial consultation with representatives from LAHC and a preliminary data review, we identified the following problems at LAHC to be addressed in this report:

- LAHC has not quantified the excess generation from their solar arrays.
- LAHC is not capturing the full value of their solar generation capacity.
- LAHC is uncertain how to maximize the economic value of any excess generation.

Our analysis evaluated the costs and benefits of utilizing energy storage to shift this excess generation to meet on-site demand during other time periods.

LAHC Solar Generation

At present, LAHC has 2,365 kW of solar generation online. In August 2010, LAHC's first solar array, an 1151 kW system was brought online. In April 2011, LAHC added a 964 kW system atop parking lot 8. The generation and insolation from both of these arrays is monitored and displayed in near real-time on Chevron's Utility Vision website.

A 250 kW array atop the west parking structure was brought online in September 2011. However, generation and insolation from this system is not monitored on the Utility Vision site. Therefore, data from this array was not available for analysis in this report. In addition to these three online systems, LAHC has approved and budgeted for an additional 517 kW of solar arrays that will be added to buildings currently under construction.

The total existing and planned solar generation capacity for LAHC is listed in Table 4.1. Once construction of new buildings and accompanying solar arrays are completed LAHC will have a solar generation capacity of 2,882 kW.

	Array	kW DC	kW AC	Annual Generation kWh
Currently Online and Measured	Carport Lot 8	964	743	1,039,709
	Carport Lots 6 & 7	1151	886	1,240,994
*Online but not measured on Utility Vision	West Parking Structure	250	192	268,422
	TOTAL SOLAR ONLINE	2365	1821	2,549,125
Planned	Health Services Building	89	68	95,726
	Library	51	39	54,978
	Science Complex Building	193	149	208,054
	Student Union Building	185	143	199,861
	TOTAL SOLAR INCLUDING PLANNED SYSTEMS	2,882	2,220	3,107,744

Table 4.1 - Existing and Planned Solar Arrays on LAHC campus

Due to LAHC's large generation capacity (2.882 MW DC), for several hours of most days of the year, LAHC's generated electrical energy exceeds campus demand for electrical energy. Excess generation during these times is fed back onto LADWP's energy grid. Entities with smaller generation capacities (less than one MW) are eligible for net metering in LADWP, a program that allows customers receive credits for any excess generated energy that is fed back onto the grid. However because LAHC's system exceeds the one MW threshold, LAHC is not eligible for net metering and does not receive any compensation for this excess generation. LAHC unique position with the utility LADWP is explained in the following section.

LAHC Institutional Issues

Several institutional issues specific to LAHC's situation complicate the campus's ability to fully realize the economic potential of their installed renewable generation. A brief summary of these issues are listed below:

- LACCD has approximately $6 billion in state bonds to revamp all nine campuses (with approximately $3 billion spent so far), but funds cannot be used for educational purposes or operating expenses. This means that the District has funds to invest in new buildings, renewable energy, demand-side management systems, energy storage, etc., but also needs improvements to help cut operating costs due to budgetary constraints.
- LAHC's tax-exempt status creates barriers for receiving renewable tax credits/rebates that might otherwise be available for renewable and energy storage investments. For example, the *Storage Technology for Renewable and Green Energy Act of 2011*, or *STORAGE 2011 Act*, was introduced in the U.S. Senate on Nov. 10, 2011 (S.1845 – 112th Congress, 2011). If approved, the bill would provide a 20% investment tax credit up to $40 million for energy storage systems that are connected to the electric grid and a 30% investment tax credit of up to $1 million to businesses and homeowners for on-site storage projects. Unfortunately, LAHC would likely not be able to take advantage of this benefit as a tax-exempt entity.
- LAHC campus only has one meter. LAHC pays their electricity bill to the utility company, but there is currently no way to measure actual energy consumption of the various campus buildings. Additionally, now that a portion of the campus's electricity needs are being met through on-site solar generation, total consumption is even less clear as the electricity used from the solar arrays is not reflected on utility bills, nor tracked elsewhere. In particular, unused or excess generation that flows onto the grid is not measured nor credited. In the future, however, LAHC does plan to install a Building Automation System (BAS) to meter each building's energy usage.

4.3 Los Angeles Department of Water & Power

The Los Angeles Department of Water & Power (LADWP) is the largest municipal utility in the United States, serving over four million residents in Los Angeles and surrounding communities. LADWP provides electricity for 1.4 million customers (LADWP website, n.d.), including Los Angeles Harbor College, our project case study.

LADWP has historically relied upon coal for base load generation. Currently, 39% of the energy delivered to LADWP customers is generated from two coal-fired generating stations: the Intermountain Power Project (IPP), located in Utah, and the Navajo Generating Station (NGS), located in Arizona. Although these coal-fired stations provide dependable, low cost base load generation to Los Angeles, they also emit about twice as much carbon dioxide (CO_2) as energy generated with natural gas (LADWP, 2011). Accordingly, LADWP's 2011 Power Integrated Resource Plan (IRP) focuses on early coal divestiture options as a means to comply with AB 32 and lower LADWP's carbon emission levels.

LADWP's current power mix consists of coal (39%), natural gas (22%), renewables (20%), nuclear (11%), large hydro (3%), and generic purchases/other (5%) (LADWP, 2011).

LADWP Institutional Issues

LAHC's situation is complicated further by the following institutional issues with LADWP:

- For generation installations over 1 MW, LADWP requires a "Vista" switch that allows the utility to shut down an end-users generation system during periods of grid-congestion. These shutdowns have resulted in several "brownouts"[4] at LAHC.
- Net-metering or energy credit benefits do not apply to LADWP customers with generation over one MW.
- The utility appears inexperienced at handling customer with such large renewable on-site generating power. LADWP will soon be switching LAHC from their current sub-transmission service rate schedule (A3-A) to a customer generation sub-transmission service schedule (CG3-A), but the primary account representative for LAHC at the utility does not know what the impact will be (See section 6.3 for a more in-depth discussion of LADWP's electric rate schedules and billing rate structure).

[4] A **brownout** is an intentional drop in voltage in an electrical power supply system used for load reduction in an emergency. The reduction lasts for minutes or hours, as opposed to short-term voltage sag or dip (Blume, 2007).

- It is difficult to determine precise rates paid by LAHC per kilowatt-hour (kWh) during high peak, low peak, and base time periods due to complex billing rate structure.

Electricity Billing Rates

LADWP's rate structure for LAHC is very complex. Actual rates paid per kilowatt-hour (kWh) of electricity drawn from the grid vary widely depending on month (high season or low season) and time of day (high peak, low peak, or base rate period). LADWP defines these rate periods as follows:

High Season: Jun – Sept

Low Season: Oct – May

HIGH PEAK PERIOD: 1:00 PM TO 4:59 PM – WEEKDAYS (20 HRS/WEEK)

LOW-PEAK PERIOD: 10:00 AM TO 12:59 PM AND 5:00 PM TO 7:59 PM - WEEKDAYS (30 HRS/WEEK)

BASE PERIOD: 8:00 PM TO 9:59 AM - WEEKDAYS AND ALL DAY SATURDAY AND SUNDAY (118 HRS/WEEK)

Figure 4.2 - LADWP rate periods applicable to LAHC. (Source: LADWP website)

LAHC's current electric rate schedule is A-3, Rate A (effective July 1, 2009) and can be accessed through the LADWP website. The overall rate per kWh, however, is a composite of many billing components, including:

- Service Fee (fixed)
- Facilities Charge (per kW) – Based on Billing kW Demand[5]
- Demand Charge (per kW) – Rates vary by high/low season and by high peak/low peak/base rate periods; Applied to Actual kW Demand during each rate period
- Energy Charge (per kWh)– Rates vary by high/low season and by high peak/low peak/base rate periods; Applied to Actual kWh usage during each rate period

[5] Billing kW Demand is determined by the highest actual power (kW) demand realized in any 15-minute interval during the last 12 months.

- Energy Cost Adjustment factor (per kWh) – Applied to total kWh usage
- Electric Subsidy Adjustment factor (per kW) – Based on Billing kW Demand
- Reliability Cost Adjustment factor (per kW) – Based on Billing kW Demand
- Reactive Energy Charge (per kvarh per power factor level) – Rates vary by high/low season and by high peak/low peak/base rate periods; Rate determined by power factor level and applied to actual KVARH total during each rate period.

The highest actual kW demand sets the Billing kW Demand for the subsequent year. For example, the Billing kW Demand for most of 2011 was 1609.9 kW. This was due to the fact that the highest actual kW demand in 2010 was 1609.9 kW, realized in July during high peak period.

As of January 2012, LAHC's Billing kW Demand has been lowered to 1523.5 kW. This is due to the fact that the highest actual kW demand in 2011 was 1523.5 kW, realized in August during the low-peak rate period. If LAHC exceeds 1523.5 KW of power demand at any time during the year, then the 2012 Billing KW Demand will increase to that new higher value.

The below calculations, using LAHC's current rate schedule, illustrate how the Billing kW Demand affects the monthly electricity bill:

Billing Demand calculation example:			
2011 Billing Demand (KW)	1,609.9		
2012 Current Billing Demand (KW)	1,523.5		
Rate components dependent on Billing Demand	Rate per KW	Monthly cost @ 1609.9 KW	Monthly cost @ 1523.5 KW
Facilities Charge	$ 4.00	$ 6,439.60	$ 6,094.00
Electric Subsidy Adjustment (ESA) factor	$ 0.46	$ 740.55	$ 700.81
Reliability Cost Adjustment (RCA) factor	$ 0.96	$ 1,545.50	$ 1,462.56
Total monthly cost due solely to Billing Demand:		**$ 8,725.66**	**$ 8,257.37**

Figure 4.3 - Sample billing demand calculation

The monthly energy charges and service fee are then added to the billing demand cost in order to determine the total monthly electricity bill. There is also a trivial amount of State Energy Tax (~$100-$150) included in the bill, although it is unclear how the tax is calculated.

It is also important to note that LAHC's electricity rates – which are currently for sub-transmission service under rate schedule A-3, Rate A – are subject to change. According to the school district's primary account representative at LADWP, Harbor college will soon be moved to a co-generation sub-transmission service, under schedule CG-3, Rate A. The LADWP representative was unsure what the cost implications of the schedule switch will be.

Our analysis of the two rate schedules (A-3 vs. CG-3) show that primary differences are:

- Monthly service fee of $75 (A-3) increases to $150 (CG-3)
- Demand charge per kW during high season, high-peak period decreases from $9.00 per kW (A-3) to $5.50 per kW (CG-3). Demand charges during low season and other rate periods remain the same.
- A new charge, *Backup Capacity Charge - per kWh of Backup Energy*, is added to the CG-3 schedule. Rates for high season are currently ~$0.13 (high-peak) and $0.03 (low-peak) per kWh. There appears to be no backup capacity charge for base periods and low season.
- A new credit, *Energy Credit per kWh,* is added to the CG-3 schedule. The energy credit rate varies but is currently about $0.03 per kWh during high-peak and low-peak periods, and about $0.02 per kWh during base periods.

In theory, the last bullet means that LAHC could begin getting paid up to $0.03 per kWh for energy sold back to the grid. However, California net metering laws only require LADWP to pay net metering credits to customers that generate under 1 MW. Since LAHC exceeds the 1 MW generation threshold, it can be assumed that the energy credits in schedule CG-3 will not apply.

5 Methods

In light of the problems outlined previously, we have identified the following steps necessary to evaluate the potential benefits of an energy storage system for Los Angeles Harbor College.

- Quantify and project excess energy generation from LAHC's existing solar array.
- Determine what, if any, is the optimal energy storage system and capacity.
- Identify economic scenarios under which energy storage becomes most attractive.
- Analyze results and develop recommendations for LAHC.

5.1 Data Collection & Analysis

Before implementing the RESET tool, it was necessary to generate hourly generation and demand profiles for an entire year at LAHC. Our data for these profiles came from the following two online sources:

1) Generation: Chevron's *Utility Vision* website
2) Demand: Energy Load Manager (ELM)

Solar Generation at LAHC

Chevron's Utility Vision website provides near real-time solar generation data in both power (kW) and energy (kWh) from the two largest solar arrays at LAHC. Generation data from these arrays is recorded and posted at one-hour intervals. Utility vision also records solar insolation and the temperature at the insolation sensor. Generation data is recorded at four separate inverters and then aggregated into a total generation figure. Inverters two and four are tied to the 1151 kW system atop carport lots six & seven. This system came online in August 2010. Inverters one and three are tied to the 964 kW system atop carport eight, which came online on July 16, 2011. The generation output of inverter two is roughly equivalent to the output of inverter four, as the same number of panels feed each inverter. Likewise the generation of inverter one is roughly equivalent to the generation of inverter three. Utility Vision does not record insolation or generation data from the 250 kW array atop the west parking structure (which came online in September 2011).

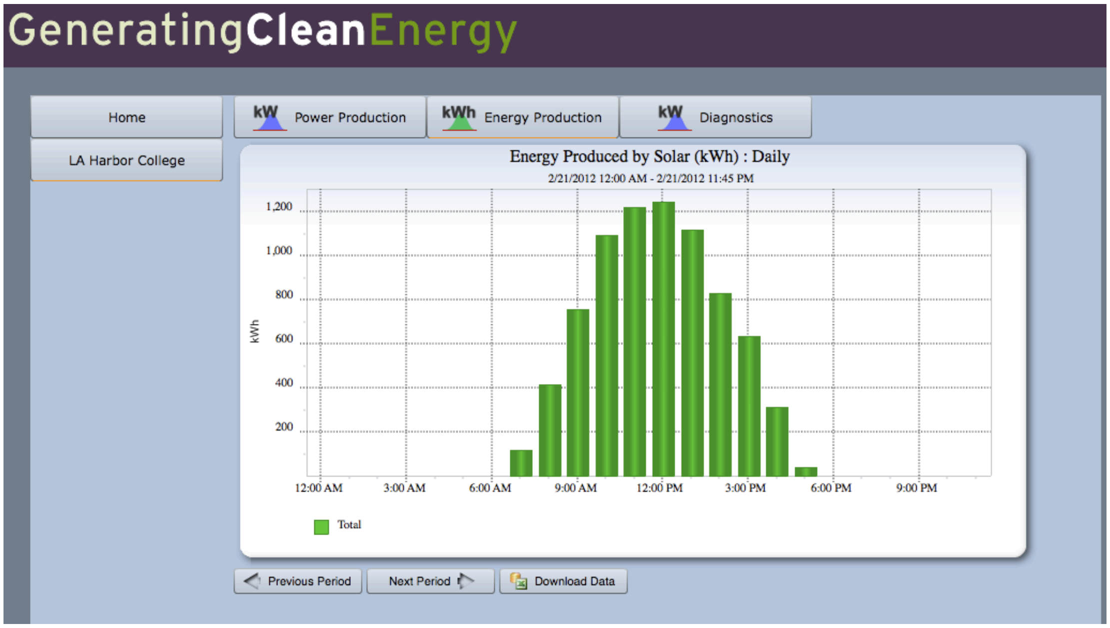


Figure 5.1 - Screenshot from Utility Vision website

System	Online	Size	Percentage of Aggregate Solar Generation	Ratio to Other Solar Generation System
Carport Lots 6 & 7 (Inverters 2 & 4)	8/1/10	1151 kW DC	0.544	1.19
Carport Lot 8 (Inverters 1 & 3)	7/15/11	964 kW DC	0.456	0.837

Table 5.1 -LAHC Solar PV systems that are measured by Utility Vision

Figure 5.2 - Lot 6 – Online August 2010 (Source: LACCD website)

Figure 5.3 - Lot 8 – Online July 2011 (Source:LACCD website)

Using raw data from Utility Vision, our group aggregated hourly energy generation (kWh) figures for every day of the year. Unfortunately, since LAHC's complete solar array has only been online from July 15, 2011, we did not have a complete generation profile for the entire year. Furthermore, we identified several data gaps, ranging from days of missing data to months of missing data. We addressed data gaps with the following assumptions and resolutions:

Data Gap	Date	Resolution / Assumption
Only Lot 6 & 7 Arrays (inverters 2 & 4) are online and producing generation data	4/15/11 – 7/16/11	Created generation data at inverters 1 & 3 (Lot 8) based on ratio of the power rating of Lots 6 & 7 array to Lot 8 array

No generation data	1/1/11 – 1/31/11	Applied generation data from January 2012 to January 2011
No generation data	2/1/11 – 4/14/11	Developed a linear regression from energy generation (kWh) data and solar insolation (W/m^2) data during time periods of full generation capacity. This regression had an R-squared value of 0.9522 and was consistent with operational specifications of the solar panels. We applied our regression equation to measured solar insolation data from 2/1/11 to 4/14/11 to produce a generation profile for that time period.
Inverter 3 down	10/19/11 – 10/24/11	Equated inverter 3 generation to inverter 1 generation
Inverters 1-4 down. (Generation system taken offline at LADWP request)	12/12/11 – 12/15/11	Applied insolation regression equation
Inverter 1 down	12/15/11-12/28/11	Equated inverter 1 generation to inverter 3 generation

Table 5.2 - Data gaps and resolutions/assumptions

A linear regression was used to create generation values in kWh from the recorded solar insolation data. Generation (kWh) is calculated from insolation with the following equation:

$$\text{Generation kWh} = \text{insolation } (W/m^2) * \text{area of panels } (m^2) * \text{rated efficiency} * \text{duration of exposure (h)}$$

During the mid-day hours of peak sunlight when insolation was greater than 50 W/m^2, the linear regression below was used:

$$\text{Generation (kWh)} = \text{insolation } (W/m^2) * 1.722$$

This equation gave an R-squared value of 0.9522 when we applied the regression to the four months of data for which we had both insolation and generation from all inverters. However, during the early and waning lit hours of low insolation, there was far more noise and scatter in the data set. This scatter led to a far less robust regression. At levels of insolation < 50 W/ m^2, the following regression gave an R-squared value of only .467.

$$\text{Generation (kWh)} = \text{insolation (W/m}^2\text{)} * 0.9798$$

This R-squared value indicates that our regression does not fit the majority of the low insolation data set. The regression during these hours was inaccurate due to several factors including: a lower angle of incidence, fog cover, and shorter duration of sunlight. For levels of insolation < 5 W/m^2, generation was set to zero.

After filling in the data gaps in LAHC's annual generation profile, the generation profile was scaled to project the anticipated generation when all of LAHC's planned solar arrays come online. The scaling factor for the generation profile was generated from the following table.

	Array	kW DC	kW AC	Annual Generation kWh
Currently Online and Measured	Carport Lot 8	964	743	1,039,709
	Carport Lots 6 & 7	1151	886	1,240,994
*Online but not measured on Utility Vision	West Parking Structure	250	192	268,422
	TOTAL SOLAR ONLINE	**2365**	**1821**	**2,549,125**
Planned	Health Services Building	89	68	95,726
	Library	51	39	54,978
	Science Complex Building	193	149	208,054
	Student Union Building	185	143	199,861

	Array	kW DC	kW AC	Annual Generation kWh
	TOTAL SOLAR INCLUDING PLANNED SYSTEMS	**2,882**	**2,220**	**3,107,744**

Table 5.3 -Current and planned solar arrays for LAHC, including projected annual generation

The ratio to total planned solar systems to the solar system currently online was 1.36. Thus, a scaling factor of 1.36 was used to project the future generation profile with all solar arrays online.

LAHC Electricity Demand

LAHC satisfies its electricity demand both with both purchased energy from LADWP and on-site solar PV generation. Data on purchased electricity is available in 15-minute intervals beginning on January 1, 2004 to the present. Energy data for LAHC was downloaded from LADWP's Energy Load Monitoring (ELM) website. Since the time period for the analysis spans January 1, 2004 00:00 to December 31, 2011 23:45, the raw data consisted of 280,512 15-minute intervals.

The data was processed using Matlab™ and was checked for missing values. If a data point was missing, it was assumed to be a linear interpolation between two neighboring points. Once the missing values were handled, the data was further checked to ensure all data points were sequential. Several three-hour periods in each year were found to repeat in the downloaded data. All repeating values were removed. The data was then checked again to ensure a continuous, sequential data series. The 280,512 15-minute data was then aggregated into 70,128 hourly energy bins to calculate the hourly energy purchased by LAHC. The aggregated hourly data were processed to into yearly matrices and then examined visually.

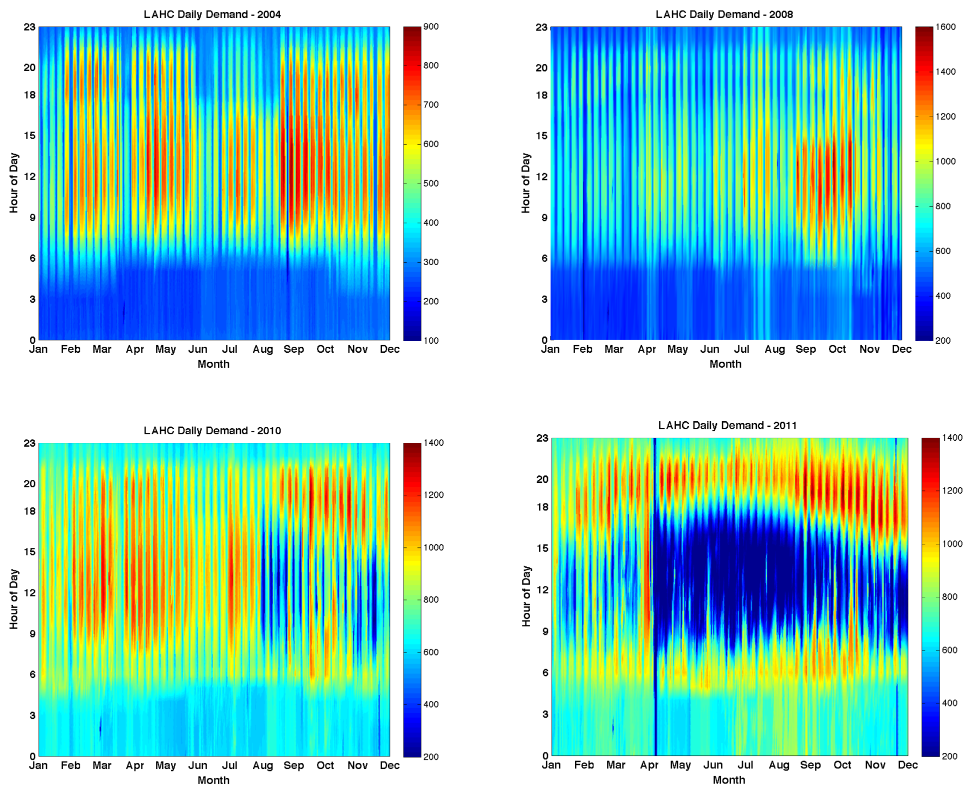


Figure 5.4 - LAHC's Temporal daily and hourly demand for 2004, 2008, 2010, & 2011 (in kWh)

As shown in the figures above, the energy LAHC purchased from LADWP has been steadily increasing since 2004 (see Appendix for full charts). A large spike occurred in the data in 2008. This spike coincided with construction activities that began at LAHC. The energy demand for LAHC decreased suddenly in August 2010. This corresponds to when the first solar array went on-line. A large decrease in energy demand continued into 2011, especially after April 2011 when the second solar array at LAHC went on-line.

Weekday and weekend temporal patterns are visible as oscillating peaks and valleys, indicating that further processing of the data into weekday and weekend panels is required. The aggregated values were used to calculate average hourly values for all years and months. The figures below illustrate the weekday and weekend demand profiles for 2011 (see Appendix for years 2004–2010)

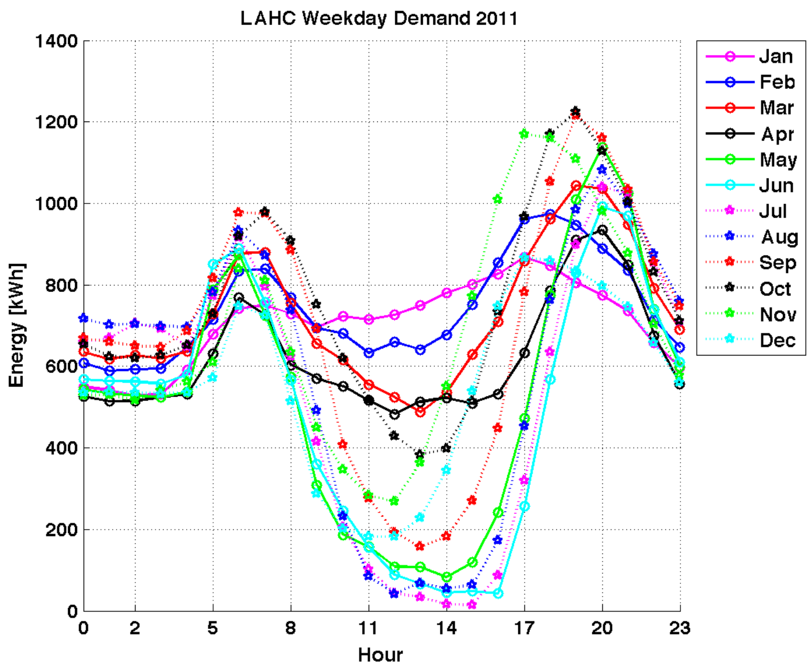


Figure 5.5 - Weekday average hour of day energy demand for 2011

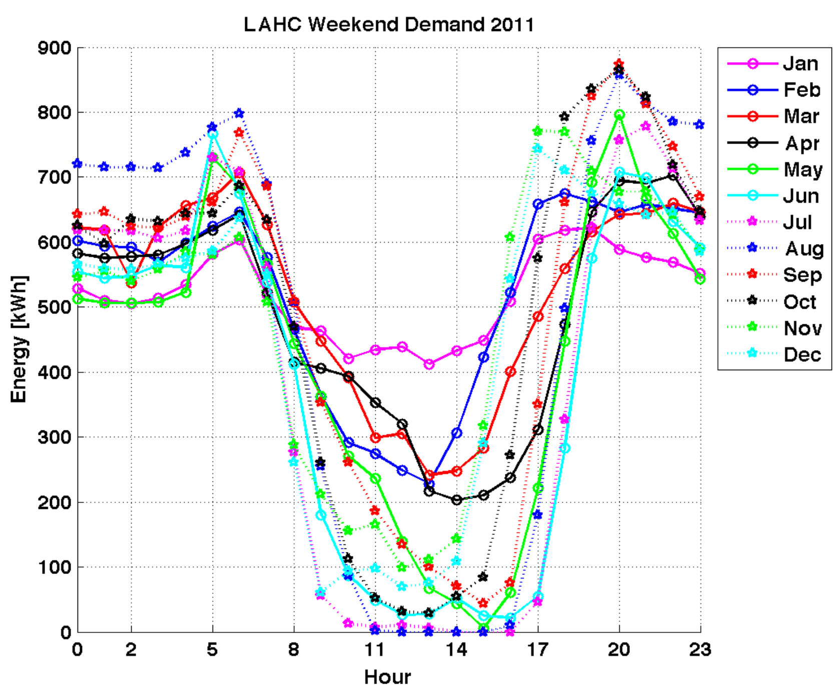


Figure 5.6 -Weekend average hour of day energy demand for 2011

The first pattern that emerges is that weekend energy demand is more erratic than weekday demand. The weekday maximum is approximately 40% higher than the weekend maximum. The solar array coming on-line significantly reduced the erratic energy demand on the weekend. Typically the highest demand occurs between June through August, and the lowest demand occurs from January through March. Prior to the solar array coming on-line, the largest demand was always near mid-day. Since the solar array coming online, the peak demand now occurs in the evening at approximately 8:00 PM.

Averaging each hour across all months reveals a continual increase in energy demand for both the weekday and weekends at LAHC (see Figures 5.7 and 5.8) impact on the first solar array coming on-line in August 2010 reduced the demand and shifted the peak towards 8:00 PM. The effect in 2011 is more pronounced than 2010 for two reasons. First, solar generated energy occurs throughout the entire year, and secondly, an additional solar array came on-line, reducing LAHC's demand even further.

There are three distinct energy demand periods. The first is 2004 – 2007. During this time, very little construction activity occurred on campus. The increase in energy demand is hypothesized to increase due to three factors: (1) building area; (2) student population; and (3) building efficiency. The second discernable energy demand period is 2008 – 2009. During this time, intense construction activities began on campus, and as a result, the energy demand increased significantly. The third and final demand period is 2010 – 2011. During this period, construction activities were still occurring, but the two solar arrays also came on-line.

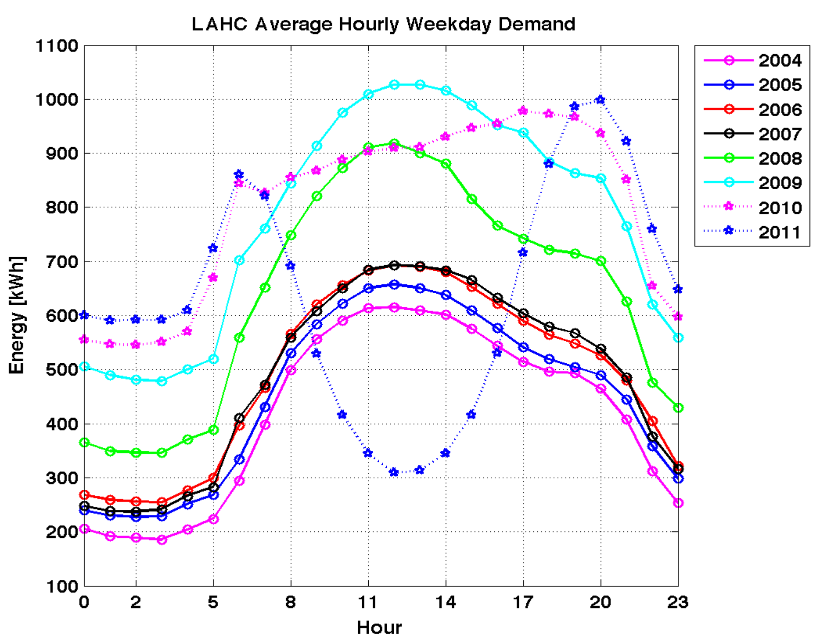


Figure 5.7 - Average hourly weekday energy demand for 2004 - 2011

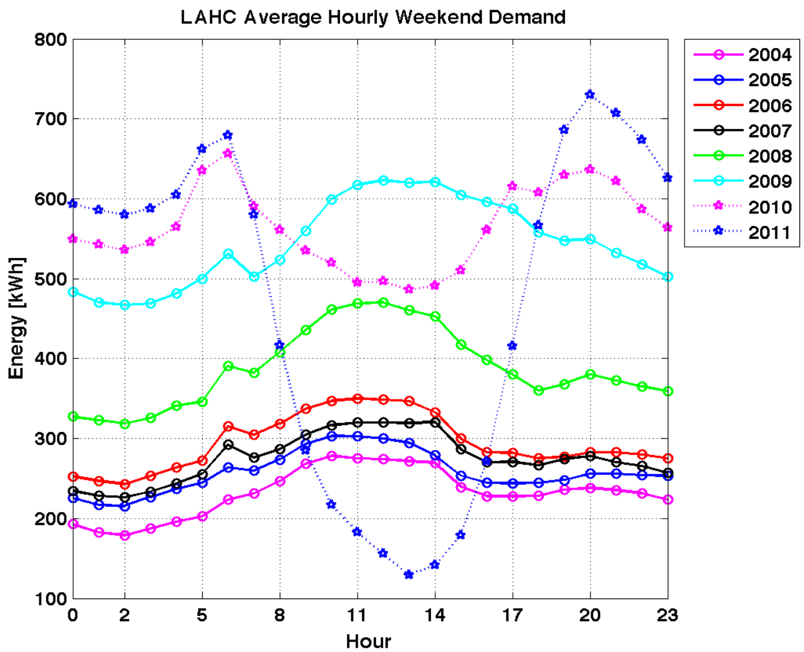


Figure 5.8 - Average hourly weekend hourly energy demand for 2004 - 2011

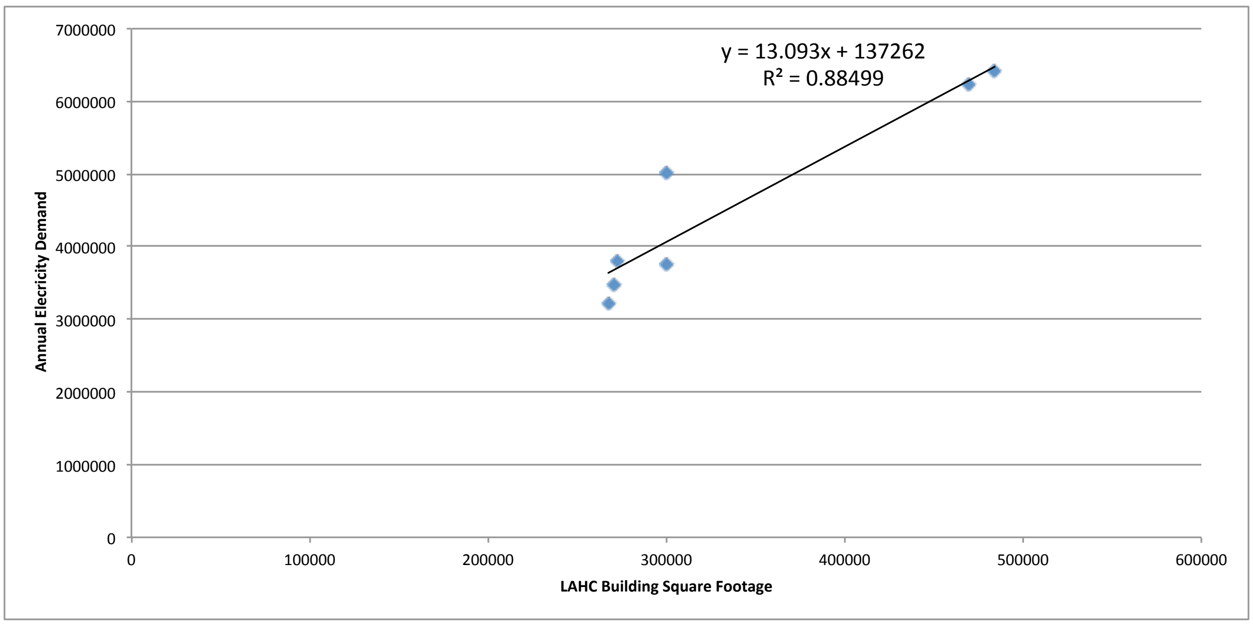
Electricity demand data for years prior to the solar PV array coming online are clear, as all of the electricity used came from the utility. However, electricity demand became uncertain once LAHC's solar PV came online in April 2011. The added generation altered the calculated electricity demand from the utility, LADWP. Since the amount of solar-generated electricity consumed by the campus (nor the excess electricity sent to the grid) is not tracked, it was necessary to estimate actual demand for 2011. In order to approximate 2011 demand, we performed linear regression analysis for the years 2004-2010 (for which we have good demand data obtained from LADWP's Energy Load Monitoring website) based on annual electricity consumption and building square footage. We regressed square footage on annual electricity demand since this provided a higher confidence level than using other variables, such as student population growth. Calculations showed that every 1 square foot added would increase electricity demand by about 13 kWh annually (see regression results below). The regression equation was then used to estimate 2011 annual electricity demand based on square footage.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1134466	3453354.948	-0.32851	0.759004	-1.1E+07	8453584
X Variable 1 (Square footage)	11.36317	5.121885869	2.218552	0.090758	-2.85746	25.58381
X Variable 2 (Student population)	210.2942	555.1293532	0.37882	0.724071	-1330.99	1751.58

Table 5.4 -Multiple regression analysis results (Square footage & student population to Electricity Demand)

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	137262.08	737143.0408	0.186208	0.859601	-1757624	2032149
X Variable (Square footage)	13.093215	2.110883544	6.202718	0.00159	7.667016	18.51941

Table 5.5 -Linear regression analysis results used (Square footage to Electricity Demand)



Using this regression equation, we scaled the preconstruction average hourly demand profile to predict current electricity demand at LAHC.

5.1.1.1 Future Electricity Demand

LAHC's future electricity demand is highly uncertain. New buildings that come online may be more energy efficient that others or the installation of demand response programs may decrease energy demands. Due to this uncertainty, we analyzed different future electricity demand scenarios to assess how this affects the final analysis of an optimal energy storage technology for LAHC. Therefore, we have included in RESET an input field for annual demand growth rate that the user can adjust according to their expected electricity demand.

5.2 Electricity Rate Derivation

In order to calculate potential electricity cost-savings, we first had to derive average electricity rates paid by LAHC during each of the following rate periods:

1) High season – High peak period
2) High season – Low peak period
3) High season – Base period
4) Low season – High peak period
5) Low season – Low peak period
6) Low season – Base period

To aid in accomplishing this, we obtained a "Billing Charges Report" that contained monthly billing charges and usage data for last year (1/13/2011 – 1/12/2012) from LADWP's Energy Load Monitoring (ELM) website. This report was chosen because it split the billing data into the various cost components (demand charges, energy charges, service fee, etc.), and also provided usage data for each rate period. Using this report in conjunction with LAHC's current rate schedule[6], we were then able to systematically allocate total monthly costs among the six rate periods.

First, months were aggregated into either ***high season*** (June–Sept.) or ***low season*** (Oct– May). Next, monthly energy charges per kWh in each rate period were directly calculated based on the energy usage that occurred in each period. Fixed and power demand charges were then allocated proportionately across each kWh in each rate period. For example, during low season months, 69% of all the energy consumed occurred during base period, 11% occurred during high peak period, and 20% occurred during low peak period. Therefore, fixed monthly charges – such as the service fee, facilities charge, and other charges based on KW demand – were allocated 69% to base kWhs, 11% to high peak kWhs, and 20% to low peak kWhs, during low season months. (During high season months, the allocation factors came out to: 82% base, 3% high peak, and 16% low peak.)

Once all costs were allocated, the resulting 2011 average electricity rates paid by LAHC for each rate period were:

---

[6] Note: Our derivation of the average rates for each rate period is based on current rate schedule A-3 (rates effective July 1, 2009), since this is the only rate schedule under which LAHC's billing information was available.

	High Peak		Low Peak		Base
High Season	$	0.94	$	0.21	$	0.11
Low Season	$	0.23	$	0.12	$	0.10

Table 5.6 - Average electricity rates for LAHC

5.3 Electricity rate growth projections

A critical component of analyzing financial savings in RESET was to incorporate the variable costs of electricity through time. Average retail electricity prices across the nation have been increasing significantly since the 1970s, with the average U.S. retail price increasing more than 85% over the past 25 years (EIA, 2009). In California, power prices rose sharply after an electricity crisis in 2001 and have been rising steadily since then.

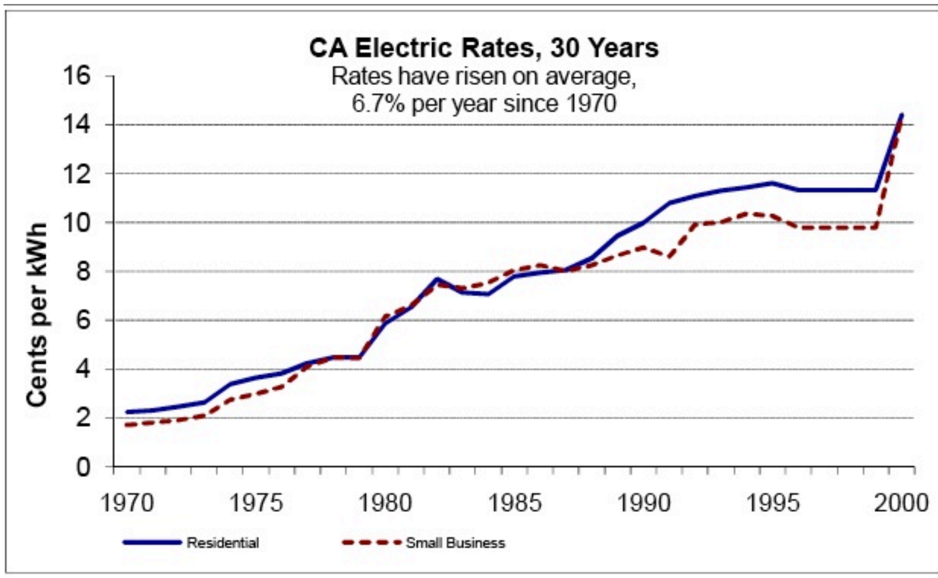


Figure 5.9 - California electricity rates 1970-2000 (Source: CPUC website, 2012)

Considering this upward trend, our financial analysis includes increasing projected costs of electricity. A report in 2007 by the California Energy Commission presented rate forecasts for the major utility providers in California (Marks, 2007). The report specified that rates for LADWP are expected to rise at a nominal rate of 2.8% annually. This projection was used in the base-case scenario in order to incorporate increasing electricity rates and thus more realistic financial savings into our model.

5.4 Selection of Energy Storage Technologies

The literature review of storage technologies in Section 6 served as guidance on what to include or not include for the purposes of our LAHC analysis.

Storage Technology	Power application	Energy application	Duration of discharge
Flooded lead-acid Batteries	Capable & Reasonable	Feasible	1-8 hours
Valve regulated lead-acid batteries	Capable & Reasonable	Feasible	1-8 hours
Vanadium Redox Batteries	Reasonable	Capable & Reasonable	1-8 hours
Zinc Bromine Batteries	Reasonable	Capable & Reasonable	1-8 hours
Nickel Cadmium Batteries	Capable & Reasonable	Reasonable	1-8 hours
Sodium Sulfur Batteries	Capable & Reasonable	Capable & Reasonable	7-10 hours
Li-ion batteries	Capable & Reasonable	Feasible	1-8 hours
Nickel Metal Hydride Batteries	Unsure	Unsure	Unsure
VRLA batteries with carbon-enhanced electrodes	Capable & Reasonable	Feasible	1-8 hours
Flywheels	Capable & Reasonable	Feasible	Mins - 1 hr
SMES	Capable & Reasonable	Not Capable	10 seconds
Capacitors	Capable & Reasonable	Not Capable	10 seconds
Pumped Hydropower	Not Capable	Capable & Reasonable	~12 hours
Compressed Air Storage	Not Capable	Capable & Reasonable	4-24 hours

Table 5.7 - Summary of application feasibility for energy storage technologies researched

The following criteria were applied to select the energy storage technologies:

- ***Duration and frequency of discharge:*** In order to serve LAHC's goal of time-shifting between peak generation and peak demand, storage systems had to be able to store energy for several hours. They also need to be able to charge and discharge frequently since LAHC will be looking to time-shift almost every day. Due to the fact that flywheels, SMES, and capacitors are only able to store energy for seconds to minutes, they were removed from our analysis.
- ***Function:*** Some storage technologies are better suited for energy management applications (such as decoupling the timing of generation and use) and some are better suited for power management applications (such as ensuring power quality). This project targets systems suited for energy management. Therefore, flywheels and capacitors are not suitable for functionality either, because they are better suited for power management applications. Also, thermal energy storage technologies were removed because they are not suitable for our intended application. Preliminary research on thermal storage revealed that, although possible, thermal storage is not an ideal candidate for pairing with solar PV, as it is better paired with solar thermal technologies or those with nighttime generation, such as wind.
- ***Maturity:*** While there are many promising battery technologies, several battery types have not yet reached demonstration level. Since they have not been proven on a commercial-scale, polysulfide bromide batteries, hydrogen bromine batteries, and Zebra batteries were not included.
- ***Practicality:*** Pumped hydro is the most established form of energy storage, but this is not practical for LAHC because special site requirements are needed. Compressed air storage is also not practical because of its special site requirements, so both of these were removed from our analysis. Hydrogen fuel cells were also removed for safety concerns.
- ***Availability of Information:*** We were unable to find any reliable cost information for Zebra batteries and Nickel-Metal Hydride batteries, so these technologies were not considered for LAHC.

6 Results

Results were derived from running multiple economic scenarios. Modified inputs fall under several unique economic scenario types to answer "what if" questions. For example: What would happen if annual electricity prices grew at 15% a year instead of 2.8%? By modifying the inputs, it is possible to determine how a scenario would affect the optimal capacity and NPV of an energy storage technology. Analyses were performed for the following scenario types:

- Base-case
- Pricing
- Technology
- Solar generation
- Demand growth rate
- Regulatory Policy

Each scenario is described below. The descriptions explicitly state assumptions and model inputs used. The results are also described and discussed.

For each scenario, the following were calculated:

- **Optimal capacity:** Determined optimal storage capacity for each technology that maximizes NPV under the scenario assumptions
- **Predetermined capacity:** Calculated NPVs for a predetermined storage capacity (e.g. 500 kWh) to compare technologies

6.1 Base-Case Scenario

The base-case scenario uses inputs that were gathered from actual LAHC data as well as conservative and/or realistic input estimates found in literature.

Assumptions

Under the base-case scenario for LAHC, the following inputs were used:

- LAHC's current estimated electricity demand profile, held constant over time (i.e. ***annual demand growth rate*** **= 0%**)
- LAHC's current solar PV generation profile – based on our analysis of 2011 insolation and generation data available from Chevron's UtilityVision® website;
- Current (2011) electricity prices paid during each rate period by LAHC, a ***2.8% annual electricity price growth rate*** (based on CPUC projections), and

no energy credits for excess electricity returned to the grid (as energy credits currently do not apply to LADWP customers with over 1MW of generation);

- Current energy storage cost estimates for each technology – calculated based on data available in the 2011 Sandia National Laboratory (SNL) Report entitled, "Energy storage systems cost update" (Schoenung, 2011);
- An assumed ***10% discount rate*** for present-value calculations, since this rate is also assumed by the 2011 SNL and other DOE reports (Schoenung, 2011); and
- No price for carbon dioxide emissions (***Carbon price = $0***).

Lastly, based on a temporal analysis of LAHC's demand and generation profiles, energy storage operating conditions were chosen to allow time-shifting of excess generation. Given that solar PV generation is greatest mid-day (10AM – 3PM, on average), and LAHC's current electricity demand from the grid is greatest on weekday evenings (5PM – 9PM), the following operating parameters were used for all scenarios:

- ***Duration of storage:*** 4 – 8 hours (so that the energy can be stored between mid-day to the evenings)
- ***Storage operating hours per day:*** 4 hours (the discharge time over which storage energy is utilized)
- ***Storage operating days****:* Weekdays only

Modifications

- Modified "weekdays only" operating assumption to view results of utilizing storage everyday.

Results

- **Base-case optimization:** Under the base-case assumptions described above, the resulting optimal storage capacity was 0 kWh. This result indicates that any investment in energy storage under those assumptions will have a 10-year net present value (NPV) that is negative. In other words, the 10-year present value costs of any of the storage technology options outweigh the projected 10-year present value electricity cost savings.
- **Base-case predetermined capacity:** Despite the negative NPV results, the various technologies were compared by assuming storage capacities of 250 kWh and 500 kWh. The resulting 10-year NPVs for each battery technology were as follows:

Technology	Base Case					
	Optimal Capacity	Optimal NPV	NPV, 250kWh	NPV including weekends, 250 kWh	NPV, 500kWh	NPV including weekends, 500 kWh
Flooded Cell Lead-Acid Batteries	0	$0	-$104,818	-$87,967	-$213,749	-$181,755
Valve Regulated Lead-Acid Batteries	0	$0	-$134,149	-$117,298	-$272,411	-$240,416
Nickel Cadmium Batteries	0	$0	-$448,426	-$429,973	-$900,965	-$865,767
Zinc Bromine Batteries	0	$0	-$188,086	-$169,633	-$380,285	-$345,087
Sodium Sulfur Batteries	0	$0	-$446,096	-$539,743	-$896,305	-$1,085,307
Lithium-ion Batteries	0	$0	-$579,604	-$673,251	-$1,163,320	-$1,352,322
Vandium Redox Batteries	0	$0	-$348,309	-$329,856	-$700,730	-$665,533

Table 6.1 -Comparison of 10-year NPVs of battery energy storage technologies. Note, parenthesis indicate negative values.

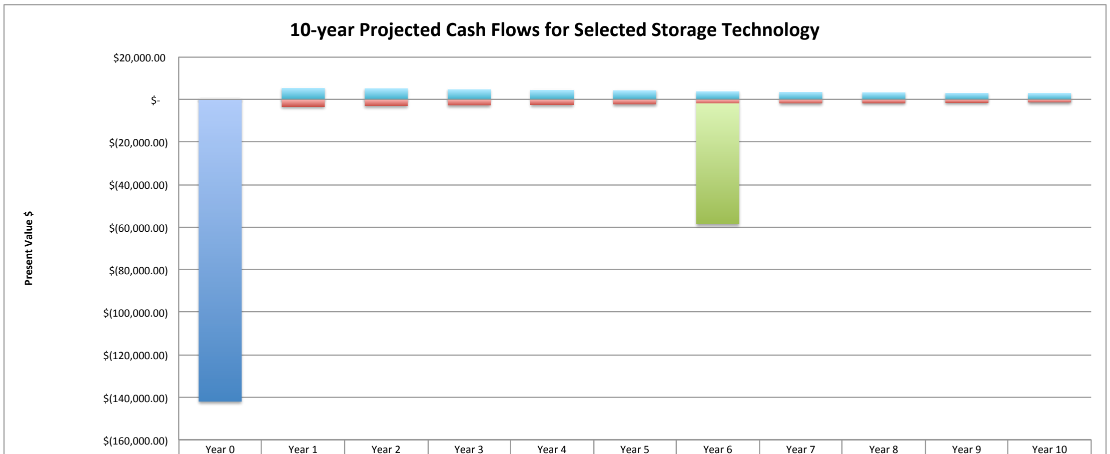
As shown in the table above, the most attractive (i.e. least negative) storage investment based solely on NPV is flooded cell lead-acid batteries, followed by valve regulated lead-acid batteries and zinc-bromine flow batteries. Since storage upfront capital costs increase with capacity, it is not surprising that the net-negative investments become even less attractive for all technologies as capacity is increased from 250 kWh to 500 kWh.

It is also shown that, for the selected capacities, operating the storage device on both weekday and weekend days would increase the NPV of the investment for most battery types (e.g., NPV becomes 4–15% less negative, depending on the technology), but not for all. Although electricity savings are greater when storage is also employed on the weekends, increasing the number of operating days also affects variable operating and maintenance (O&M) costs and expedites replacement costs. Therefore, the NPV actually decreases (i.e. becomes more negative) for sodium sulfur and lithium-ion battery technologies due to their relatively high variable O&M costs.

Discussion

In addition to NPV results for each technology considered, RESET also provides the user with more detailed information, such as the 10-year projected cash flows by year, for the most attractive storage investment.

Since flooded cell lead-acid batteries are the most attractive (least negative) storage investment under the base-case assumptions for LAHC, a predetermined capacity of 500 kWh was chosen to illustrate the potential economic costs and benefits of investing in a flooded cell lead-acid battery system, over a period of 10 years (see Figures below.) All base-case assumptions were held, except in this case weekend storage operation, was also included in order to reflect the total savings potential under this scenario.



	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
GHG savings w/ carbon price	$-	$-	$-	$-	$-	$-	$-	$-	$-	$-	$-
Electricity cost savings	$-	$5,320.11	$4,950.67	$4,606.89	$4,286.98	$3,989.29	$3,712.26	$3,454.48	$3,214.59	$2,991.37	$2,783.64
Replacement costs	$-	$-	$-	$-	$-	$-	$(56,447.39)	$-	$-	$-	$-
O&M costs	$-	$(3,364.77)	$(3,058.88)	$(2,780.80)	$(2,528.00)	$(2,298.19)	$(2,089.26)	$(1,899.33)	$(1,726.66)	$(1,569.69)	$(1,426.99)
Initial investment	$(141,875.00)	$-	$-	$-	$-	$-	$-	$-	$-	$-	$-

Figure 6.1 - Ten-year projected cash flows for an investment in a 500 kWh capacity flooded cell lead-acid battery storage system at Los Angeles Harbor College. Negative values represent a cash outlay, whereas positive values represent financial savings or benefits. All values are discounted to present value (discount rate = 10%).

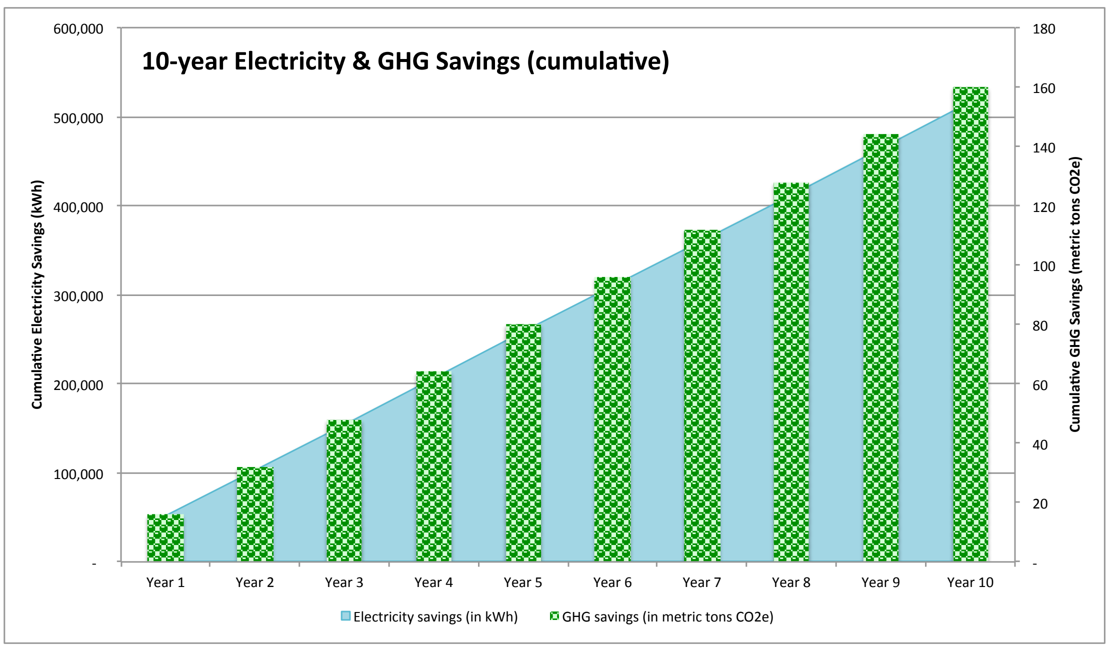


Figure 6.2 -Cumulative 10-year electricity savings (in KWh) and GHG savings (in metric tons CO2e)

RESET also generates comparative results among storage technologies. For example, Figures 6.1 and 6.2 indicate the total 10-year present-value lifetime costs and relative energy densitites plotted for each battery technology, respectively. Figure 6.3 shows the total expected 10-year lifetime costs for each battery technology, assuming each has a 500 kWh capacity. The relative energy densities of each technology are also displayed by the size of the bubbles, with larger bubbles corresponding to higher energy densities.

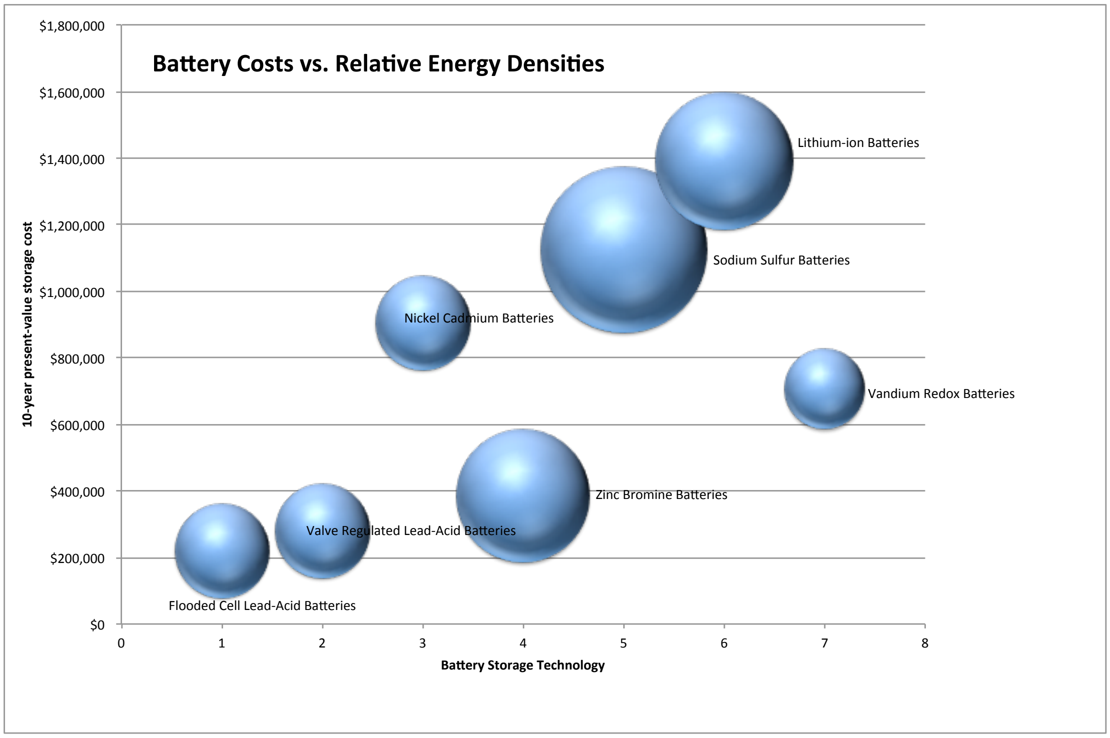


Figure 6.3 -Comparative analysis provided by RESET: Total 10-year present-value lifetime costs and relative energy densities are plotted for each battery technology. Larger bubbles correspond to higher energy densities.

6.2 Pricing Scenario

The pricing scenario analysis examined modified discount rates, electricity credits from the utilities, a price on carbon, and electricity rates.

Modifications and Assumptions

- **Discount rate**: The base-case includes a discount rate of 10%. In this price modification scenario, the discount rate was lowered to 2% to place greater emphasis on future benefits and costs. A high discount rate of 55% was also examined, as there is extensive literature on the use of high discount rates (>50%) for technology adoption, based on the argument that newly implemented technologies, such as energy-efficiency investments, are generally illiquid, financially risky, and have long payback periods (Anderson & Newell, 2004; Rivers & Jaccard, 2006; Sutherland, 1991). This argument also currently applies to investment in energy storage technologies. Lastly, a scenario eliminating discounting was conducted for contrast.

- **Electricity credits**: One way to incentivize renewable energy projects is to offer credits for any kilowatts a generator feeds back to the grid. However, LAHC does not qualify for these credits. Electricity credits were modified to show what would happen if LAHC did receive this financial incentive. To be realistic, we used typical electricity credit rates given by LADWP. Typical rates were 3 cents per kWh for both high and low peak hours and 1.6 cents during base hours.
- **Price on carbon**: Low and high projections for the price of carbon were run, as California will be placing a price on carbon emissions through the soon to be implemented cap-and-trade scheme under Assembly Bill 32 (AB 32), California's Global Warming Solutions Act of 2006. The prices used were \$15/ton and \$80/ton (Johnston et al., 2011).
- **Electricity rates:** A report by the California Energy Commission forecasted that the price of electricity for LADWP will grow annually at 2.8%. This report was written before the AB 32 Scoping Plan was released, which describes implementation measures for the bill. AB 32 will implement a cap-and-trade system to reduce greenhouse gas emissions (GHG) from stationary sources such as power plants and utilities. LADWP may pass on costs associated with cap-and-trade to consumers. With AB 32 and other uncertainties in electricity supply and demand, this analysis examined an extreme rate increase projection of 10%.
- **Electricity rates, price on carbon, electricity credits and discount rate**: A combination of the three aforementioned scenarios were used to examine the effects of multiple pricing changes. Low and high estimates for each variable, as detailed above, were analyzed. No electricity credits were input for the low estimate scenario.
- **Electricity rates, price on carbon, and discount rate:** Low and high estimates, as described above, for all of the variables were analyzed.
- **Electricity rates, price on carbon:** High and low estimates only for these variables (\$80 per ton on CO2e and 28% annual electricity rate growth) were analyzed.

Results (See the Appendix for tables depicting the results.)

- **Discount rate:** Lowering the discount rate to 2% yielded no positive NPVs for storage technologies. At a predetermined capacity of 500 kWh, NPV decreased by about \$45,000, but was still negative. Eliminating a discount rate altogether decreased the NPV even further, because even though future savings are worth more without discounting, future costs are higher as well. A discount rate of 55% yielded the least negative NPVs for the energy storage technologies.

- **Electricity credits:** Adding electricity credits made the NPV for all technologies less attractive. This shows that if LAHC were able to sell excess electricity to the grid, the case for investing in energy storage would be weakened.
- **Price on Carbon:** Adding a price on carbon emissions did increase the total savings that could be captured by using energy storage (due to avoided electricity from fossil fuels purchased from the grid).
- **Electricity Rates:** Modifying the base-case annual electricity price growth rate increase from 2.8 to 10% generated no positive NPVs.
- **Electricity rates, price on carbon, electricity credits and discount rate**: Low and high estimates both generated negative NPVs.
- **Electricity rates, price on carbon, and discount rate:** Low and high estimates both generated negative NPVs.
- **Electricity rates, price on carbon:** This generated no positive NPVs.

Discussion

Varying the inputs related to price at realistic low and realistic high estimates will not produce any positive NPVs.

6.3 Technology Scenarios

The technology scenario analysis examined the effects of modifying the storage technology parameters on NPV.

Modifications and Assumptions

- **Technology efficiencies:** The round-trip efficiencies of each storage technology were increased to view the impact on results.
- **Storage capital costs:** The capacity costs of the technologies were modified to reflect their 10 year projected values. The projected costs were compiled by Sandia National Laboratories from the results of a literature review and through discussions with technology experts and industry leaders (Hanley et al., 2008). Power conversion system costs are included in these projected figures.

The projected 10-year costs are based on 2008 cost estimates. However, current costs for some of these technologies have already reached the projected cost estimates as of 2011. Therefore, the 10-year percentage change reflected in Table 6.2 below were used to reduce storage technology costs in our analysis.

Technologies	2008 Costs ($/kWh)	10 year projected costs ($/kWh)	10 year % change
Flooded cell lead acid	150	150	0
Valve regulated lead acid (VRLA)	200	200	0
Nickel Cadmium	600	600	0
Zinc Bromine	30 kW/45 kWh=$500/kWh 2 MWh=$300/kWh	250	-37.5
Sodium Sulfur	450	350	-22.2
Lithium Ion	1300	150	-88.5
Vanadium Redox	20 kWh=$1,800/kWh; 100 kWh =$600/kWh	25 kWh=$1 ,200/kWh 100 kWh =$500/kWh	-16.7

Table 6.2 -2008 and 10-year projected costs for technologies (Source: Hanley et al., 2008)

- **Total costs of technologies (Energy related costs, power related costs, fixed and variable O&M costs and replacement costs):** The costs of storage technologies are projected to significantly decrease in the future because of increases in investment and in demand for energy storage technologies. The likely competitor for energy storage over the next decade, natural gas, is expected to experience an increase in price by 2020, thus leading to greater market opportunities for energy storage (Intrator et al., 2011). Scenarios of a 50% and 75% decrease from the current costs of these technologies were explored.
- **Total costs and efficiency:** The efficiency of storage technologies is projected to increase with developments in technology. The effect of combining an increase in efficiency with decrease in total costs was explored in this scenario. The total costs of technologies (energy related costs, power related costs, fixed and variable O&M costs and replacement costs) were each

decreased by 75% from a base-case scenario and the efficiency of all technologies was increased to 90%, and then 100%.

- **"Dream" technology scenario:** Additionally, we created a "dream" technology to determine the capital costs at which an investment decision in energy storage would be neutral. In other words, what should the capital costs of a storage device be in order for NPV to be $0 when storage is employed? Attributes for the dream technology were assumed to be the same as the best attributes achieved by existing technologies. For example, a round-trip efficiency of 95% was used, since this is the current estimated efficiency of flywheels, capacitors, and superconducting magnetic energy storage (SMES). O&M costs are the same as those for VRLA batteries, and lifetime is same as that of pumped hydro and compressed air storage (CAES). Break-even energy-related and power-related costs were found through an iterative process to be $100/kWh and $100/kW, respectively.

The following attributes were used for the dream technology:

Technology	Roundtrip Efficiency	Energy-related cost ($/kWh)	Power-related cost $/kW	Fixed O&M ($/kW-yr)	Variable O&M ($/kWh)	10-yr Replacement Costs ($/kWh)	Replacement Year	Environmental Impacts
"Dream" technology	0.95	**100**	**100**	5	0.01	0	30	Low

Table 6.3 -Dream technology attributes and costs

Results (See the Appendix for tables depicting the results.)

- **100% efficiency:** Increasing all technologies efficiencies to an ideal 100%, while holding costs at their current levels, resulted in negative NPVs for all technologies.
- **10 year projected costs**: Replacing current costs of the technologies with the 10-year projected costs still resulted in negative NPV's for all technologies.
- **Reducing the capital costs of all technologies by 50%:** This still resulted in a negative NPV for all technologies.
- **Reducing the capital costs of all technologies by 75%:** This resulted in a positive NPV for two technologies, flooded cell lead acid batteries and VRLA batteries at optimal capacities of 358 kWh and 115 kWh, respectively.
- **Capital costs and efficiency:** At 100% efficiency and 75% decrease in total costs lead acid, VRLA, and zinc bromine batteries were found to have positive NPV's at optimal capacities of 1299 kWh, 1078 kWh, and 115 kWh, respectively. These capacities and resulting NPV values were much higher than those obtained with a cost reduction alone, demonstrating that efficiency improvements and cost reductions have a strong combined effect. Also, zinc

bromine batteries became economically attractive, whereas they were not under a cost reduction only scenario.

- **"Dream" Technology**: The break-even energy-related and power-related capital costs of \$100/kWh and \$100/kW were found to create an NPV-neutral decision at a capacity of 419 kWh. Further, the optimal capacity for LAHC at those capital costs was 115 kWh, with a resulting NPV of \$1,914.

Discussion

Solely reducing the capacity cost of technologies over the next 10 years (assuming the projected costs reflected by Sandia National Laboratories) will not result in a positive NPV for the technologies. This could be potentially due to these 10-year projected costs still being high relative to the price of electricity. Also, along with capacity costs other parameters could potentially need to be changed in order to have a positive effect on NPV. Drastic reductions in costs are required to make even the least expensive technologies economically feasible. Increasing the efficiency of technologies has a significant (positive) effect on NPV. The NPV results obtained from solely decreasing the total costs of technologies by 75% were much lower than the results obtained from additionally increasing efficiency to 90% and 100%.

If a "dream" technology that combines the best attributes of existing technologies were to be developed, and the capital costs of this technology were approximately \$100/kWh and \$100/kW (a 50-75% reduction in the costs of flooded-cell lead acid batteries), then this would be economically attractive for LAHC. Unfortunately, the development of such a technology does not seem reasonable in the near future.

6.4 Solar Generation Scenario

The solar generation scenario examined the impact additional generating capacity would have the economic feasibility of energy storage for LAHC.

Modifications and Assumptions

- **Solar generation:** The existing solar generating capacity of LAHC is 2,115 kW and when all the proposed solar generating capacity comes on-line, the total generating capacity will be 2,882 kW. The existing solar generation data was scaled by a factor of 2882/2115 or 1.36. All other parameters/values were left the same as for the base-case scenario.

Results (See the Appendix for a table depicting the results.)

Increasing the solar generation by 36% did not have a positive impact on the NPV of the energy storage technologies examined for the optimal case. Examining non-optimal allocation of energy storage for LAHC resulted in all energy storage technologies having negative NPV; the least negative was flooded cell lead-acid batteries.

Discussion

Increasing the renewable energy generation at LAHC so that more energy is available for storage did not change the results from the base-case scenario; the optimal energy storage capacity is still zero. The best utilization of the solar generation on campus is to use it as it is generated with no storage given the current pricing structure.

6.5 Demand Growth Rate Scenario

The demand growth rate scenario analyzed the effects of reduced annual energy demand on LAHC campus. Energy demand could be reduced due to several factors including: decreased enrollment, budgetary cuts and improvements in efficiency.

Modifications and Assumptions

- **Energy demand:** All inputs from the base-case were maintained with the exception of the energy demand factor, which was set to negative two percent (-2%)

Results (See the Appendix for tables depicting the results.)

Setting energy demand to decrease by 2% annually yielded no optimal energy storage system (optimal capacity for all storage systems was calculated to be zero). At a capacity of 500 kWh, no storage systems became economically attractive investments.

Discussion

Adjusting the energy demand by 2% did not appreciably improve the NPV of any of the storage technologies.

6.6 Recommendations

Based solely on NPV results, we do not recommend storage for LAHC at this point in time. However, if considered under a total cost analysis (TCA) framework, then a storage investment may appear more attractive. For example, LAHC may benefit in numerous ways from an investment in energy storage, despite the negative NPV implications that our analysis concluded.

Potential non-market benefits of an energy storage system for LAHC include:

- Vocational training for students
- Reputation / model for others

- Environmental / Health
- Risk aversion

If funds become or are available for capital investments, LAHC could choose to purchase an energy storage system in order to reap both the projected operational savings and potential non-market benefits.

Additionally, significant economic benefits associated with demand peak shaving are not captured in RESET's costs savings calculations. Specifically, LAHC's electric billing rate structure includes a monthly billing demand charge per kW, which is determined by the single highest power demand at any point in the year. While our analysis includes potential financial savings from reduced energy consumption with energy storage, it does not account for reductions in the billing demand charge that may arise due to lower instantaneous peak consumption. If LAHC was able to lower their billing rate demand, this would provide significant monthly savings on their utility bill.

Financial savings from reducing peak power demand were not incorporated into our tool because on any given day, there is the possibility that a single anomalous peak power usage can set the billing demand rate for the subsequent year. Therefore, there is no guarantee that energy storage alone will reduce billing demand. However, if energy storage was implemented coupled with a demand-response management system (DRMS), then demand peaks could be better controlled. This in turn would reduce billing demand and consequently electric utility bills. A DRMS enables consumers of electricity to monitor real time energy consumption, allowing them to alter the timing, level of instantaneous demand, or total electricity consumption (Albadi & El-Saadany, 2007). For example, customers may want to modify behaviors to curtail energy usage from high usage appliances or HVAC systems as demand is peaking. Thus, regardless of whether or not that LAHC installs an electrical energy storage system, we recommend that LAHC should further investigate a DRMS to implement on their campus.

Lastly, we recommend that LAHC install a two-way meter at their interconnection with the LADWP grid. This meter would accurately record excess generation being fed back to the grid and provide valuable input data for evaluating energy storage solutions.

6.7 Limitations

The results and recommendations mentioned previously should not be considered outside of the following limitations of the model input data:

Generation and Demand Profile Limitations

The analysis in this report was conducted with the best generation and demand data available. However, there were many gaps in the data that needed to be addressed. The data sets suffered from a number of deficiencies, including the significant limitation that the generation profile was created from less than a single year of observed data. Therefore, the results of the analysis should be considered with the understanding that the generation data is not averaged over several years and could be skewed due to an annual anomaly.

Ideally, the generation profile input into the RESET tool would be an average of several years of data. One solution to the issue of data quality would be to conduct the same analysis in two years when there is three years of generation data to average.

Alternatively, generation data could be input from a simulation model that creates an annual generation profile. One of the more sophisticated models is TRNSYS (A Transient System Simulation Program) based at University of Wisconsin (Borenstien, 2008). The TRNSYS model uses the following inputs: average hourly meteorological data from NREL (including insolation, temperature, and cloud-cover), geographic coordinates, rated capacity, orientation and tilt angle of the solar array. From these inputs TRNSYS generates hourly generation profiles with significant day-to-day variation reflecting weather variation. TRNSYS was not used on the analysis presented here due to the expense of acquiring this modeling software.

LAHC's demand profile varied greatly over the past decade due to factors including major construction, efficiency improvements, on-site generation and changing enrollment. A post-construction demand profile would have been the optimal input into a RESET run and to yield the most accurate model results.

Cost Data Limitations

The energy storage cost data incorporated into this report was assembled from the most recent report available, the Sandia National Laboratories Energy Storage Systems Cost Update from April 2011. Despite these recent figures, costs of storage technologies are changing rapidly due to technological advancements, commodity prices, economies of scale, and government subsidies. Consequently, the replacement costs for energy storage technologies will likely have changed significantly by the time of replacement.

All subsequent analyses performed using RESET will require updates and adjustments to costs of energy storage technologies as the market continues to evolve.

PART III: CONCLUSION

A comprehensive literature review of mature and emerging energy storage technologies revealed that there are many feasible and reasonable energy storage options currently available.

However, for many technologies, more research and testing is needed before deployment of utility or large-user scale applications. For our case study, which analyzed systems suitable for peak shaving, we identified seven battery types as possible solutions to LAHC's problems: flooded lead-acid batteries, valve regulated lead-acid batteries, zinc-bromine batteries, vanadium redox batteries, lithium-ion batteries, nickel-cadmium batteries, and sodium-sulfur batteries.

Based on our analysis of the advantages and disadvantages of the energy storage technologies reviewed, we believe that flow batteries are ideal candidates to be analyzed further within a total cost analysis (TCA) framework. TCA attempts to capture cost items that are not covered by traditional cost accounting - such as hidden regulatory costs, liability costs, and image costs (Suh et al., 2005). In doing so, TCA encompasses the full range of environmental-related costs and savings associated with an investment (White et al., 1992; EPA, 1995; Suh et al., 2005). Though flooded lead-acid batteries and valve regulated lead-acid batteries are the least expensive, flow batteries have a number of benefits that are not fully captured in our analysis. They have low environmental impacts, can be sized independently for energy and power, and are able to be fully charged and discharged without damage to the battery. This will save costs because oversizing of the system is not needed. More research is needed to examine the life-cycle costs of these batteries, and more demonstration projects are needed to test real-world applications.

One of the main objectives for our case study was to evaluate the economic profitability of energy storage systems and determine the optimal energy storage system and capacity. The optimization function in RESET allowed us to accomplish this goal for our case study site and also run multiple scenarios under which storage may become more attractive. Using the base-case assumptions for LAHC, RESET calculated that no energy storage technology option had a present value lifetime savings that exceeded costs. In other words, investing in energy storage is not economically justified at any capacity. However, this is based on our estimates for direct costs associated with installing, operating, and replacing an energy storage system and the financial savings from decreased electricity usage from the grid. There are other benefits and/or ways to reduce costs that have not been included in this analysis. For example, bond money or grants could be use to offset capital costs. Since upfront capital costs make up the largest portion of total costs, finding government incentives could go a long way towards making energy storage systems more attractive.

Scenarios other than the base-case revealed that under certain economic conditions, energy storage could prove to benefit LAHC, with one or more technologies yielding a positive NPV. However, the parameters yielding positive NPVs were extreme (cost reductions of 75%, or increase in electricity price by 28%) and unlikely to occur in the near-term.

While our results apply specifically to the LAHC case study, our methodology and analysis tools are designed to be used by *any* electrical utility customer seeking to identify and optimally size an energy storage system to match their generation and demand profile.

In a broader context, we recommend that further research be performed to help quantify the potential benefits that we were unable to capture in RESET, due to a knowledge gap. Moreover, we still believe that energy storage will assist in the deployment of renewable energy technologies to reduce greenhouse gas emissions and provide greater energy security with an inexhaustible supply of energy resources for future generations. Therefore, further research should be conducted to help bring down the costs of energy storage technologies to enable increased worldwide adoption. For this to occur, there must be congruent policies that will further this critical research and development.

REFERENCES

A123 Systems (2011). A123 Systems to Supply 20MW of Advanced Energy Storage Solutions to AES Generation for Spinning Reserve Project in Chile. Retrieved November 26, 2011from http://ir.a123systems.com/releasedetail.cfm?ReleaseID=547986

APS (2007). American Physics Society. Challenges of electricity storage technologies - A report from the APS Public Affairs Committee. Retrieved January 5,2012 from http://www.aps.org/policy/reports/popa-reports/upload/Energy-2007-Report-ElectricityStorageReport.pdf

Anderson S. & R. Newell (2004). Information programs for technology adoption: the case of energy-efficiency audits. *Resource and Energy Economics* **26**, 27-50. (DOI: 10.1016/j.reseneeco.2003.07.001).

Albadi, M.H., El-Saadany, E.F. (2007). Demand Response in Electricity Markets: An Overview. *Power Engineering Society General Meeting, 2007, IEEE*, 1-5, 24-28 June 2007. doi:10.1109/PES.2007.385728

ASHRACE -American Society of Heating, Refrigeration, and Air Conditioning Engineers (2012). Thermal Ice Storage Systems. Retrieved February 20, 2012 from http://www.ashraebistate.org/sites/all/files/events/ice_storage_systems.pdf. Lasted updated February 19, 2012.

Arizona Solar Center (2012). Handbook of Secondary Storage Batteries and Charge Regulators in Photovoltaic Systems. Retrieved January 26, 2012 from http://www.azsolarcenter.org/images/docs/tech-science/papers/batteries/HandbookOfSecondaryStorageBatteries.pdf

Ballard. (2012). Distributed Generation Applications, Retrieved February 22, 2012 from http://www.ballard.com/fuel-cell-applications/distributed-generation.aspx

Baltimore Aircoil Company. (2012). Experience – Baltimore Aircoil Company. Retrieved February 20, 2012 from http://www.baltimoreaircoil.com/english/products/ice-thermal-storage/district-cooling/experience.

Baum, T., Grewal, G., & Heffernan, D. (2010). An investigation into energy storage technologies for the University of British Columbia's new student union building. UBC Social Ecological Economic Development Studies (SEEDS) Student Reports. Retrieved February 21, 2012 from https://circleprod.library.ubc.ca/bitstream/handle/2429/34065/APSC261_StorageAssessment_Group04_Clean.pdf?sequence=1

Beck, Brian. Telephone Interview. February 10, 2012.

Beckwith & Associates. 1983. Review of Environmental Studies and Issues on Compressed Air Energy Storage. Web. Retrieved February 2012. http://www.osti.gov/bridge/servlets/purl/6390927-1vsed0/6390927.pdf

Benitez, L., Benitez, P., & van Kooten, G. (2008). The economics of wind power with energy storage. *Energy Economics*, *30*, 1973-1989.

Berkeley Law / UCLA Law (2010). The Power of Energy Storage - How to increase deployment in California to decrease Greenhouse Gas Emissions. Presentation by Berkeley Law/ UCLA Law. Retrieved February 10, 2011 from http://www.law.berkeley.edu/files/Power_of_Energy_Storage_July_2010.pdf

Blume, S. W. (2007). System Overview, Terminology, and Basic Concepts, in Electric Power System Basics: For the Nonelectrical Professional. Hoboken, NJ: John Wiley & Sons, Inc. doi: 10.1002/9780470185810.ch1

Borenstien, S. (2008). *The Market Value and Cost of Solar Photovoltaic Electricity Production.* Berkeley: Center for the Study of Energy Markets.

British Petroleum (2011). Statistical Review of World Energy - Annual Energy Audit 2011. Retrieved January 11, 2012 from http://www.bp.com/sectionbodycopy.do?categoryId=7500&contentId=7068481

Bradbury Kyle (2010). Energy Storage Technology Review. Retrieved January 5, 2012 from
http://www.duke.edu/~kjb17/tutorials/Energy_Storage_Technologies.pdf

Brigham, E. and J. Houston. (2009). Fundamentals of Financial Management. Florence, KY: Cengage Learning, 752 pp., ISBN 9780324597714

Butler, P., Eidler P, Grimes P., Klassen S. & Miles R. (2004). *Handbook of Batteries.* New York: McGraw-Hill.

Cavallo, A. (2006). Controllable and affordable utility-scale electricity from intermittent wind resources and compressed air energy storage. *Energy*. 32(2), 120-127.

CEC/DOE Energy Storage Collaboration (2011). Zinc Bromine Battery (ZBB)

Energy Storage Demonstration: Project Overview. Retrieved January 26, 2012 from http://energystoragedemo.epri.com/cec/zbb/zbb.asp

CEC/DOE Energy Storage Collaboration (2011a). Zinc Bromine Battery (ZBB): Technology Description." Retrieved January 26, 2012 from http://energystoragedemo.epri.com/cec/zbb/tech_desc.asp

Chae, J.H., Ng, K.C., & Chen, G.Z. (2010). Nanostructured materials for the construction of asymmetrical supercapacitors. *Journal of Power and Energy,* 224, 479-503

Chen H., Cong T., Yang W., Tan C., Li Y. & Ding Y (2009). Progress in electrical energy storage system: A critical review. *Progress in Natural Science.* 19(2009): 291-312.

Clark, M.S. (2009). *Lead-Antimony, Lead-Calcium, Lead-Selenium, VRLA, NI-CD. What's in a Name?* Presentation Paper: Battcon Stationary Battery Conference – 2010. Retrieved from December 12, 2011 from http://www.battcon.com/PapersFinal2009/ClarkPaper2009FINAL_12.pdf

Deane J., Ó Gallachóir B. & McKeogh E. (2010) Techno-economic review of existing and new pumped hydro energy storage plant. *Renewable and Sustainable Energy Reviews* 14(4), 1293-1302.

Denholm, P. (2006). Improving the Technical, Environmental, and Social Performance of Wind Energy using Biomass-based energy storage. *Renewable Energy.* 31, 1355-1370

DOE (2002). U.S. Department of Energy. A National Vision of America's Transition to a Hydrogen Economy To 2030 and Beyond. Retrieved January 26 from http://www.hydrogen.energy.gov/pdfs/vision_doc.pdf

DOE (2012). Hydrogen an Fuel Cells Program Applications/Technology Validation. Retrieved February 22, 2012 from http://www.hydrogen.energy.gov/enduse.html

EA Technology (2004). Review of Electrical Energy Storage Technologies and Systems and of their Potential for the UK. Retrieved February 3, 2012 from http://www.wearemichigan.com/JobsAndEnergy/documents/file15185.pdf

EIA (2009). Annual Energy Outlook 2009 - Electricity. Retrieved May 11, 2011, from
http://www.eia.doe.gov/oiaf/aeo/

EPA (2011). eGRID2010 Version 1.1 Year 2007 GHG Annual Output Emission Rates. Retrieved February 21, 2012 from http://www.epa.gov/egrid

ESA (2010). Electricity Storage Association Zinc/Bromine (ZN/BR) Batteries. Retrieved February 3, 2012 from http://www.electricitystorage.org/technology/storage_technologies/batteries/zinc_bromine_batteries

EES (2011). Electric Energy Storage Pew center on Global Climate Change. Retrieved February 3, 2012 from http://www.pewclimate.org/docUploads/ElectricEnergyStorage_0.pdf

Energy 2020 model overview (n.d.). Systematic Solutions, Inc. Retrieved March 17 2012 from http://www.energy2020.com/ENERGY%202020%20Model%20Overview.htm

EPRI (2010). Electric Power Research Institute. Electricity Energy Storage Technology Options A White Paper Primer on Applications, Costs and Benefits. Retrieved February 2, 2012 from http://www.electricitystorage.org/images/uploads/static_content/technology/resources/ESA_TR_5_11_EPRIStorageReport_Rastler.pdf

EPRI-DOE. (2003). *EPRI-DOE Handbook of Energy Storage for Transmission & Distribution Applications* (No. 1001834). Washington, DC: EPRI and U.S. DOE.

EPRI-DOE. (2010). *Electricity Energy Storage Technology Options: A white paper primer on applications, costs, and benefits* (No. 1020676). Washington, DC: EPRI and U.S. DOE.

Electropaedia (2011). Lead Acid Batteries. *Electropaedia, Energy Sources and Energy Storage, Battery and Energy Encyclopaedia and History of Technology*. Retrieved February 3, 2012 from http://www.mpoweruk.com/leadacid.htm.

Electropaedia (2011). Lead Acid Batteries. *Electropaedia, Energy Sources and Energy Storage, Battery and Energy Encyclopaedia and History of Technology*. Retrieved February 3, 2012 from http://www.mpoweruk.com/flow.htm.

EV Battery Monitoring: Sponsored by Curtis Instruments. Section 1. Types of Lead-Acid Batteries." (2010). Retrieved November 26, 2011 from http://evbatterymonitoring.com/BatteryBook2/Types_of_Lead-Acid_Batteries.htm.

Evapco. (2012). Thermal Ice Storage. Retrieved February 20, 2012 from http://www.evapco.com/products/thermal_ice_storage.

Eyer J. & Corey, G. (2010). Energy Storage for the Electricity Grid: Beneifts and Market Potential Assessment Guide. A study for the DOE Energy Storage Systems Program. Washington DC: US DOE. Retrieved January 21, 2012 from http://www.sandia.gov/ess/publications/ESHB%201001834%20reduced%20size.pdf

FuelCell Energy. (2012). Products. Retrieved February 22, 2012 from http://www.fuelcellenergy.com/products.php

FERC (2012). Order Number 755. "Frequency Regulation Compensation in the Organized Wholesale Power Markets." Retrieved December 23, 2011 from http://www.ferc.gov/whats-new/comm-meet/2011/102011/E-28.pdf

Frost & Sullivan (2004). Lead acid batteries: the choices available. Retrieved April 11, 2001 from http://www.frost.com/prod/servlet/market-insight-top.pag?docid=10290755

Gardner, J., & Haynes,T. (2007). Overview of Compressed Air Energy Storage. *Boise State University, Office of energy Research, Policy, and Campus Sustainability*, Whitepaper ER-07-001. Retrieved February 21, 2012 from http://coen.boisestate.edu/windenergy/files/2011/10/ER-07-001.pdf

GE Energy (2009). MAPS regional databases for accurate market simulation. Retrieved February 19 2012 from http://site.geenergy.com/prod_serv/products/utility_software/en/downloads/10316_MAPSdatabase_2009-09-03.pdf

Gelman, R. (2010). *2009 Renewable Energy Data Book* (No. DOE/GO-102010-3074). U.S. Department of Energy. Retrieved from http://www.nrel.gov/analysis/

GL group (n.d.). Synergee Electric. Retrieved February 9 2012 from http://www.gl-group.com/en/powergeneration/SynerGEE_Electric.php

Halper, S. & Ellenbogen, J. (2006). Supercapacitors: A brief overview. MITRE Nanosystems Group. Retrieved January 5, 2012 from http://www.mitre.org/work/tech_papers/tech_papers_06/06_0667/06_0667.pdf

Hanley C., Ton D., Boyes J. & Peek, G. (2008). Solar Enegy Grid Integrations Systems. Sandia National Laboratories. Retrieved February 18 2012 from http://www1.eere.energy.gov/solar/pdfs/segis-es_concept_paper.pdf

Hasnain, S. (1998). Review on sustainable thermal energy storage technologies, Part II: cool thermal storage, *Energy Conversion and Management.* 39(11). Pages 1139-1153.

Henault, J., Sime, J. & Romano, F. (2008). Integrated Photovoltaics in Nickel Cadmium Battery Electric Vehicles. Connecticut Department of Transportation. Retrieved December 1, 2011 from http://www.ct.gov/dot/LIB/dot/documents/dresearch/CT-2223-F-08-8.pdf

History of Solar Power. Retrieved May 13, 2011, from http://www.historyofsolarpower.com/

Hoffman, M., Sadovsky, P., Kintner-Meyer, M & DeSteese J (2010). Analysis Tools for Sizing and Placement of Energy Storage in Grid Applications- A Literature Review. Pacific Northwest National Laboratory. Retrieved February 6 2012 from http://www.pnl.gov/main/publications/external/technical_reports/PNNL-19703.pdf

Ibrahim, H., & Ilinca, A., Perron,J. (2008). Energy storage systems - Characteristics and comparisons. *Renewable & Sustainable Energy Reviews*, *12*, 1221-1250.

ICF International (n.d). Integrated Planning Model. Retrieved February 15 2012 from http://www.icfi.com/insights/products-and-tools/ipm

Intrator et al (2011). 2020 Strategic Analysis of Energy Storage in California. Public Interest Energy Research (PIER) Project. California Energy Commission. Retrieved February 19 from http://www.energy.ca.gov/2011publications/CEC-500-2011-047/CEC-500-2011-047.pdf

Johnston, L., Hausman, E., Biewald, B., Wilson, R. & White, D. 2011 Carbon Dioxide Price Forecast. Synapse Energy Economics, Inc. 2011. Retrieved February 1, 2011 from http://www.synapse-energy.com/Downloads/SynapsePaper.2011-02.0.2011-Carbon-Paper.A0029.pdf

Joos, G., Chahwan, J., Gattrell, M. Transient Modeling and Simulation of Wind Turbine Generator and Storage. Retrieved From: http://www.vanadiumsite.com/vanadium-redox-battery-wind-turbine-generator-and-storage/

Kirby B. & Hirst E. (1996). Electric Power and Ancillary Services. Retrieved February 19 2012 from http://www.consultkirby.com/files/con426_Ancillary_Services.pdf

Kleijn, R. & van der Voet, E. (2010). Resource constraints in a hydrogen based economy based on renewable resources: an exploration. *Renewable and Sustainable Energy Reviews,* 14, 2784-2795.

Kopera John J.C (2005).Considerations for the Utilization of NiMH Battery Technology in Stationary Applications. Retrieved January 15 2012 from http://www.cobasys.com/pdf/tutorial/Considerations-for-NiMH-in-Stationary-Apps-battcon05paper.pdf

LACCD (n.d.). Los Angeles Community Colleges, Proposition A/AA. *LACCD Sustainable Building Program*. Retrieved Feb 16, 2012. From http://www.build-laccd.org/los_angeles_harbor_college.html

LACCD Builds Green. (n.d.). LACCB BUILDS GREEN // FACT SHEET // 2009. Retrieved February 22, 2012, from http://www.laccdbuildsgreen.org/factsheetHTML/laccd_factsheet_2010.html

LaCommare K. & Eto J., Understanding the Cost of Power Interruptions to U.S. Electricity Con
sumers (LBNL-55718). Berkeley: LBNL. Retrieved from: http://repositories.cdlib.org/lbnl/LBNL-55718.

LADWP (2009). LADWP Electric Rate Schedule A-3, Rate A (Effective July 1, 2009). Retrieved from http://www.ladwp.com/ladwp/cms/ladwp001753.jsp

LADWP (2009a). LADWP Electric Rate Schedule CG-3, Rate A (Effective July 1, 2009). Retrieved from http://www.ladwp.com/ladwp/cms/ladwp001756.jsp

LADWP (2008). LADWP Website, Electric rates, General provisions (Effective Sept. 1, 2008). Retrieved from http://www.ladwp.com/ladwp/cms/ladwp002256.jsp

LADWP (2011). LADWP Website, “Water and Power Today.” Retrieved from http://www.ladwp.com/ladwp/cms/ladwp001557.jsp

LADWP (2011). LADWP’s 2011 Power Integrated Resource Plan (December 22, 2011). Retrieved From: http://www.ladwp.com/ladwp/cms/ladwp015019.pdf

LADWP (Los Angeles Department of Water and Power) ELM (Energy Load Monitoring). (2012). Los Angeles Harbor College Energy Demand January 1, 2004 – December 31, 2011. Retrieved January 12, 2012 from https://elm.ladwp.com/itron/

Lake Balboa Neighborhood. (2010). Lake Balboa Council Board Meeting. [Meeting Minutes]. Retrieved from http://lakebalboanc.org/wp-content/uploads/docs/Minutes_2010-04-07.pdf

LaMonica, M. (2010). Giant battery smoothes out variable wind power | Green Tech - CNET News. Retrieved December 5, 2011, from http://news.cnet.com/8301-11128_3-20012597-54.html

LBNL (2011). Hydrogen-Bromine flow battery for grid-scale energy storage. Larwence Berkeley National Lab. Retrieved November 11, 2011 from http://ei.haas.berkeley.edu/c2m/Flow_Battery_Abstract.pdf

Leonardo Energy (2007). Flow Batteries Briefing Paper. Retrieved from: http://www.leonardo-energy.org/webfm_send/164

Li, L., Kim, S., Wang, W., Vijayakumar, M., Nie, Z., Baowei Chen, B., Zhang, J., Xia, G., Hu, J.,Graff, G., Liu, J., Yang, Z. (2011). A Stable Vanadium Redox-Flow Battery with High Energy Density for Large-Scale Energy Storage. *Advanced Energy Materials.* 1(3): 394-400.

Lipman T., E Timothy, Ramos R. & Kammen, D. (2005). An assessment of Battery and Hydrogen Energy Storage Systems integrated with Wind Energy Resources in California. Berkeley: University of California Berkeley Press.

Lipman, T., Kammen, D., Ogden J., and Sperling, D. (2004), *An Integrated Hydrogen Vision for California,* prepared for the Kirsch Foundation, Renewable and Appropriate Energy Laboratory, UC Berkeley.

Long, J. (2009). Opportunities for Electrochemical Capacitors as Energy-Storage Solutions in Present and Future Navy and Marine Corps Missions. Retrieved January 5, 2012, from http://www.dtic.mil/cgibin/GetTRDoc?AD=ADA514457&Location=U2&doc=GetTRDoc.pdf

Makai Ocean Engineering. (2012). Cold Seawater Air Conditioning. Retrieved February 19, 2012 from: http://www.makai.com/p-swac.htm.

Makarov YV, Kintner-Meyer, M., Du, P, Jin, C., and Illian, H. (2010). Sizing Energy Storage to Accommodate High Penetration of Variable Energy Resources (PNNL-SA-75846). Richland, WA: Pacific Northwest National Laboratory.

Makarov, Y., Yang, B, DeSteese, J., Lu, S., Miller, C., Nyeng, P., Ma, J., Hammerstrom, D. & Vishwanathan, V. (2008). Wide-Area Energy Storage and Management System to Balance Intermittent Resources in the Bonneville. Retrieved January 5, 2012, from http://www.pnl.gov/main/publications/external/technical_reports/PNNL-17574.pdf

Marks, M. (2007). Staff Forecast of Average Retail Electricity Prices: 2005 to 2018.

California Energy Commission. July 2007. (CEC-200-2007-013-SD)

Masiello, R., Vu, K., Deng, L., Abrams, A., Corfee, K., Harrison, J., Hawkins, D. & Yagnik, K. (2010). Research evaluation of wind generation, solar generation, and storage impact on the California grid. Public Interest Energy Research Program and KEMA. California Energy Commission. Retrieved February 20 2012 from http://www.energy.ca.gov/2010publications/CEC-500-2010-010/CEC-500-2010-010.PDF

Meeker, N. & Walker, B. (2010). Flywheel Technology for Energy Storage. Retrieved February 9, 2011 from http://www.nicholasmeeker.com/files/flywheel_report.pdf

Milborrow D. & Harrison, L. (2003), Hydrogen Myths and Renewables Reality. *Windpower Monthly*, May: 47–53

Mosher, T. 2010. "Economic Valuation of Energy Storage Coupled with Photovoltaics: Current Technologies and Future Projections." MIT. Retrieved from: http://dspace.mit.edu/bitstream/handle/1721.1/59563/668235913.pdf?sequence=1.

NGK Insolators, Inc. NGK Responds to News Reports Today. Retrieved March 15, 2011 from http://www.ngk.co.jp/english/news/2011/1025.html

NREL (2003). National Renewable Energy Laboratory. Advanced Energy Storage U.S. Climate Change Technology Program. Technology Options: For the Near and Long Term. Retrieved February 7, 2012 from http://www.nrel.gov/analysis/power_databook_3ed/docs/pdf/db_chapter02_adv_storage.pdf

NREL-EnergyPlus, (n.d). Fact sheet on Energy Plus. Retrieved February 14, 2012 from http://apps1.eere.energy.gov/buildings/energyplus/pdfs/energyplus_fs.pdf

NREL-HOMER (2004). HOMER Brochure. Retreived February 15 20120 from https://analysis.nrel.gov/homer/includes/downloads/HOMERBrochure_English.pdf

NREL-HOMER (n.d). Retrieved February 18 2012, from https://analysis.nrel.gov/homer/

NREL-ReEDS (n.d). Retrieved February 18 ,2012 from http://www.nrel.gov/analysis/reeds/qualitative.html

NREL (2011). NREL: Learning - Batteries. Retrieved from: http://www.nrel.gov/learning/eds_batteries.html.

NREL (2003). Advanced Energy Storage - Technology Options: For the Near and Long Term. Retrieved February 7, 2012 from http://www.nrel.gov/analysis/power_databook_3ed/docs/pdf/db_chapter02_adv_storage.pdf

NREL(2009a). Energy Storage-National Renewable Energy Laboratory: Battery Types-Nickel Metal Hydride. Retrieved January 9, 2012 from http://www.nrel.gov/vehiclesandfuels/energystorage/battery_types.html

NREL (2009b). Ultracapacitors - National Renewable Energy Laboratory. Retrieved January 17 from http://www.nrel.gov/vehiclesandfuels/energystorage/ultracapacitors.html

Pacific Gas & Electric (PG&E). (1997). Thermal Energy Storage Strategies for Commercial HVAC Systems. Retrieved February 19, 2012 from http://www.pge.com/includes/docs/pdfs/about/edusafety/training/pec/inforesource/thrmstor.pdf

Papaefthymiou, S., Karamanou, E., Papathanassiou, S. & Papadopulos, M. (2010). Pumped Storage Station Leading to High RES Penetration in the Autonomous Island System of Ikaria. *IEEE Transactions on Sustainable Energy*. 1(3), 163-172.

Pew Center on Global Climate Change (2011). Electric Energy Storage. Retrieved February 3, 2012 from http://www.pewclimate.org/docUploads/ElectricEnergyStorage_0.pdf

Polk C, Boom R.W, Eyssa Y.M (1992). Superconducting Magnetic Energy Storage (SMES) External Fields and Safety considerations. IEEE Transactions on Magnetics Vol. 28

PNNL (n.d). GridLab –D, The smart grid simulator. Retrieved February 17 2012 from http://www.gridlabd.org/brochures/20090902_gridlabd_brochure.pdf

PNRL (2011). Planar ZEBRA Battery for Renewable Integration and Grid Applications. Presentation retrieved from: http://energyenvironment.pnnl.gov/presentations/pdf/Planar%20Zebra.pdf

PowerWorld Corporation (n.d). PowerWorld Simulator. Retrieved February 10 2012 from http://www.powerworld.com/products/simulator.asp

Raugei, M. (2009). Life cycle impacts and costs of photovoltaic systems: Current state of the art and future outlooks. Energy. 34(3), 392-399.

Recovery Act Smart Grid Programs. SmartGrid.gov: Southern California Edison

Company (Tehachapi Wind Energy Storage Project). Retrieved February 20, 2012 from http://www.smartgrid.gov/project/southern_california_edison_company_tehachapi_wind_energy_storage_project

REEP (n.d). Renewable Energy and Energy Efficiency partnership. The RetScreen Tool. Retrieved February 15 2012 from http://www.reeep.org/132/retscreen.htm

Rivers N., and M. Jaccard (2006). Useful models for simulating policies to induce technological change. Energy Policy 34, 2038-2047. (DOI: 10.1016/j.enpol.2005.02.003).

Rydh, C. (1999). Environmental assessment of vanadium redox and lead-acid batteries for stationary energy storage. *Journal of Power Sources*. 80(1-2):21-29.

Schaber C., Mazza P. &Hammerschlar R. (2004). Utility-Scale Storage of Renewable Energy. *The Electricity Journal.* 17(6):21-29.

Schoenung, S. (2001). Characteristics and Technologies for Long-vs. Short-Term Energy Storage.A Study by the DOE Energy Storage Systems Program. Sandia National Laboratories. Retrieved January 5, 2012 from http://prod.sandia.gov/techlib/access-control.cgi/2001/010765.pdf

Schoenung, S. (2011). Energy Storage Systems Cost Update: A Study for the DOE Energy Storage Systems Program. Sandia National Laboratories. Retrieved February 20, 2012 from http://prod.sandia.gov/techlib/access-control.cgi/2011/112730.pdf

Schoenung, S. & Hassenzahl W. (2007). Long vs Short Term Energy Storage: Sensitivity Analysis. A Study for the DOE Energy Storage Systems Program. Retrieved February 2, 2012 from http://www.industrializedcyclist.com/Energy_storage_sandia.pdf

Sioshansi, R., Denholm, P. & Jenkin, T. (2012). Market and Policy Barriers to Deployment of Energy Storage. Forthcoming in *Economics of Energy and Environmental Policy*. Retrieved from http://www.ise.osu.edu/ISEFaculty/sioshansi/papers/mkt_policy_barriers.pdf

Stefula, D. (2007). NASA Collaboration Benefits International Priorities of Energy Management. Researcher News. NASA: Langley Research Center. Retrieved February 20, 2012 from http://www.nasa.gov/centers/langley/news/researchernews/rn_RETscreen.html
Sullivan, J., & Gaines, L. (2010) A Review of Battery Life-Cycle Analysis: State of Knowledge and Critical Needs. Argonne National Laboratory. ANL/ESD/10-7.
Supercapacitors-NREL (2009). National Renewable Energy Laboratory. Retrieved

January 5, 2012, from http://www.nrel.gov/learning/eds_supercapacitors.html

Sutherland R.J. (1991). Market barriers to energy-efficiency investments. *Energy Journal* 12, 15-34.

System Optimizer (n.d). Ventyx product overview-System Optimizer. Retrieved February 16 2012 from http://www.ventyx.com/~/media/Files/Brochures/System-Optimizer-datasheet.ashx?download=1

Systematic Solutions Inc (n.d). Energy 2020 documentation. Professional History and Bibliography. Systematic Solutions Inc. Retrieved February 20 2012 from http://www.arb.ca.gov/cc/scopingplan/economics-sp/models/V6_Professional_History.pdf

Tahil, W. The Trouble with Lithium: Implications of Future PHEV Production for Lithium Demand. New York: Meridian International Research. 2006.

Ton, D., Peek, G.H., Hanley, C., & Boyes, J. (2008). Solar Energy Grid Integration Systems Energy Storage (SEGIS-ES). Retrieved January 9, 2012 from http://www1.eere.energy.gov/solar/pdfs/segis-es_concept_paper.pdf

Trane. (2012). Shift Technologies – Trane Shift & Save. Retrieved February 19, 2012 from: http://www.trane.com/commercial/shiftsave/trane/tech/index.html

Trickett, D. (1998). Current Status of Health and Safety Issues of Sodium/Metal Chloride (Zebra) Batteries. National Renewable Energy Laboratory. NREL/TP-460-25553. http://www.nrel.gov/docs/fy99osti/25553.pdf

Union of Concerned Scientists (2007). Findings of the IPCC fourth assessment report: Climate change mitigation. Retrieved February 17 2012 from http://www.ucsusa.org/global_warming/science_and_impacts/science/findings-of-the-ipcc-fourth-1.html#8

US DOE (2002). A National Vision of America's Transition to a Hydrogen Economy - To 2030 and Beyond. Washington DC: United States Department of Energy. Retrieved January 26 from http://www.hydrogen.energy.gov/pdfs/vision_doc.pdf

US DOE (2010). Wind and Water Power Program: How Wind Turbines Work. Retrieved May 13, 2011, from http://www1.eere.energy.gov/windandhydro/wind_how.html

US DOE (2011). Fuel Cell Technologies Program. Hydrogen Storage Technologies. Retrieved February 2 from http://www1.eere.energy.gov/hydrogenandfuelcells/storage/storage_challenges.html

Ventyx (n.d). Company Overview. Retrieved February 14 2012 from http://www.ventyx.com/en/company/

Wagner, L. (2007). Overview of Energy Storage Methods - Mora Associates. Retrieved January 5 2012 from http://www.moraassociates.com/publications/0712%20Energy%20storage.pdf

Walawalkar R. & Apt J. (2008). Market analysis of Emerging Electric Energy Storage. Retrieved January 2012 from http://www.netl.doe.gov/energy-analyses/pubs/Final%20Report-Market%20Analysis%20of%20Emerging%20Electric%20Energy%20Sto.pdf

Walmet, P. (2009). Evaluation of Lead/Carbon devices for Utility Applications. A Study for the DOE Energy Storage Program. Sandia National Laboratories. Retrieved January 20 2012 from http://prod.sandia.gov/techlib/access-control.cgi/2009/095537.pdf

WAPA (n.d). Western Area Power Association Presentation Retrieved February 19 2012 from www.wapa.gov/rm/LMP%20Overview%20v%2010-30-02.ppt

Yang, C-J., & Jackson, R.B. (2011). Opportunities and Barriers to Pumped-hydro Storage in the United States. *Renewable and Sustainable Energy Reviews*, 15(1), 839-844.

Yang, Z., Zhang, J., Kintner-Meyer, M., Lu, X., Choi, D., Lemmon, J., Liu, J. (2010). Electrochemical Energy Storage for Green Grid. Chemical Reviews: Pacific Northwest National Laboratory. Retrieved February 2012 from http://energyenvironment.pnnl.gov/ei/pdf/Chemical%20Reviews.pdf

ZBB Energy Corporation (2011). Advanced Energy Storage. Retrieved from: http://www.zbbenergy.com/products/flow-battery/

ZBB Energy Corporation (2011). A 400 kWh Advanced Battery Energy Storage System (ABESS) for Utility Applications. Retrieved from: http://www.sandia.gov/ess/docs/pr_conferences/2001/MikeHughes.pdf

APPENDICES

Additional charts

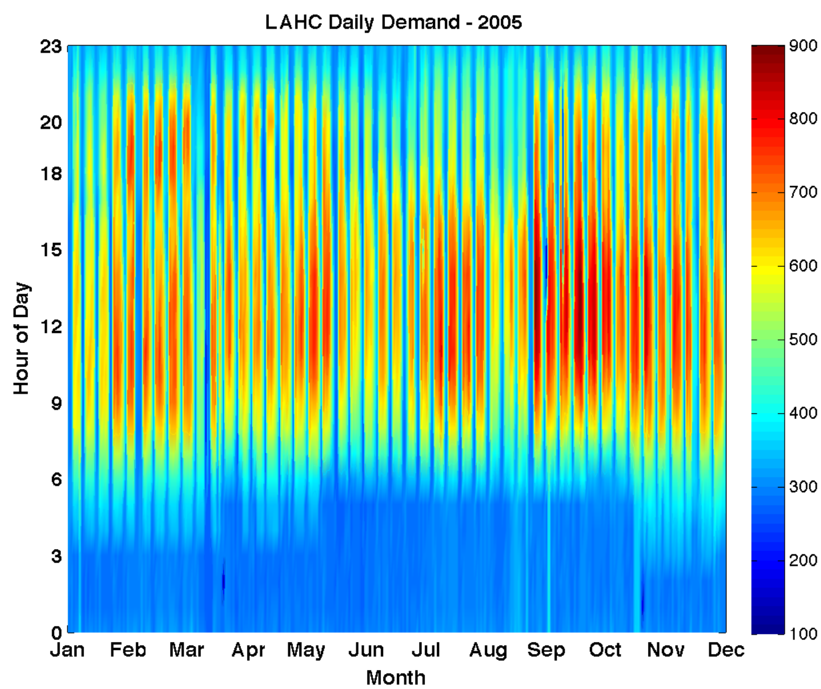


Figure A-0.1: Temporal daily and hourly demand for LAHC for 2005 in kWh

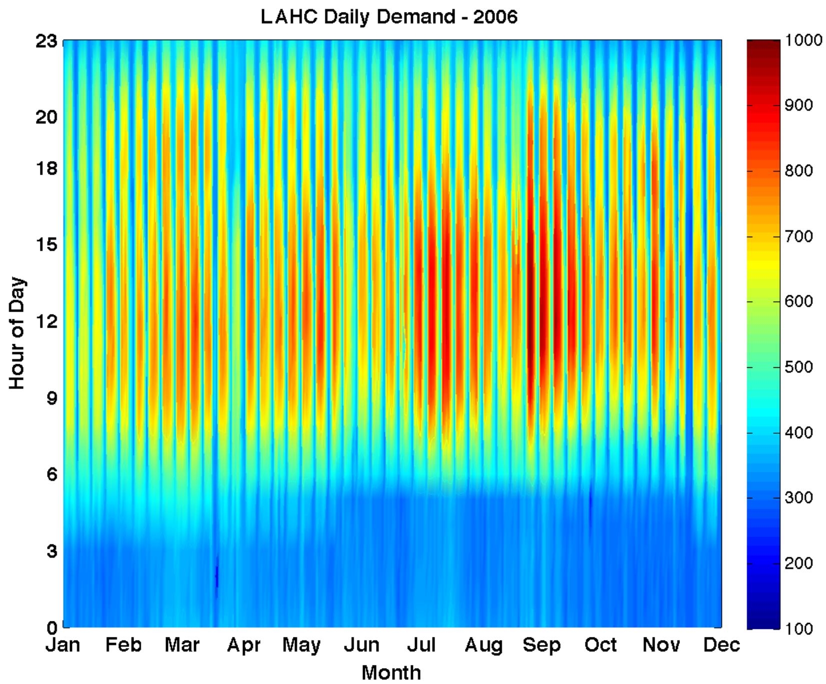


Figure A-0.2: Temporal daily and hourly demand for LAHC for 2006 in kWh

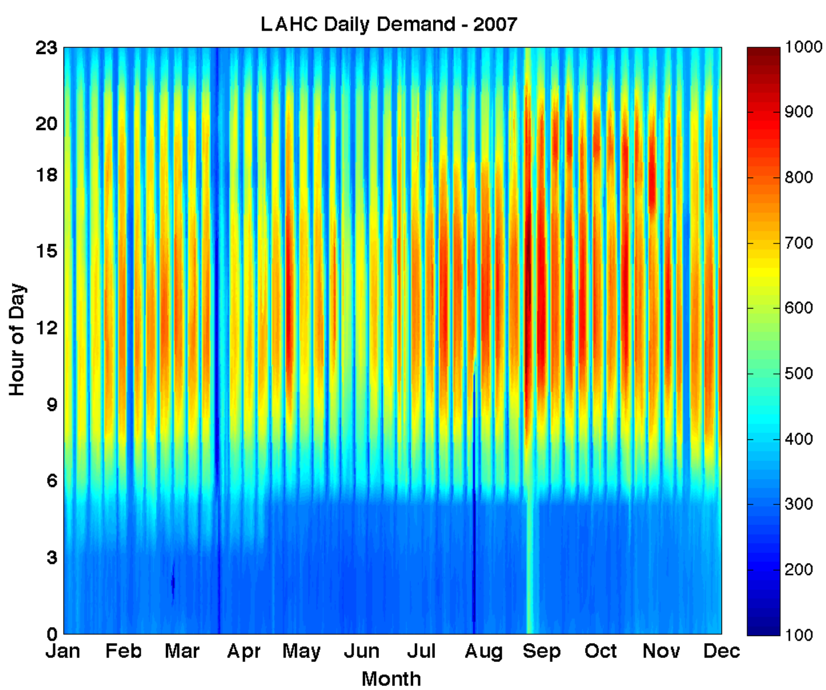


Figure 0.3Figure A-0.4: Temporal daily and hourly demand for LAHC for 2007 in kWh

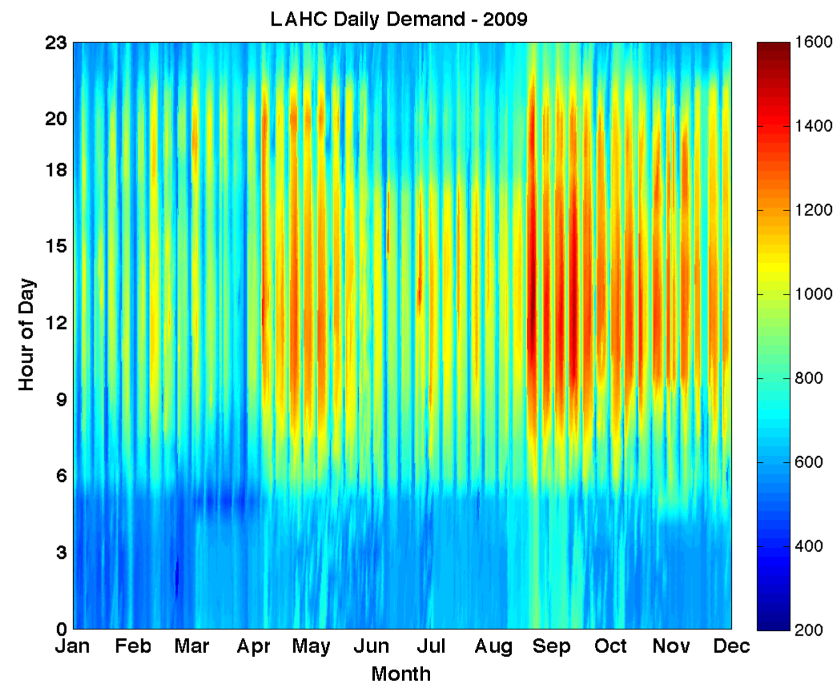


Figure A-0.5: Temporal daily and hourly demand for LAHC for 2009 in kWh

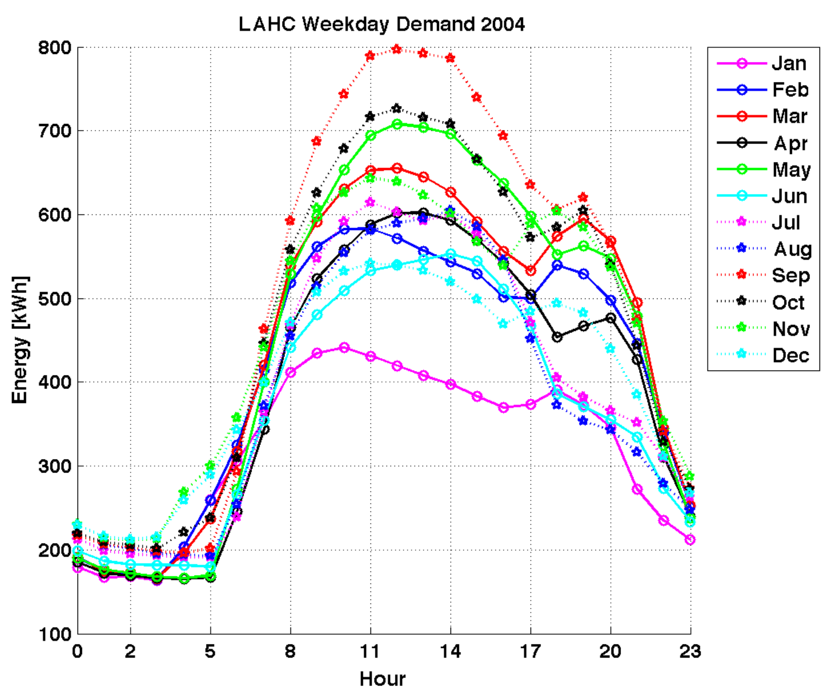


Figure A-0.6: Average weekday day of hour energy demand for 2004

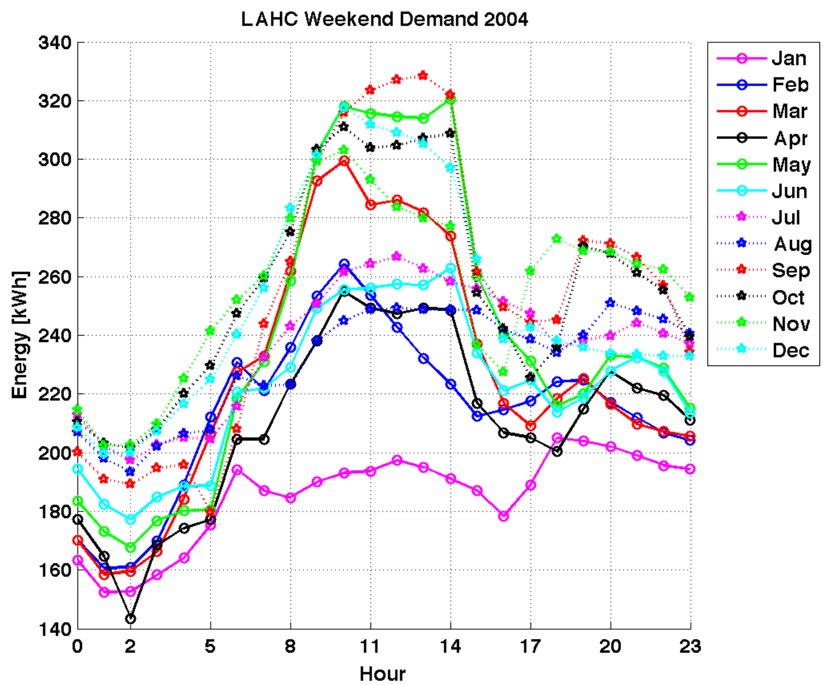


Figure A-0.7: Average weekend day of hour energy demand for 2004

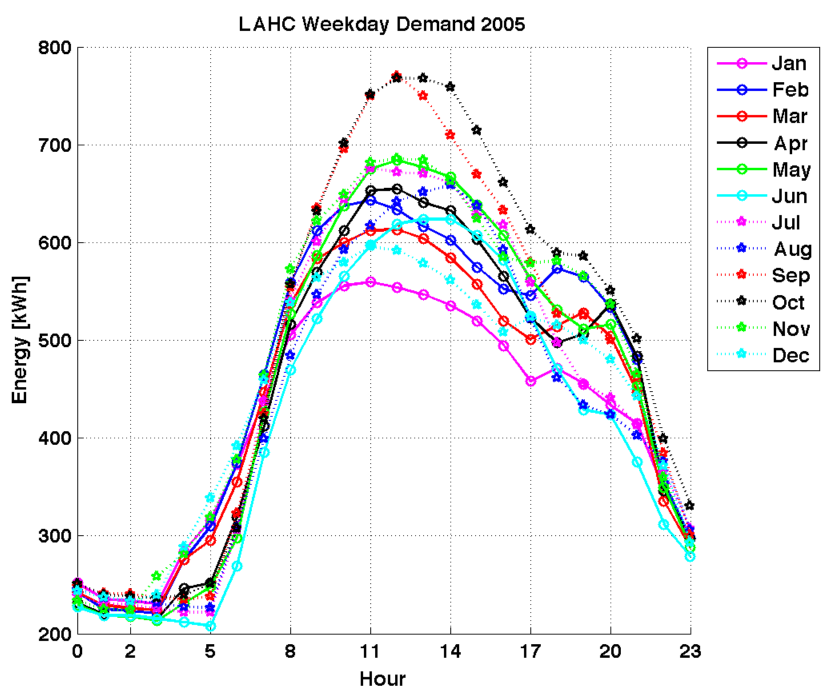


Figure A-0.8: Average weekday day of hour energy demand for 2005

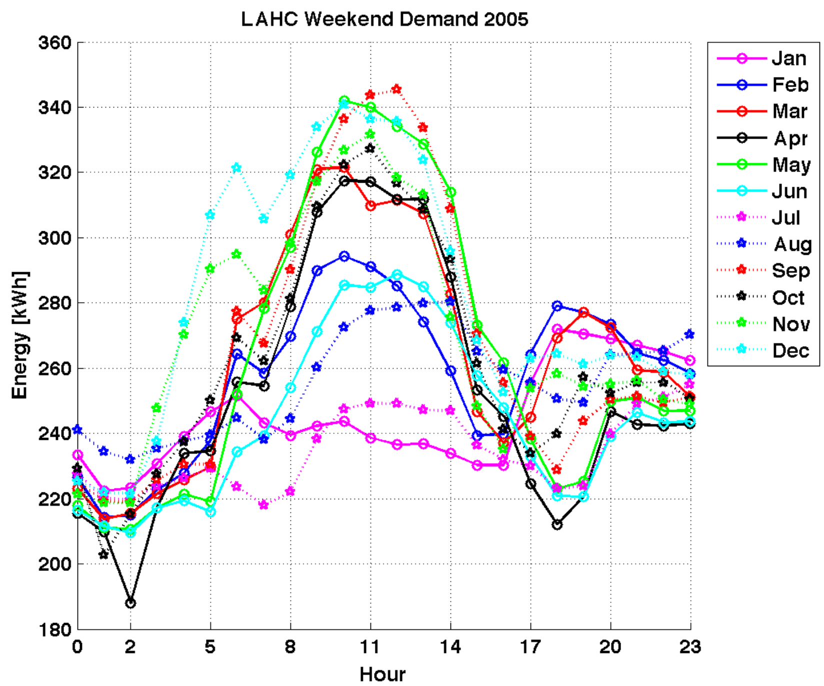


Figure A-0.9: Weekend average hour of day energy demand for 2005

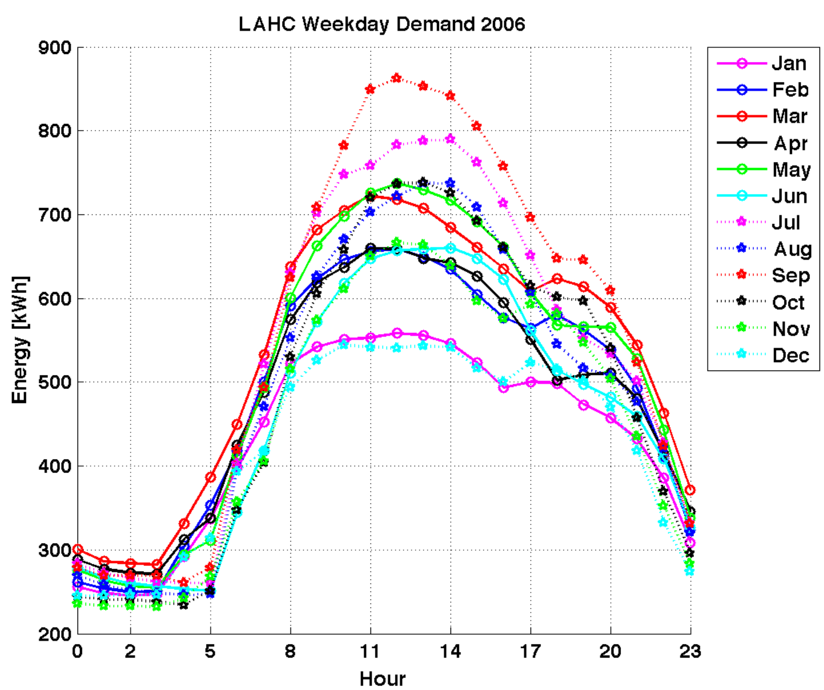


Figure A-0.10: Weekday average hour of day energy demand for 2006

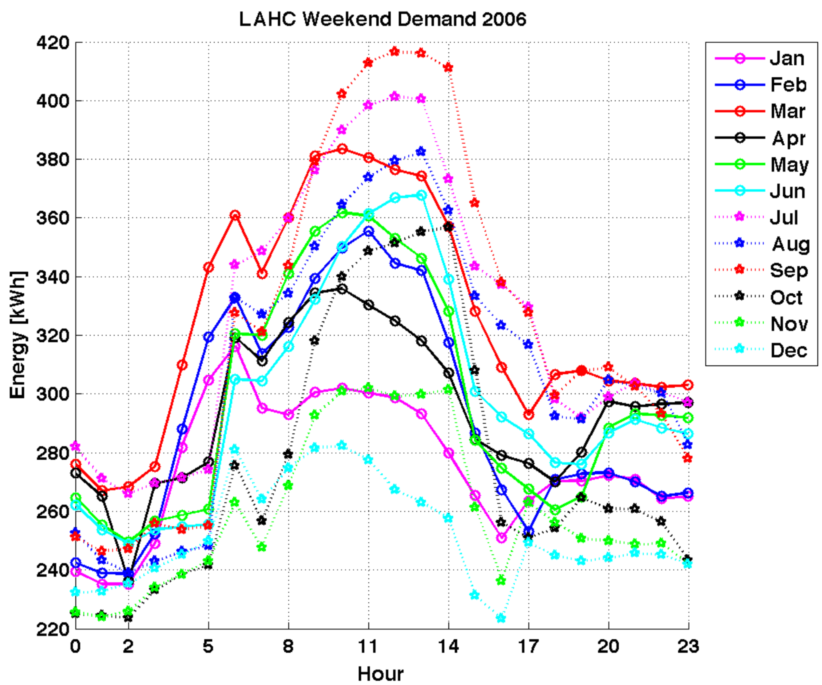


Figure A-0.11: Weekend average hour of day energy demand for 2006

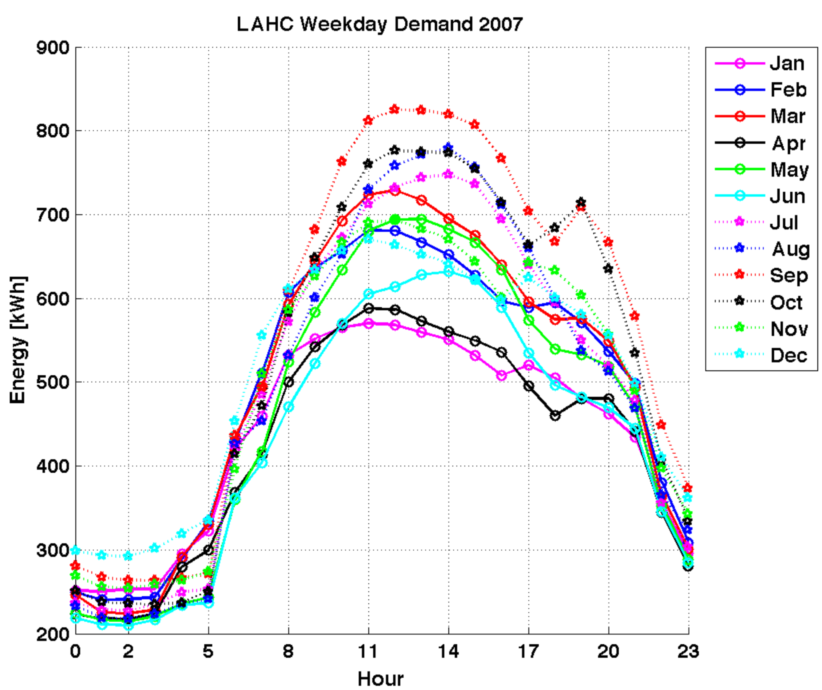


Figure A-0.12: Weekday average hour of day energy demand for 2007

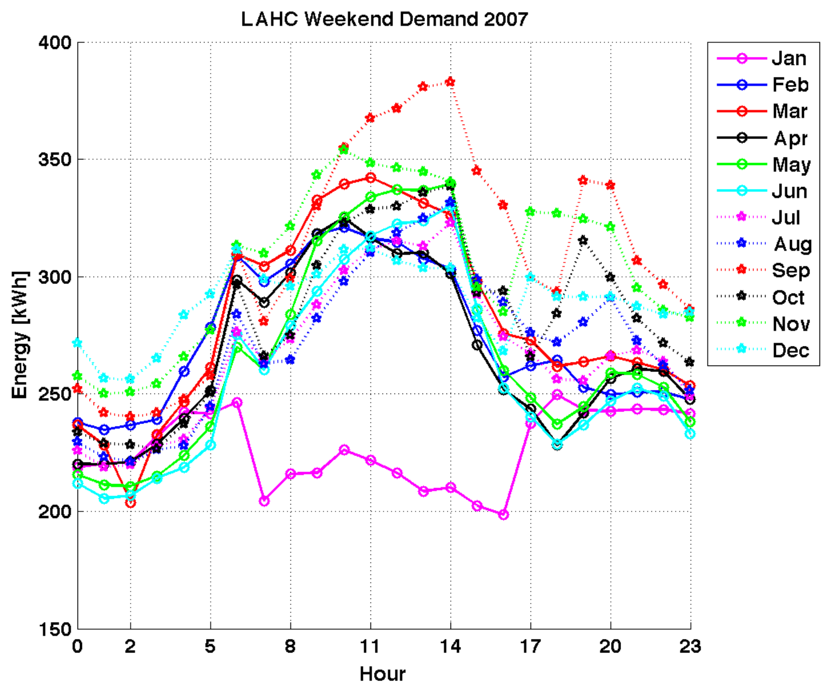


Figure A-0.13: Weekend average hour of day energy demand for 2007

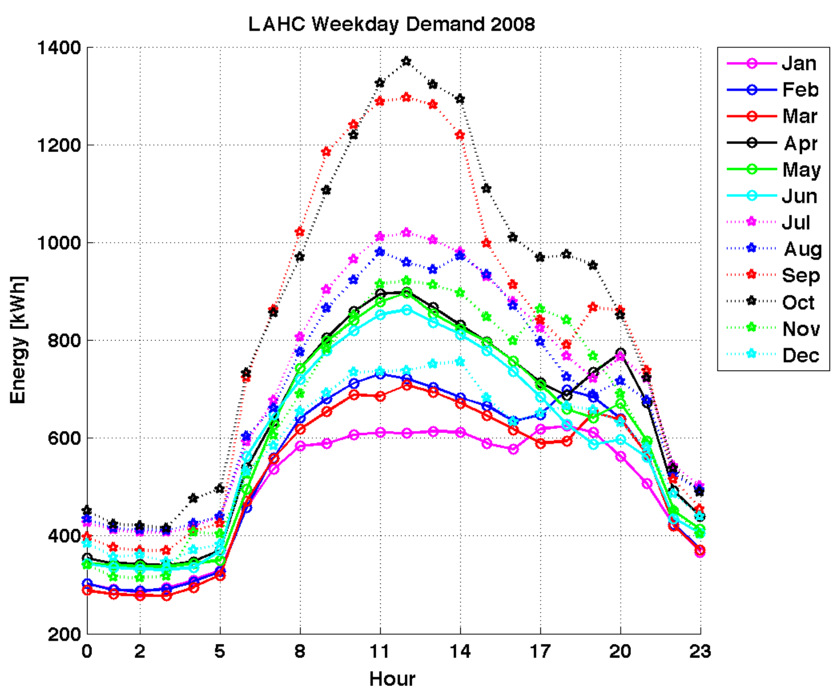


Figure A-0.14: Weekend average hour of day energy demand for 2008

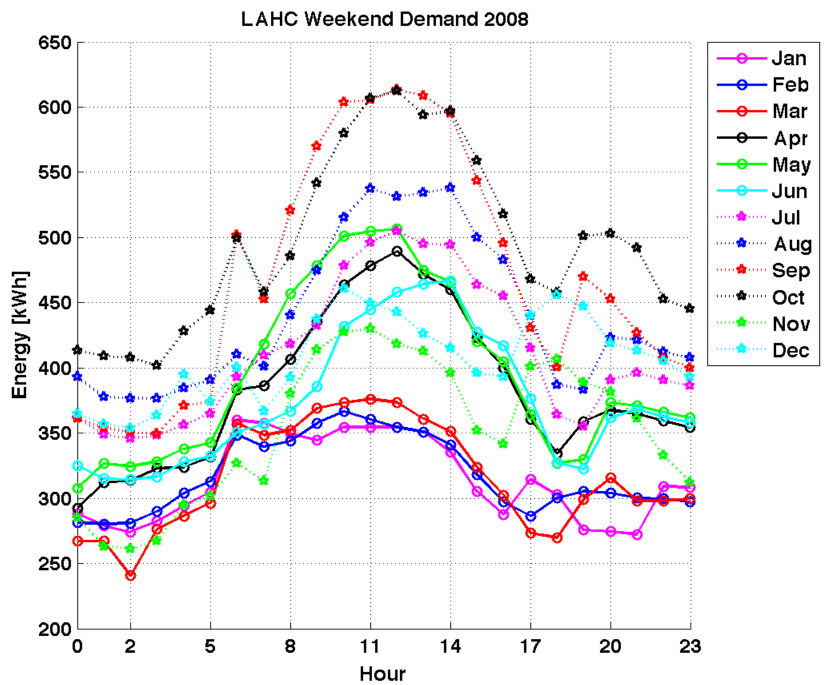


Figure A-0.15: Weekend average hour of day energy demand for 2008

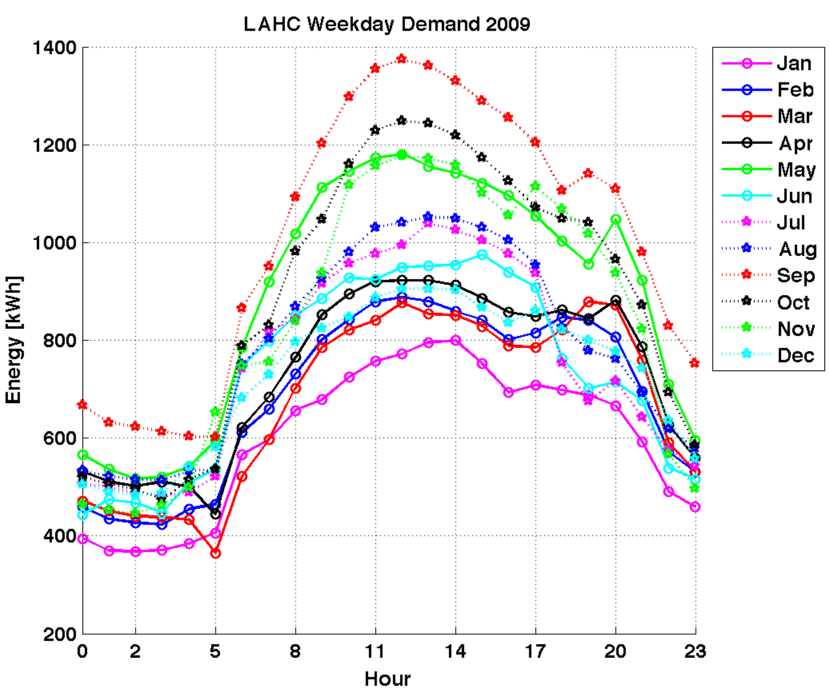


Figure A-0.16: Weekday average hour of day energy demand for 2009

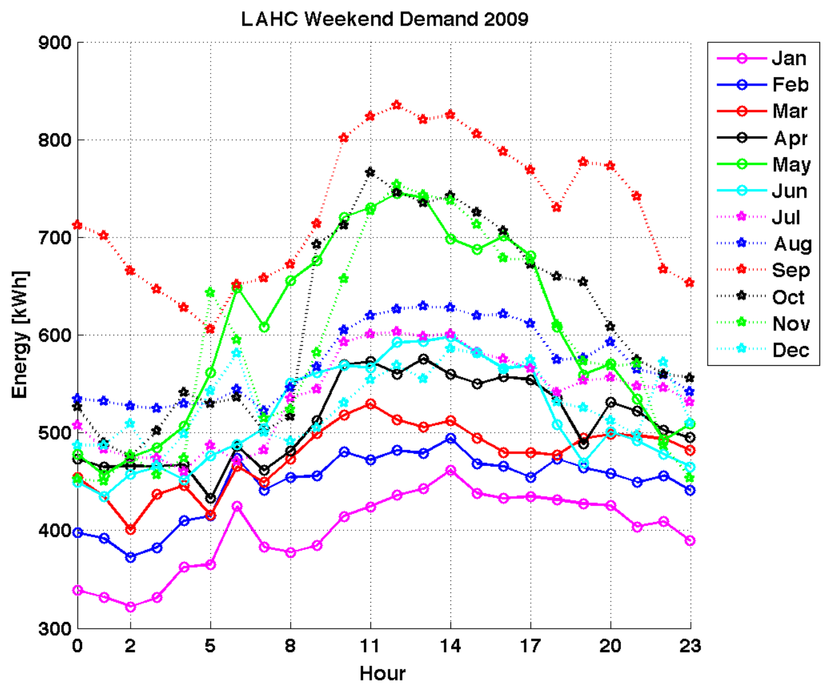


Figure A-0.17: Weekend average hour of day energy demand for 2009

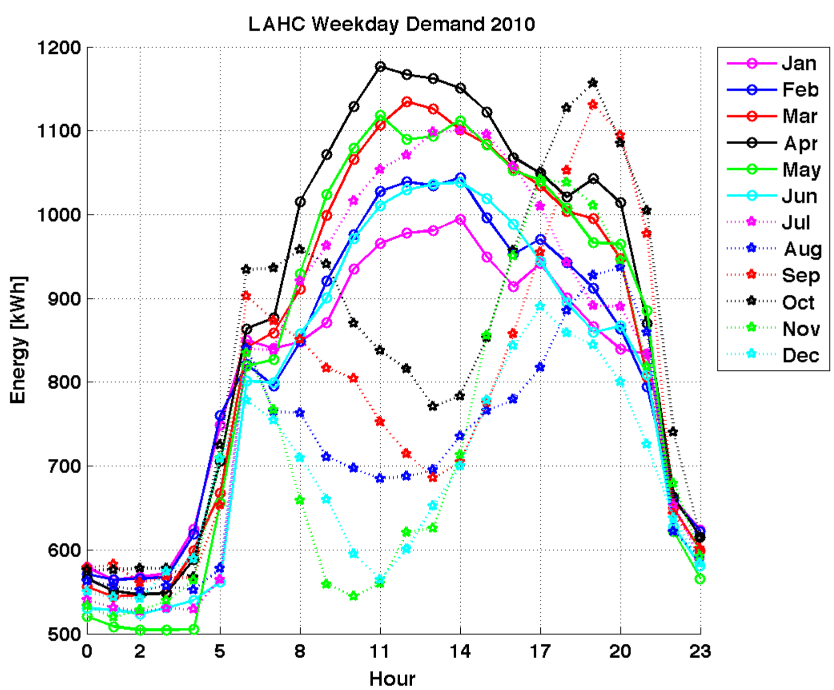


Figure A-0.18: Weekday average hour of day energy demand for 2010

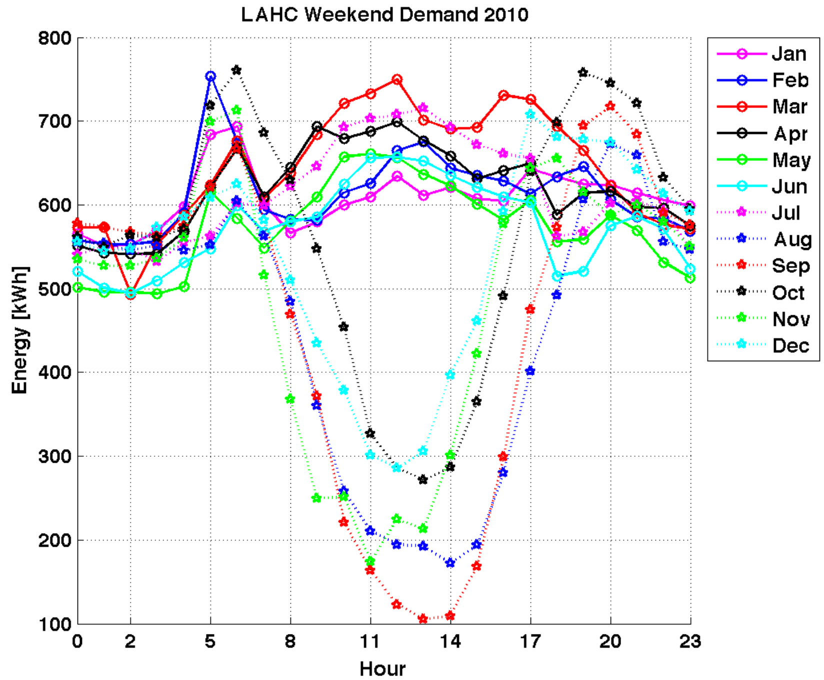


Figure A-0.19: Weekend average hour of day energy demand for 2010

Matlab Codes

Read_dwp.m

```
%% read_dwp
% AECOM Group Project
%
% OBJECTIVE:
%==========================================================================
% This program will search the current directory for csv files. The user
% must pick the appropriate file containing Los Angeles Department of Water
% and Power (LADWP) data for Los Angeles Harbor College (LAHC). It is
% assumed the power purchased from LADWP is in 15 minute intervals. Once
% the data is loaded, the program will aggregate the data into hour bins.
% The program will then subset the data by year. The mean and standard
% deviation will be calculated for hour of the day and day of year. Seasonal
% data for each year will be determined as well.
%
%==========================================================================
% ASSUMPTIONS
% 1. The data file must be saved as a MS-DOS csv file and not as a
%    Microsoft csv file.
% 2. The first column contains the date as a string
% 3. The second column contains the purchased power as a floating point
%    number.
%
```

```
%=========================================================================
% AUTHOR INFORMATION
% Kurt Heinze
% Bren School of Environmental Science & Management
% University of California Santa Barbara
% 2400 Bren Hall
% Santa Barbara, CA 93106
% email: kheinze@bren.ucsb.edu
% email: kurt.heinze@gmail.com
% mobile: +1-310-775-1774
% home: +1-805-893-1813
%
%=========================================================================
% VARIABLE DEFINITIONS
%
% ftype - The file type to be loaded. It is currently set for a csv file.
%         The user can change the file type but there is no guarantee the
%         program will work. The user must debug it.
%
% d - Is a structure containing the following:
%     name: name of files in the present working directory
%     date: date the files were created
%     bytes: number of bytes in each file
%     isdir: a binary variable defining if the items in the d structure are
%            a directory. A zero indicates not a directory and a one
%            indicates directory
%     datenum: an integer value of the date the file was created.
%     dir is a native Matlab function
%
% file - A string matrix with all the file names found with the file type
%        varialbe specified.
%        char is a native Matlab function and ensures a string matrix is
%        created
%        nf: is a variable containing the number of files found with ftype
%        mf: is a variable containing the maximum length of the file
%            strings
%
%
% fnum - the string representation of the file selected from the list
%        printed to the screen to be loaded
%
% fid - a integer value representing the file to be loaded.
%
% dl - a string value representing how the data is separated in the file
%
% hl - integer value representing how many header lines need to be skipped
%      before the data is loaded.
%
% ev - numeric value representing how missing values are handled.
%
%
% fmat - vector containing the formats of the data. The number of entries
%        in this vector needs to be the same as the number of columns in
%        the file loaded.
%
% data - a cell containing all the data loaded
%
% dnum - character string with date information
%
% pow - vector with power purchased from LADWP in 15 minute intervals
%
```

```
% dayofweek - string vector containing single character to define the day
%             of the week
%
% wkday_in - vector containing all the indices for Monday - Friday
%
% wkend_in - vector containing all the indices for Saturday and Sunday
%
% wd_pow - vector containing all the power values for Monday - Friday
%
% we_pow - vector containing all the power values for Saturday and Sunday
%
% year - vector containing year in which power was purchased
%
% month - vector containing month in which power was purchased
%
% day - vector containing day in which power was purchased
%
% hour - vector containing hour in which power was purchased
%
% minute - vector containing minute in which power was purchased
%
% second - vector containing minute in which power was purchased
%
% ag_pow - vector containing the 15 minute purchased power summed into
%          hourly bins
%
% ag_dnum - vector containing the date number for the hourly summed
%           purchased power
%
% sday - starting date number used to create the ag_dnum vector
%
% dy - vector containing zeros or ones used to determine the years data is
%      available
%
% in - index variable
%
% yr - vector containing the individual years which data has been loaded
%
% n,m,p - variables holding the size of the data cubes
%
% i,j,k - loop counters
%
% yr_pow - data cube containing all hourly aggregated LADWP purchased power
%
% wkday_pow - data cube containing all the hourly aggregated LADWP power
%             purchased for Monday - Friday
%
% wkend_pow - data cube containing all the hourly aggregated LADWP power
%             purchased for Saturday and Sunday
%
% hr_stats - data cube containing the mean in the first data sheet and
%            standard deviation in the second sheet for the hourly data for
%            each year
%
% wkday_hr_stats - data cube containing the mean in the first data sheet
%                  and standard deviation in the second sheet for the
%                  weekday hourly data for each year
%
% wkend_hr_stats - data cube containing the mean in the first data sheet
%                  and standard deviation in the second sheet for the
%                  weekend hourly data for each year
```

```
%
% doy_stats - data cube containing the same information as hr_stats for
%             daily data over all hours
%
% win_pow - data cube containing seasonal data for winter only
%
% win_wkday_pow - data cube containing seasonal data for Monday - Friday
%                 for winter only
%
% win_wkend_pow - data cube containing seasonal data for Saturday and
%                 Sunday for winter only
%
% win_hr_stats - data cube same as hr_stats but for winter only
%
% win_wkday_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data from Monday - Friday for winter only
%
% win_wkend_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data for Saturday and Sunday during the winter only
%
% win_doy_stats - data cbue same as doy_stats except for winter only
%
% win_doy_hr_stats -   data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data from Monday - Friday for winter only
%
% win_doy_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data for Saturday and Sunday during the winter only
%
% spr_pow - data cube containing seasonal data for spring only
%
% spr_wkday_pow - data cube containing seasonal data for Monday - Friday
%                 for spring only
%
% spr_wkend_pow - data cube containing seasonal data for Saturday and
%                 Sunday for spring only
%
% spr_hr_stats - data cube same as hr_stats but for spring only
%
% spr_wkday_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data from Monday - Friday for spring only
%
% spr_wkend_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data for Saturday and Sunday during the spring only
%
% spr_doy_stats - data cbue same as doy_stats except for spring only
%
% spr_doy_hr_stats -   data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data from Monday - Friday for spring only
%
% spr_doy_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data for Saturday and Sunday during the spring only
%
% sum_pow - data cube containing seasonal data for summer only
```

```
%
% sum_wkday_pow - data cube containing seasonal data for Monday - Friday
%                 for summer only
%
% sum_wkend_pow - data cube containing seasonal data for Saturday and
%                 Sunday for summer only
%
% sum_hr_stats - data cube same as hr_stats but for summer only
%
% sum_wkday_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data from Monday - Friday for summer only
%
% sum_wkend_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data for Saturday and Sunday during the summer only
%
% sum_doy_stats - data cbue same as doy_stats except for summer only
%
% sum_doy_hr_stats -   data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data from Monday - Friday for summer only
%
% sum_doy_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data for Saturday and Sunday during the summer only
%
% aut_pow - data cube containing seasonal data for autumn only
%
% aut_wkday_pow - data cube containing seasonal data for Monday - Friday
%                 for autumn only
%
% aut_wkend_pow - data cube containing seasonal data for Saturday and
%                 Sunday for autumn only
%
% aut_hr_stats - data cube same as hr_stats but for autumn only
%
% aut_wkday_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data from Monday - Friday for autumn only
%
% aut_wkend_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for hourly
%                      data for Saturday and Sunday during the autumn only
%
% aut_doy_stats - data cbue same as doy_stats except for spring only
%
% aut_doy_hr_stats -   data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data from Monday - Friday for autumn only
%
% aut_doy_hr_stats - data cube containing the mean in the first sheet and
%                      standard deviation in the second sheet for daily
%                      data for Saturday and Sunday during the autumn only
%
% len - variable containing the length of a vector
%
% in_win - vector containing the indicies for winter data only
%
% in_spr - vector containing the indicies for spring data only
%
```

```
% in_sum - vector containing the indicies for summer data only
%
% in_aut - vector containing the indicies for autumn data only
%
% l_win - variable containing the length of the in_win vector
%
% l_spr - variable containing the length of the in_spr vector
%
% l_sum - variable containing the length of the in_sum vector
%
% l_aut - variable containing the length of the in_aut vector
%
% yr - vector containing the different years in the dataset
%
% styl - string matrix containing the different line styles and markers
%        used in plotting the data
%
% lgnd - string matrix of all the years in the dataset. Used for creating
%        the legend in the figures
%
% h - vector from 0 - 23 representing all the hours in the day
%
% xthr - vector containing the horizontal axis tick mark locations used for
%        plotting purposes
%
% tle - string matrix of all the hourly or daily power. Used for creating
%       the title for each figure and also saving the figure
%
% xl - string matrix for horizontal axis label. Used for plotting purposes
%
% yl - string matrix for vertical axis label. Used for plotting purposes
%
% t - vector containing the date number for a leap year in the dataset.
%
% xtyr - vector containing the horizontal axis tick mark locations used for
%        plotting purposes
%
% figfile - string vector containing the name of the figure file
%
% figtype - string vector containing the type of figure

%==========================================================================
% Clear the workspace, close all open figures and clear the command windoow

clear all;
close all;
clc;
t0=tic;
% Define a variable containing the type of file the program will load.
ftype = 'csv';

% Define a temporary structure variable containing information from the
% present working directory. The * is a wildcard indicating any possible
% name for the file.
d=dir(fullfile(pwd,['*.' ftype]));

% Define a temporary variable containing all the names of the files found
% with the file type.
file=char(d.name);

% define variable with the number of files and maximum length of the file
```

```
% string
nf=min(size(file));

% print a message to the screen with the files found in the directory
% meeting the file type criteria. Then ask the user to select the
% appropriate file to load.
fprintf('\nThe following is a list of csv files to load\n');
for j=1:nf
        fprintf('\n%i.\t%s',j,file(j,:))
    if j == nf
        fprintf('\n')
    end
end

% read the file to be loaded
fnum=input('\nPlease choose a file from the above list to load\n','s');
fprintf('\n')

% get the file identifier for file to be loaded
fid1=fopen(deblank(file(str2double(fnum),:)));

% define the delimiter, the header lines to be skipped and the empty value
dl = ',';
hl = 1;
ev = NaN;
fmat = ['%s','%f'];

% load the file
data=...
    textscan(fid1,fmat,'headerlines',hl,'delimiter',dl,'emptyvalue',ev);

% close the file
fclose(fid1);
clear ftype d file nf j
% define the cell with the date information and power purchased
dnum=char(deblank(data{1,1}));
pow=data{1,2};
n=length(pow)/4;

% initialize the vectors for the agregated power and datenum and year,
% month, day, hour, minute and second.
ag_pow=NaN*ones(n,1);
ag_dnum=NaN*ones(n,1);
sday=datenum(dnum(1,:));
year=NaN*ones(n,1);
month=NaN*ones(n,1);
day=NaN*ones(n,1);
hour=NaN*ones(n,1);
minute=NaN*ones(n,1);
second=NaN*ones(n,1);

% create the hourly data for the power purchased from LADWP and
% corresponding date number
for j=1:n
    ag_pow(j)=nansum(pow(1+4*(j-1):4*(1+(j-1))));
    ag_dnum(j)=sday+(j-1)/24;
    [year(j),month(j),day(j),hour(j),minute(j),...
        second(j)]=datevec(ag_dnum(j));
end

% set the inital power and date number to the aggregated values
```

```
pow=ag_pow;
dnum=ag_dnum;
dayofweek=datestr(dnum,'d');
wkend_in=sort(strfind(dayofweek','S'));
wkday_in=sort([strfind(dayofweek','M'),strfind(dayofweek','T'),...
    strfind(dayofweek','W'),strfind(dayofweek','F')]);
we_pow=pow;
we_pow(wkday_in)=NaN;
wd_pow=pow;
wd_pow(wkend_in)=NaN;

% determine the years
yr=year(1):1:year(end);

% set the size the data cubes by maximum days in a leap year, hours in a
% day and the number of years data is available
n=366;
m=24;
p=length(yr);

% initialize all the data cubes
% overall data
yr_pow=NaN*ones(n,m,p);
hr_stats=NaN*ones(m,p,2);
wkday_hr_stats=NaN*ones(m,p,2);
wkend_hr_stats=NaN*ones(m,p,2);
doy_stats=NaN*ones(n,p,2);
wkday_pow=NaN*ones(n,m,p);
wkend_pow=NaN*ones(n,m,p);
wkday_doy_stats=NaN*ones(n,p,2);
wkend_doy_stats=NaN*ones(n,p,2);

% winter data
win_pow=NaN*ones(91,m,p);
win_wkday_pow=NaN*ones(91,m,p);
win_wkend_pow=NaN*ones(91,m,p);
win_hr_stats=NaN*ones(m,p,2);
win_wkday_hr_stats=ones(m,p,2);
win_wkend_hr_stats=ones(m,p,2);
win_doy_stats=NaN*ones(91,p,2);
win_wkday_doy_stats=NaN*ones(91,p,2);
win_wkend_doy_stats=NaN*ones(91,p,2);

% spring data
spr_pow=NaN*ones(91,m,p);
spr_wkday_pow=NaN*ones(91,m,p);
spr_wkend_pow=NaN*ones(91,m,p);
spr_hr_stats=NaN*ones(m,p,2);
spr_wkday_hr_stats=ones(m,p,2);
spr_wkend_hr_stats=ones(m,p,2);
spr_doy_stats=NaN*ones(91,p,2);
spr_wkday_doy_stats=NaN*ones(91,p,2);
spr_wkend_doy_stats=NaN*ones(91,p,2);

% summer data
sum_pow=NaN*ones(92,m,p);
sum_wkday_pow=NaN*ones(92,m,p);
sum_wkend_pow=NaN*ones(92,m,p);
sum_hr_stats=NaN*ones(m,p,2);
sum_wkday_hr_stats=ones(m,p,2);
sum_wkend_hr_stats=ones(m,p,2);
```

```
sum_doy_stats=NaN*ones(92,p,2);
sum_wkday_doy_stats=NaN*ones(92,p,2);
sum_wkend_doy_stats=NaN*ones(92,p,2);

% autumn data
aut_pow=NaN*ones(92,m,p);
aut_wkday_pow=NaN*ones(92,m,p);
aut_wkend_pow=NaN*ones(92,m,p);
aut_hr_stats=NaN*ones(m,p,2);
aut_wkday_hr_stats=ones(m,p,2);
aut_wkend_hr_stats=ones(m,p,2);
aut_doy_stats=NaN*ones(92,p,2);
aut_wkday_doy_stats=NaN*ones(92,p,2);
aut_wkend_doy_stats=NaN*ones(92,p,2);

% Loop through and calculate all relevant statistics
for i=1:p
    for j=1:m
        % search for all the individual hours and determine their
        % statistics
        in=find(year==yr(i)&hour==j-1);
        len=length(in);
        hr_stats(j,i,1)=nanmean(pow(in));
        hr_stats(j,i,2)=nanstd(pow(in));
        wkday_hr_stats(j,i,1)=nanmean(wd_pow(in));
        wkday_hr_stats(j,i,2)=nanstd(wd_pow(in));
        wkend_hr_stats(j,i,1)=nanmean(we_pow(in));
        wkend_hr_stats(j,i,2)=nanstd(we_pow(in));


        % Determine the indicies for the winter, spring, summer and autumn
        % power usage. The following are the assumptions for the seasonal
        % indicies
        % Winter: Jan 1 - Mar 31
        % Spring: Apr 1 - Jun 30
        % Summer: Jul 1 - Sep 30
        % Autumn: Oct 1 - Dec 31
        % Note julian is a function I wrote to determine the Julian or day
        % of the year using a cummulative sum of the native Matlab function
        % eomday (end of month day).
        in_win=(julian(1,1,yr(i)):1:julian(3,31,yr(i)));
        in_spr=(julian(4,1,yr(i)):1:julian(6,30,yr(i)));
        in_sum=(julian(7,1,yr(i)):1:julian(9,30,yr(i)));
        in_aut=(julian(10,1,yr(i)):1:julian(12,31,yr(i)));

        % Calculate the length of the seasonal vectors
        l_win=length(in_win);
        l_spr=length(in_spr);
        l_sum=length(in_sum);
        l_aut=length(in_aut);

        % Determine the jth hour power purchased.
        yr_pow(1:len,j,i)=pow(in);
        wkend_pow(1:len,j,i)=we_pow(in);
        wkday_pow(1:len,j,i)=wd_pow(in);

        % Determine the jth hour seasonal power purchased and statistics
        win_pow(1:l_win,j,i)=yr_pow(in_win,j,i);
        win_wkday_pow(1:l_win,j,i)=wkday_pow(in_win,j,i);
        win_wkend_pow(1:l_win,j,i)=wkend_pow(in_win,j,i);
        win_hr_stats(j,i,1)=nanmean(win_pow(:,j,i));
```

```
win_hr_stats(j,i,2)=nanstd(win_pow(:,j,i));
win_wkday_hr_stats(j,i,1)=nanmean(win_wkday_pow(:,j,i));
win_wkday_hr_stats(j,i,2)=nanstd(win_wkday_pow(:,j,i));
win_wkend_hr_stats(j,i,1)=nanmean(win_wkend_pow(:,j,i));
win_wkend_hr_stats(j,i,2)=nanstd(win_wkend_pow(:,j,i));

spr_pow(1:l_spr,j,i)=yr_pow(in_spr,j,i);
spr_wkday_pow(1:l_spr,j,i)=wkday_pow(in_spr,j,i);
spr_wkend_pow(1:l_spr,j,i)=wkend_pow(in_spr,j,i);
spr_hr_stats(j,i,1)=nanmean(spr_pow(:,j,i));
spr_hr_stats(j,i,2)=nanstd(spr_pow(:,j,i));
spr_wkday_hr_stats(j,i,1)=nanmean(spr_wkday_pow(:,j,i));
spr_wkday_hr_stats(j,i,2)=nanstd(spr_wkday_pow(:,j,i));
spr_wkend_hr_stats(j,i,1)=nanmean(spr_wkend_pow(:,j,i));
spr_wkend_hr_stats(j,i,2)=nanstd(spr_wkend_pow(:,j,i));


sum_pow(1:l_sum,j,i)=yr_pow(in_sum,j,i);
sum_wkday_pow(1:l_sum,j,i)=wkday_pow(in_sum,j,i);
sum_wkend_pow(1:l_sum,j,i)=wkend_pow(in_sum,j,i);
sum_hr_stats(j,i,1)=nanmean(sum_pow(:,j,i));
sum_hr_stats(j,i,2)=nanstd(sum_pow(:,j,i));
sum_wkday_hr_stats(j,i,1)=nanmean(sum_wkday_pow(:,j,i));
sum_wkday_hr_stats(j,i,2)=nanstd(sum_wkday_pow(:,j,i));
sum_wkend_hr_stats(j,i,1)=nanmean(sum_wkend_pow(:,j,i));
sum_wkend_hr_stats(j,i,2)=nanstd(sum_wkend_pow(:,j,i));


aut_pow(1:l_aut,j,i)=yr_pow(in_aut,j,i);
aut_wkday_pow(1:l_aut,j,i)=wkday_pow(in_aut,j,i);
aut_wkend_pow(1:l_aut,j,i)=wkend_pow(in_aut,j,i);
aut_hr_stats(j,i,1)=nanmean(aut_pow(:,j,i));
aut_hr_stats(j,i,2)=nanstd(aut_pow(:,j,i));
aut_wkday_hr_stats(j,i,1)=nanmean(aut_wkday_pow(:,j,i));
aut_wkday_hr_stats(j,i,2)=nanstd(aut_wkday_pow(:,j,i));
aut_wkend_hr_stats(j,i,1)=nanmean(aut_wkend_pow(:,j,i));
aut_wkend_hr_stats(j,i,2)=nanstd(aut_wkend_pow(:,j,i));

% if the statistics for the last hour of the day has been
% evaluated, calculate the statisitcs for the entire day
if j==m
    % calculate the overall statistics
    for k=1:len
        doy_stats(k,i,1)=nanmean(yr_pow(k,:,i));
        doy_stats(k,i,2)=nanstd(yr_pow(k,:,i));
        wkday_doy_stats(k,i,1)=nanmean(wkday_pow(k,:,i));
        wkday_doy_stats(k,i,2)=nanstd(wkday_pow(k,:,i));
        wkend_doy_stats(k,i,1)=nanmean(wkend_pow(k,:,i));
        wkend_doy_stats(k,i,2)=nanstd(wkend_pow(k,:,i));
    end

    % calculate the winter statistics
    for k=1:l_win
        win_doy_stats(k,i,1)=nanmean(win_pow(k,:,i));
        win_doy_stats(k,i,2)=nanstd(win_pow(k,:,i));
        win_wkday_doy_stats(k,i,1)=nanmean(win_wkday_pow(k,:,i));
        win_wkday_doy_stats(k,i,2)=nanstd(win_wkday_pow(k,:,i));
        win_wkend_doy_stats(k,i,1)=nanmean(win_wkend_pow(k,:,i));
        win_wkend_doy_stats(k,i,2)=nanstd(win_wkend_pow(k,:,i));
    end
```

```
            % calculate the spring statisitcs
            for k=1:l_spr
                spr_doy_stats(k,i,1)=nanmean(spr_pow(k,:,i));
                spr_doy_stats(k,i,2)=nanstd(spr_pow(k,:,i));
                spr_wkday_doy_stats(k,i,1)=nanmean(spr_wkday_pow(k,:,i));
                spr_wkday_doy_stats(k,i,2)=nanstd(spr_wkday_pow(k,:,i));
                spr_wkend_doy_stats(k,i,1)=nanmean(spr_wkend_pow(k,:,i));
                spr_wkend_doy_stats(k,i,2)=nanstd(spr_wkend_pow(k,:,i));
            end

            % calculate the summer statistics
            for k=1:l_sum
                sum_doy_stats(k,i,1)=nanmean(sum_pow(k,:,i));
                sum_doy_stats(k,i,2)=nanstd(sum_pow(k,:,i));
                sum_wkday_doy_stats(k,i,1)=nanmean(sum_wkday_pow(k,:,i));
                sum_wkday_doy_stats(k,i,2)=nanstd(sum_wkday_pow(k,:,i));
                sum_wkend_doy_stats(k,i,1)=nanmean(sum_wkend_pow(k,:,i));
                sum_wkend_doy_stats(k,i,2)=nanstd(sum_wkend_pow(k,:,i));
            end

            % calculate the autumn statistics
            for k=1:l_aut
                aut_doy_stats(k,i,1)=nanmean(aut_pow(k,:,i));
                aut_doy_stats(k,i,2)=nanstd(aut_pow(k,:,i));
                aut_wkday_doy_stats(k,i,1)=nanmean(aut_wkday_pow(k,:,i));
                aut_wkday_doy_stats(k,i,2)=nanstd(aut_wkday_pow(k,:,i));
                aut_wkend_doy_stats(k,i,1)=nanmean(aut_wkend_pow(k,:,i));
                aut_wkend_doy_stats(k,i,2)=nanstd(aut_wkend_pow(k,:,i));
            end
        end
    end
end

% wkend_month_hr and wkday_month_hr are data cubes containing the hourly
% monthly averages by hour x month x year
wkend_month_hr=NaN*ones(m,12,p);
wkday_month_hr=NaN*ones(m,12,p);
all_month_hr=NaN*ones(m,12,p);
sday=[1,cumsum(eomday(2008,1:11))+1]';
eday=cumsum(eomday(2008,1:12))';

for k=1:p
    for j=1:12
        for i=1:m
            wkend_month_hr(i,j,k)=nanmean(wkend_pow(sday(j):eday(j),i,k));
            wkday_month_hr(i,j,k)=nanmean(wkday_pow(sday(j):eday(j),i,k));
            all_month_hr(i,j,k)=nanmean(yr_pow(sday(j):eday(j),i,k));
        end
    end
end

% end calculations

% open the data files for writing

if ~isdir('./Data/')
    mkdir ./Data/LADWP
    mkdir ./Data/Solar_PV
end
```

```
fid2=fopen('./Data/LADWP/LAHC_preconstruction_demand.dat','w');
fid3=fopen('./Data/LADWP/LAHC_construction_demand.dat','w');
fid4=fopen('./Data/LADWP/LAHC_construction_PV_demand.dat','w');
for i=1:n

    if(i==1)
        % creating the header
        fprintf(fid2,'Date\t');
        fprintf(fid3,'Date\t');
        fprintf(fid4,'Date\t');
        for k=1:m
            fprintf(fid2,'%4.0f:00\t',k-1);
            fprintf(fid3,'%4.0f:00\t',k-1);
            fprintf(fid4,'%4.0f:00\t',k-1);
            if k==m
                fprintf(fid2,'\n');
                fprintf(fid3,'\n');
                fprintf(fid4,'\n');
            end
            % finished creating the header
        end
    end
    % write the dates to the files
    fprintf(fid2,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    fprintf(fid3,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    fprintf(fid4,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    for j=1:m
        % calculate the averages
        % preconstruction period 2004 - 2007
        fprintf(fid2,'%7.2f\t',nanmean(yr_pow(i,j,1:4)));
        % construction period 2008 - 2009
        fprintf(fid3,'%7.2f\t',nanmean(yr_pow(i,j,5:6)));
        % construction period with PV 2010 - 2011
        fprintf(fid4,'%7.2f\t',nanmean(yr_pow(i,j,7:8)));
        if j==m
            fprintf(fid2,'\n');
            fprintf(fid3,'\n');
            fprintf(fid4,'\n');
        end
    end
end

%close the data files
fclose(fid2);
fclose(fid3);
fclose(fid4);


% fid5=fopen('./Data/LADWP/LAHC_monthly_weekday_2004-2007.dat','w');
% fid6=fopen('./Data/LADWP/LAHC_monthly_weekday_2008-2009.dat','w');
% fid7=fopen('./Data/LADWP/LAHC_monthly_weekday_2010-2011.dat','w');
% fid8=fopen('./Data/LADWP/LAHC_monthly_weekend_2004-2007.dat','w');
% fid9=fopen('./Data/LADWP/LAHC_monthly_weekend_2008-2009.dat','w');
% fid10=fopen('./Data/LADWP/LAHC_monthly_weekend_2010-2011.dat','w');

for n=1:8
    fid5=fopen(['./Data/LADWP/LAHC_monthly_weekday_' num2str(yr(n))
'.dat'],'w');
    fid6=fopen(['./Data/LADWP/LAHC_monthly_weekend_' num2str(yr(n))
'.dat'],'w');
    for i=1:12
```

```
        if(i==1)
            % creating the header
            fprintf(fid5,'Date\t');
            fprintf(fid6,'Date\t');
            %              fprintf(fid7,'Date\t');
            %              fprintf(fid8,'Date\t');
            %              fprintf(fid9,'Date\t');
            %              fprintf(fid10,'Date\t');
            for k=1:m
                fprintf(fid5,'%4.0f:00\t',k-1);
                fprintf(fid6,'%4.0f:00\t',k-1);
                %                  fprintf(fid7,'%4.0f:00\t',k-1);
                %                  fprintf(fid8,'%4.0f:00\t',k-1);
                %                  fprintf(fid9,'%4.0f:00\t',k-1);
                %                  fprintf(fid10,'%4.0f:00\t',k-1);
                if k==m
                    fprintf(fid5,'\n');
                    fprintf(fid6,'\n');
                    %                      fprintf(fid7,'\n');
                    %                      fprintf(fid8,'\n');
                    %                      fprintf(fid9,'\n');
                    %                      fprintf(fid10,'\n');
                end
                % finished creating the header
            end
        end
        % write the dates to the files
        fprintf(fid5,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        fprintf(fid6,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        %          fprintf(fid7,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        %          fprintf(fid8,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        %          fprintf(fid9,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        %          fprintf(fid10,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        for j=1:m
            % calculate the averages
            % preconstruction period 2004 - 2007

%fprintf(fid5,'%7.2f\t',mean(nanmean(wkday_pow(sday(i):eday(i),j,1:4))));
            fprintf(fid5,'%7.2f\t',nanmean(wkday_month_hr(j,i,n)));
            fprintf(fid6,'%7.2f\t',nanmean(wkend_month_hr(j,i,n)));

            % construction period 2008 - 2009
            %
fprintf(fid6,'%7.2f\t',nanmean(wkday_month_hr(j,i,5:6)));
            %
fprintf(fid9,'%7.2f\t',nanmean(wkend_month_hr(j,i,5:6)));
            %              % construction period with PV 2010 - 2011
            %
fprintf(fid7,'%7.2f\t',nanmean(wkday_month_hr(j,i,7:8)));
            %
fprintf(fid10,'%7.2f\t',nanmean(wkend_month_hr(j,i,7:8)));
            if j==m
                fprintf(fid5,'\n');
                fprintf(fid6,'\n');
                %                  fprintf(fid7,'\n');
                %                  fprintf(fid8,'\n');
                %                  fprintf(fid9,'\n');
                %                  fprintf(fid10,'\n');
            end
        end
    end
```

```
    fclose(fid5);
    fclose(fid6);
end

% fclose(fid7);
% fclose(fid8);
% fclose(fid9);
% fclose(fid10);

% end writing data files and begin plotting
%===============================================================================
% open new figure window
styl=['mo-';'bo-';'ro-';'ko-';'go-';'co-';...
      'mp:';'bp:';'rp:';'kp:';'gp:';'cp:'];
lgnd=num2str(yr');
h=(0:1:23)';
xthr=[0,2,5,8,11,14,17,20,23];
tle=['Average Hourly         ';...
     'Winter Hourly          ';...
     'Spring Hourly          ';...
     'Summer Hourly          ';...
     'Autumn Hourly          ';...
     'Average Hourly Weekday';...
     'Winter Hourly Weekday ';...
     'Spring Hourly Weekday ';...
     'Summer Hourly Weekday ';...
     'Autumn Hourly Weekday ';...
     'Average Hourly Weekend';...
     'Winter Hourly Weekend ';...
     'Spring Hourly Weekend ';...
     'Summer Hourly Weekend ';...
     'Autumn Hourly Weekend ';...
     'Average Daily          ';...
     'Winter Daily           ';...
     'Spring Daily           ';...
     'Summer Daily           ';...
     'Autumn Daily           ';...
     'Average Daily Weekday ';...
     'Winter Daily Weekday  ';...
     'Spring Daily Weekday  ';...
     'Summer Daily Weekday  ';...
     'Autumn Daily Weekday  ';...
     'Average Daily Weekend ';...
     'Winter Daily Weekend  ';...
     'Spring Daily Weekend  ';...
     'Summer Daily Weekend  ';...
     'Autumn Daily Weekend  ';...
     ];
xl=[' Hour ';' Date '];
yl=' Energy [kWh] ';


% plot average and seasonal hourly and daily power purchased
for j=1:length(tle)
    figure(j)
    for i=1:p
        if j==1
            plot(h,hr_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
            set(gca,'xlim',[0,23],'xtick',xthr,...
                'fontweight','bold','fontsize',12);
        elseif j==2
```

```
        plot(h,win_hr_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==3
        plot(h,spr_hr_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==4
        plot(h,sum_hr_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==5
        plot(h,aut_hr_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==6
        plot(h,wkday_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==7
        plot(h,win_wkday_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==8
        plot(h,spr_wkday_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==9
        plot(h,sum_wkday_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==10
        plot(h,aut_wkday_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==11
        plot(h,wkend_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==12
        plot(h,win_wkend_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==13
        plot(h,spr_wkend_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==14
        plot(h,sum_wkend_hr_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
    elseif j==15
```

```
    plot(h,aut_wkend_hr_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[0,23],'xtick',xthr,...
        'fontweight','bold','fontsize',12);
elseif j==16
    t=linspace(datenum(2004,1,1),datenum(2004,12,31),...
        length(doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,1,15),datenum(2004,12,15),7);
    plot(t,doy_stats(:,i,1),deblank(styl(i,:)),'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',3,'keepticks')
elseif j==17
    t=linspace(datenum(2004,1,1),datenum(2004,3,31),...
        length(win_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,1,1),datenum(2004,3,31),7);
    plot(t,win_doy_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',6,'keepticks')
elseif j==18
    t=linspace(datenum(2004,4,1),datenum(2004,6,30),...
        length(spr_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,4,1),datenum(2004,6,30),7);
    plot(t,spr_doy_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',6,'keepticks')
elseif j==19
    t=linspace(datenum(2004,7,1),datenum(2004,9,30),...
        length(sum_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,7,1),datenum(2004,9,30),7);
    plot(t,sum_doy_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',6,'keepticks')
elseif j==20
    t=linspace(datenum(2004,10,1),datenum(2004,12,31),...
        length(aut_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,10,1),datenum(2004,12,31),7);
    plot(t,aut_doy_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',6,'keepticks')
elseif j==21
    t=linspace(datenum(2004,1,1),datenum(2004,12,31),...
        length(wkday_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,1,15),datenum(2004,12,15),7);
    plot(t,wkday_doy_stats(:,i,1),deblank(styl(i,:)),...
        'linewidth',1.5)
    set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
        'fontweight','bold','fontsize',12);
    datetick('x',3,'keepticks')
elseif j==22
    t=linspace(datenum(2004,1,1),datenum(2004,3,31),...
        length(win_wkday_doy_stats(:,i,1)))';
    xtdy=linspace(datenum(2004,1,1),datenum(2004,3,31),7);
```

```
        plot(t,win_wkday_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==23
        t=linspace(datenum(2004,4,1),datenum(2004,6,30),...
            length(spr_wkday_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,4,1),datenum(2004,6,30),7);
        plot(t,spr_wkday_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==24
        t=linspace(datenum(2004,7,1),datenum(2004,9,30),...
            length(sum_wkday_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,7,1),datenum(2004,9,30),7);
        plot(t,sum_wkday_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==25
        t=linspace(datenum(2004,10,1),datenum(2004,12,31),...
            length(aut_wkday_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,10,1),datenum(2004,12,31),7);
        plot(t,aut_wkday_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==26
        t=linspace(datenum(2004,1,1),datenum(2004,12,31),...
            length(wkend_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,1,15),datenum(2004,12,15),7);
        plot(t,wkend_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',3,'keepticks')
    elseif j==27
        t=linspace(datenum(2004,1,1),datenum(2004,3,31),...
            length(win_wkend_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,1,1),datenum(2004,3,31),7);
        plot(t,win_wkend_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==28
        t=linspace(datenum(2004,4,1),datenum(2004,6,30),...
            length(spr_wkend_doy_stats(:,i,1)))';
        xtdy=linspace(datenum(2004,4,1),datenum(2004,6,30),7);
        plot(t,spr_wkend_doy_stats(:,i,1),deblank(styl(i,:)),...
            'linewidth',1.5)
        set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
            'fontweight','bold','fontsize',12);
        datetick('x',6,'keepticks')
    elseif j==29
        t=linspace(datenum(2004,7,1),datenum(2004,9,30),...
```

```
                length(sum_wkend_doy_stats(:,i,1)))';
            xtdy=linspace(datenum(2004,7,1),datenum(2004,9,30),7);
            plot(t,sum_wkend_doy_stats(:,i,1),deblank(styl(i,:)),...
                'linewidth',1.5)
            set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
                'fontweight','bold','fontsize',12);
            datetick('x',6,'keepticks')
        else
            t=linspace(datenum(2004,10,1),datenum(2004,12,31),...
                length(aut_wkend_doy_stats(:,i,1)))';
            xtdy=linspace(datenum(2004,10,1),datenum(2004,12,31),7);
            plot(t,aut_wkend_doy_stats(:,i,1),deblank(styl(i,:)),...
                'linewidth',1.5)
            set(gca,'xlim',[t(1) t(end)],'xtick',xtdy,...
                'fontweight','bold','fontsize',12);
            datetick('x',6,'keepticks')
        end
        if i==1
            hold on;
            grid on;
        end
    end
    if j<16
        xlabel(xl(1,:))
    else
        xlabel(xl(2,:))
    end
    ylabel(yl)
    legend(lgnd,'location','BestOutside')
    title(['  LAHC ' deblank(tle(j,:)) ' Demand  '])
    figext='.png';
    figtype='png';
    if ~isdir('./Figures/')
        mkdir ./Figures/LADWP
        mkdir ./Figures/Solar_PV
    end
    q=strfind(deblank(tle(j,:)),' ');
    if length(q)==1
        figfile=['./Figures/LADWP/LAHC_' tle(j,1:q-1) '_'...
            deblank(tle(j,q+1:end)) figext];
    else
        figfile=['./Figures/LADWP/LAHC_' tle(j,1:q(1)-1) ...
            '_' tle(j,q(1)+1:q(2)-1) '_' deblank(tle(j,q(2)+1:end))...
            figext];
    end

    saveas(gcf,figfile,figtype);
end

monstr=['Jan';'Feb';'Mar';'Apr';'May';'Jun';'Jul';'Aug';'Sep';'Oct';...
    'Nov';'Dec'];
for i=1:8
    figure(j+i)
    for k=1:12
        if k==1
            hold on;
            grid on;
        end
        plot(h,wkday_month_hr(:,k,i),deblank(styl(k,:)),...
            'linewidth',1.5)
        xlabel(xl(1,:))
```

```
        ylabel(' Energy [kWh] ')

        title([' LAHC Weekday Demand ' num2str(yr(i)) '  '])
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
        if k==12

        end
    end
    legend(monstr,'location','bestoutside')
    figfile=['./Figures/LADWP/LAHC_Weekday_Monthly_Demand_' ...
        num2str(yr(i)) figext];
    saveas(gcf,figfile,figtype)

end

for a=1:8
    figure(j+i+a)
    for k=1:12
        if k==1
            hold on;
            grid on;
        end
        plot(h,wkend_month_hr(:,k,a),deblank(styl(k,:)),...
            'linewidth',1.5)
        xlabel(xl(1,:))
        ylabel(' Energy [kWh] ')

        title(['  LAHC Weekend Demand ' num2str(yr(a)) '  '])
        set(gca,'xlim',[0,23],'xtick',xthr,...
            'fontweight','bold','fontsize',12);
        if k==12

        end
    end
    legend(monstr,'location','bestoutside')
    figfile=['./Figures/LADWP/LAHC_Weekend_Monthly_Demand_' ...
        num2str(yr(a)) figext];
    saveas(gcf,figfile,figtype)
end
te=toc(t0);
fprintf('\nThe program run time was %6.2f seconds.\n',te)
```

write_dwp_data.m

```
%% write_dwp_data
clear all;
close all;
clc;
t0=tic;
% Define a variable containing the type of file the program will load.
ftype = 'csv';

% Define a temporary structure variable containing information from the
% present working directory. The * is a wildcard indicating any possible
% name for the file.
d=dir(fullfile(pwd,['*.' ftype]));

% Define a temporary variable containing all the names of the files found
% with the file type.
```

```
file=char(d.name);

% define variable with the number of files and maximum length of the file
% string
nf=min(size(file));

% print a message to the screen with the files found in the directory
% meeting the file type criteria. Then ask the user to select the
% appropriate file to load.
fprintf('\nThe following is a list of csv files that can be loaded\n');
for j=1:nf
        fprintf('\n%i.\t%s',j,file(j,:))
    if j == nf
        fprintf('\n')
    end
end

% read the file to be loaded
fnum=input('\nPlease select the file with LAHC''s electricity
demand\n','s');
fprintf('\n')

% get the file identifier for file to be loaded
fid1=fopen(deblank(file(str2double(fnum),:)));

% define the delimiter, the header lines to be skipped and the empty value
dl = ',';
hl = 1;
ev = NaN;
fmat = ['%s','%f'];

% load the file
fprintf('%s is now loading. ',deblank(file(str2double(fnum),:)))
fprintf('Please wait.\n')
data=...
    textscan(fid1,fmat,'headerlines',hl,'delimiter',dl,'emptyvalue',ev);

% close the file
fclose(fid1);
% define the cell with the date information and power purchased
dnum=char(deblank(data{1,1}));
pow=data{1,2};
n=length(pow)/4;
clear ftype d nf j data

fnum=input('\nPlease select the file with LAHC''s attributes\n','s');
fprintf('\n')

% get the file identifier for file to be loaded
fid2=fopen(deblank(file(str2double(fnum),:)));

% define the delimiter, the header lines to be skipped and the empty value
dl = ',';
hl = 1;
ev = NaN;
fmat =['%f','%f','%f','%f'];

% load the file
fprintf('%s is now loading. ',deblank(file(str2double(fnum),:)))
fprintf('Please wait.\n')
data=...
```

```
    textscan(fid2,fmat,'headerlines',hl,'delimiter',dl,'emptyvalue',ev);
ypop=data{1,1};
building=data{1,2};
students=data{1,3};
efficiency=data{1,4};

% close the file
fclose(fid2);
clear ftype d file nf j data


% initialize the vectors for the agregated power and datenum and year,
% month, day, hour, minute and second.
ag_pow=NaN*ones(n,1);
ag_dnum=NaN*ones(n,1);
sday=datenum(dnum(1,:));
year=NaN*ones(n,1);
month=NaN*ones(n,1);
day=NaN*ones(n,1);
hour=NaN*ones(n,1);
minute=NaN*ones(n,1);
second=NaN*ones(n,1);

% create the hourly data for the power purchased from LADWP and
% corresponding date number
for j=1:n
    ag_pow(j)=nansum(pow(1+4*(j-1):4*(1+(j-1))));
    ag_dnum(j)=sday+(j-1)/24;
    [year(j),month(j),day(j),hour(j),minute(j),...
        second(j)]=datevec(ag_dnum(j));
end

% set the inital power and date number to the aggregated values
pow=ag_pow;
dnum=ag_dnum;
dayofweek=datestr(dnum,'d');
wkend_in=sort(strfind(dayofweek','S'));
wkday_in=sort([strfind(dayofweek','M'),strfind(dayofweek','T'),...
    strfind(dayofweek','W'),strfind(dayofweek','F')]);
we_pow=pow;
we_pow(wkday_in)=NaN;
wd_pow=pow;
wd_pow(wkend_in)=NaN;

% determine the years
yr=year(1):1:year(end);

% set the size the data cubes by maximum days in a leap year, hours in a
% day and the number of years data is available
n=366;
m=24;
p=length(yr);

% initialize all the data cubes
% overall data
yr_pow=NaN*ones(n,m,p);
hr_stats=NaN*ones(m,p,2);
wkday_hr_stats=NaN*ones(p,m);
wkend_hr_stats=NaN*ones(p,m);
doy_stats=NaN*ones(n,p,2);
wkday_pow=NaN*ones(n,m,p);
```

```
wkend_pow=NaN*ones(n,m,p);
wkday_doy_stats=NaN*ones(n,p,2);
wkend_doy_stats=NaN*ones(n,p,2);

fprintf('\nStatistics for each day being calculated now. Please wait.\n')
% Loop through and calculate all relevant statistics
for i=1:p
    for j=1:m
        % search for all the individual hours and determine their
        % statistics
        in=find(year==yr(i)&hour==j-1);
        len=length(in);
        hr_stats(j,i,1)=nanmean(pow(in));
        hr_stats(j,i,2)=nanstd(pow(in));
        wkday_hr_stats(i,j)=nanmean(wd_pow(in));
        wkend_hr_stats(i,j)=nanmean(we_pow(in));


        % Determine the indicies for the winter, spring, summer and autumn
        % power usage. The following are the assumptions for the seasonal
        % indicies
        % Winter: Jan 1 - Mar 31
        % Spring: Apr 1 - Jun 30
        % Summer: Jul 1 - Sep 30
        % Autumn: Oct 1 - Dec 31
        % Note julian is a function I wrote to determine the Julian or day
        % of the year using a cummulative sum of the native Matlab function
        % eomday (end of month day).

        % Determine the jth hour power purchased.
        yr_pow(1:len,j,i)=pow(in);
        wkend_pow(1:len,j,i)=we_pow(in);
        wkday_pow(1:len,j,i)=wd_pow(in);

        % if the statistics for the last hour of the day has been
        % evaluated, calculate the statisitcs for the entire day
        if j==m
            % calculate the overall statistics
            for k=1:len
                doy_stats(k,i,1)=nanmean(yr_pow(k,:,i));
                doy_stats(k,i,2)=nanstd(yr_pow(k,:,i));
                wkday_doy_stats(k,i,1)=nanmean(wkday_pow(k,:,i));
                wkday_doy_stats(k,i,2)=nanstd(wkday_pow(k,:,i));
                wkend_doy_stats(k,i,1)=nanmean(wkend_pow(k,:,i));
                wkend_doy_stats(k,i,2)=nanstd(wkend_pow(k,:,i));
            end
        end
    end
end

% wkend_month_hr and wkday_month_hr are data cubes containing the hourly
% monthly averages by hour x month x year
wkend_month_hr=NaN*ones(m,12,p);
wkday_month_hr=NaN*ones(m,12,p);
all_month_hr=NaN*ones(m,12,p);
sday=[1,cumsum(eomday(2008,1:11))+1]';
eday=cumsum(eomday(2008,1:12))';
fprintf('\nDaily statistics calculations are now finished.\n')
fprintf('\nMonthly statistics now being calculated. Please wait.\n')
for k=1:p
    for j=1:12
```

```
        for i=1:m
            wkend_month_hr(i,j,k)=nanmean(wkend_pow(sday(j):eday(j),i,k));
            wkday_month_hr(i,j,k)=nanmean(wkday_pow(sday(j):eday(j),i,k));
            all_month_hr(i,j,k)=nanmean(yr_pow(sday(j):eday(j),i,k));
        end
    end
end
fprintf('\nmonthly statistics calculations are now finished.\n')
% end calculations

% open the data files for writing

if ~isdir('./Data/')
    mkdir ./Data/LADWP
    mkdir ./Data/Solar_PV
end
fprintf('\nbegin writing data to files.\n')

fid3=fopen('./Data/LADWP/LAHC_preconstruction_demand.dat','w');
fid4=fopen('./Data/LADWP/LAHC_construction_demand.dat','w');
fid5=fopen('./Data/LADWP/LAHC_construction_PV_demand.dat','w');
for i=1:n
    if(i==1)
        % creating the header
        fprintf(fid3,'Date\t');
        fprintf(fid4,'Date\t');
        fprintf(fid5,'Date\t');
        for k=1:m
            fprintf(fid3,'%4.0f:00\t',k-1);
            fprintf(fid4,'%4.0f:00\t',k-1);
            fprintf(fid5,'%4.0f:00\t',k-1);
            if k==m
                fprintf(fid3,'\n');
                fprintf(fid4,'\n');
                fprintf(fid5,'\n');
            end
            % finished creating the header
        end
    end
    % write the dates to the files
    fprintf(fid3,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    fprintf(fid4,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    fprintf(fid5,'%s\t',datestr(dnum((24*i)),'mmm-dd'));
    for j=1:m
        % calculate the averages
        % preconstruction period 2004 - 2007
        fprintf(fid3,'%7.2f\t',nanmean(yr_pow(i,j,1:4)));
        % construction period 2008 - 2009
        fprintf(fid4,'%7.2f\t',nanmean(yr_pow(i,j,5:6)));
        % construction period with PV 2010 - 2011
        fprintf(fid5,'%7.2f\t',nanmean(yr_pow(i,j,7:8)));
        if j==m
            fprintf(fid3,'\n');
            fprintf(fid4,'\n');
            fprintf(fid5,'\n');
        end
    end
end

%close the data files
fclose(fid3);
```

```
fclose(fid4);
fclose(fid5);

for n=1:8
    fid6=fopen(['./Data/LADWP/LAHC_monthly_weekday_' num2str(yr(n))
'.dat'],'w');
    fid7=fopen(['./Data/LADWP/LAHC_monthly_weekend_' num2str(yr(n))
'.dat'],'w');
    for i=1:12
        if(i==1)
            % creating the header
            fprintf(fid6,'Date\t');
            fprintf(fid7,'Date\t');
            for k=1:m
                fprintf(fid6,'%4.0f:00\t',k-1);
                fprintf(fid7,'%4.0f:00\t',k-1);
                if k==m
                    fprintf(fid6,'\n');
                    fprintf(fid7,'\n');
                end
                % finished creating the header
            end
        end
        % write the dates to the files
        fprintf(fid6,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        fprintf(fid7,'%s\t',datestr(dnum((1+24*32*(i-1))),3));
        for j=1:m
            fprintf(fid6,'%7.2f\t',nanmean(wkday_month_hr(j,i,n)));
            fprintf(fid7,'%7.2f\t',nanmean(wkend_month_hr(j,i,n)));
            if j==m
                fprintf(fid6,'\n');
                fprintf(fid7,'\n');
            end
        end
    end
    fclose(fid6);
    fclose(fid7);
end
fprintf('\nData file are now finished.\n')
% create the matrices for the regression of weekday and weekend energy
% demand. Each matrix is the difference from the baseline year, which is
% defined as the first year with available data.
wkday_hr_stats_diff=zeros(size(wkday_hr_stats));
wkday_hr_stats_diff(2:end,:)=cumsum(diff(wkday_hr_stats));
wkend_hr_stats_diff=zeros(size(wkend_hr_stats));
wkend_hr_stats_diff(2:end,:)=cumsum(diff(wkend_hr_stats));

% find the attributes of LAHC for the preiod when demand data exists
rein=find(ypop>=yr(1)&ypop<yr(end-1));
darea=zeros(length(yr)-2,1);
darea(2:end,:)=cumsum(diff(building(rein)));
dstudents=zeros(length(yr)-2,1);
dstudents(2:end,:)=cumsum(diff(students(rein)));
defficiency=zeros(length(yr)-2,1);
defficiency(2:end,:)=cumsum(diff(efficiency(rein)));

% create the regressor matrices
fprintf('\ncreating the regression equations now.\n')
regressor1=[ones(length(yr)-2,1),darea/1000];
regressor2=[ones(length(yr)-2,1),darea/1000,dstudents,...
    darea/1000.*dstudents];
```

```
alpha=0.05;
b_wkday=NaN*ones(4,24);
bint_wkday_lower=NaN*ones(4,24);
bint_wkday_upper=NaN*ones(4,24);
r_wkday=NaN*ones(6,24);
rint_wkday_lower=NaN*ones(6,24);
rint_wkday_upper=NaN*ones(6,24);
stats_wkday=NaN*ones(4,24);
b_wkend=NaN*ones(4,24);
bint_wkend_lower=NaN*ones(4,24);
bint_wkend_upper=NaN*ones(4,24);
r_wkend=NaN*ones(6,24);
rint_wkend_lower=NaN*ones(6,24);
rint_wkend_upper=NaN*ones(6,24);
stats_wkend=NaN*ones(4,24);

for i=1:m
    if(i<7||i>20)
        [b,bint,r,rint,stats]=...
            regress(wkday_hr_stats_diff(1:end-2,i),regressor1,alpha);
        b_wkday(1:2,i)=b;
        bint_wkday_lower(1:2,i)=bint(:,1);
        bint_wkday_upper(1:2,i)=bint(:,2);
        r_wkday(:,i)=r;
        rint_wkday_lower(:,i)=rint(:,1);
        rint_wkday_upper(:,i)=rint(:,2);
        stats_wkday(:,i)=stats';
        [b,bint,r,rint,stats]=...
            regress(wkend_hr_stats_diff(1:end-2,i),regressor1,alpha);
        b_wkend(1:2,i)=b;
        bint_wkend_lower(1:2,i)=bint(:,1);
        bint_wkend_upper(1:2,i)=bint(:,2);
        r_wkend(:,i)=r;
        rint_wkend_lower(:,i)=rint(:,1);
        rint_wkend_upper(:,i)=rint(:,2);
        stats_wkend(:,i)=stats';
    else
        [b,bint,r,rint,stats]=...
            regress(wkday_hr_stats_diff(1:end-2,i),regressor2,alpha);
        b_wkday(:,i)=b;
        bint_wkday_lower(:,i)=bint(:,1);
        bint_wkday_upper(:,i)=bint(:,2);
        r_wkday(:,i)=r;
        rint_wkday_lower(:,i)=rint(:,1);
        rint_wkday_upper(:,i)=rint(:,2);
        stats_wkday(:,i)=stats';
        [b,bint,r,rint,stats]=...
            regress(wkend_hr_stats_diff(1:end-2,i),regressor2,alpha);
        b_wkend(:,i)=b;
        bint_wkend_lower(:,i)=bint(:,1);
        bint_wkend_upper(:,i)=bint(:,2);
        r_wkend(:,i)=r;
        rint_wkend_lower(:,i)=rint(:,1);
        rint_wkend_upper(:,i)=rint(:,2);
        stats_wkend(:,i)=stats';
    end
end

fprintf('\nAll regression equations now finished.\n')
regin=find(ypop>2009);
n=length(regin);
```

```
regress_input=zeros(n,4);
regress_input(:,1)=ypop(regin);
regress_input(2:end,2)=cumsum(diff(building(regin)/1000));
regress_input(2:end,3)=cumsum(diff(students(regin)));
regress_input(:,4)=regress_input(:,2).*regress_input(:,3);

wkday_month_yr_predict=NaN*ones(m,12,n);
wkend_month_yr_predict=NaN*ones(m,12,n);

fprintf('\nCreating demand predictions from %4.0f ',regress_input(1,1))
fprintf('to %4.0f\n',regress_input(end,1))
for i=1:n
    for j=1:m
        if j<7||j>20
        wkday_month_yr_predict(j,:,i)=wkday_month_hr(j,:,6)+...
            b_wkday(1,j)+b_wkday(2,j)*regress_input(i,2);
        wkend_month_yr_predict(j,:,i)=wkend_month_hr(j,:,6)+...
            b_wkend(1,j)+b_wkend(2,j)*regress_input(i,2);
        end
        if j>=7&&j<=20
        wkday_month_yr_predict(j,:,i)=wkday_month_hr(j,:,6)+...
            b_wkday(1,j)+b_wkday(2,j)*regress_input(i,2)+...
            b_wkday(3,j)*regress_input(i,3)+...
            b_wkday(4,j)*regress_input(i,4);
        wkend_month_yr_predict(j,:,i)=wkend_month_hr(j,:,6)+...
            b_wkend(1,j)+b_wkend(2,j)*regress_input(i,2)+...
            b_wkend(3,j)*regress_input(i,3)+...
            b_wkend(4,j)*regress_input(i,4);
        end
    end
end
fprintf('\nFinished creating demand predictions.\n')
fprintf('\nNow begin writing data to files for use in RESET.\n')

for p=1:n
    fid8=fopen(['./Data/LADWP/LAHC_monthly_weekday_demand_predictions_'...
        num2str(regress_input(p,1)) '.dat'],'w');
    fid9=fopen(['./Data/LADWP/LAHC_monthly_weekend_demand_predictions_'...
        num2str(regress_input(p,1)) '.dat'],'w');
    for i=1:12
        if(i==1)
            % creating the header
            fprintf(fid8,'Date\t');
            fprintf(fid9,'Date\t');
            for k=1:m
                fprintf(fid8,'%4.0f:00\t',k-1);
                fprintf(fid9,'%4.0f:00\t',k-1);
                if k==m
                    fprintf(fid8,'\n');
                    fprintf(fid9,'\n');
                end
                % finished creating the header
            end
        end
        % write the dates to the files
        fprintf(fid8,'%s\t',datestr(datenum(regress_input(p,1),i,14),3));
        fprintf(fid9,'%s\t',datestr(datenum(regress_input(p,1),i,14),3));
        for j=1:m
            fprintf(fid8,'%7.2f\t',wkday_month_yr_predict(j,i,p));
            fprintf(fid9,'%8.2f\t',wkend_month_yr_predict(j,i,p));
            if j==m
```

```
                fprintf(fid8,'\n');
                fprintf(fid9,'\n');
            end
        end
    end
    fclose(fid8);
    fclose(fid9);
end
fprintf('\nFinished writing data files for demand predictions.\n')


for i=1:length(yr)
    Hour_vector=linspace(0,23,24);
    Day_vector=linspace(1,366,366);
    Month_vector=(15:30:366)';
    figure;
    pcolor(Day_vector,Hour_vector,yr_pow(:,:,i)');
    shading interp
    hold on
    [c,h]=contour(Day_vector,Hour_vector,yr_pow(:,:,i)');
    xt=15:30:366;
    yt=[0,3:3:18,20,23]';
    set(gca,'fontweight','bold','fontsize',12,...
        'xlim',[Day_vector(1) Day_vector(end)],'xtick',xt,'ytick',yt);
    datetick('x',3,'keepticks')
    colorbar
    xlabel(' Month ')
    ylabel(' Hour of Day ')
    title([' LAHC Daily Demand - ' num2str(yr(i)) '   '])
    figext='.png';
    figtype='png';
    figfile=['./Figures/LADWP/LAHC_Demand.' num2str(yr(i)) figext];
    saveas(gcf,figfile,figtype);
end

for i=1:length(yr)
    figure;
    pcolor(Month_vector,Hour_vector,wkday_month_hr(:,:,i));
    shading interp
    hold on;
    [c,h]=contour(Month_vector,Hour_vector,wkday_month_hr(:,:,i),...
        'linestyle',':','linecolor','k','linewidth',1.0);
    clabel(c,h,'fontweight','bold','color','k');
    set(gca,'fontweight','bold','fontsize',12,...
        'xtick',xt,'ytick',yt);
    datetick('x',3,'keepticks')
    colorbar
    xlabel(' Month ')
    ylabel(' Hour of Day ')
    title([' LAHC Monthly Demand - ' num2str(yr(i)) '   '])
    figext='.png';
    figtype='png';
    figfile=['./Figures/LADWP/LAHC_Demand_Monthly.' num2str(yr(i)) figext];
    saveas(gcf,figfile,figtype);
end


te=toc(t0);
fprintf('\nThe program run time was %6.2f seconds.\n\n',te)
```

Scenario Results

Solar Generation Scenario

Technology	Renewable Generation Factor: 1.36		
	Optimal Capacity	Optimal NPV	NPV, 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$152,796
Valve Regulated Lead-Acid Batteries	0	$0.00	-$211,457
Nickel Cadmium Batteries	0	$0.00	-$884,497
Zinc Bromine Batteries	0	$0.00	-$419,297
Sodium Sulfur Batteries	0	$0.00	-$835,351
Lithium-ion Batteries	0	$0.00	-$1,125,045
Vandium Redox Batteries	0	$0.00	-$639,776

Electricity Demand Scenario

Technology	Electricity Demand: -2%		
	Optimal Capacity	Optimal NPV	NPV, 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$192,765
Valve Regulated Lead-Acid Batteries	0	$0.00	-$251,426
Nickel Cadmium Batteries	0	$0.00	-$924,466
Zinc Bromine Batteries	0	$0.00	-$459,266
Sodium Sulfur Batteries	0	$0.00	-$875,320
Lithium-ion Batteries	0	$0.00	-$1,165,014
Vandium Redox Batteries	0	$0.00	-$679,745

Pricing Scenarios

Technology	Discount Rate, 0%			Discount Rate, 2%		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$272,896	0	$0.00	-$258,470
Valve Regulated Lead-Acid Batteries	0	$0.00	-$333,730	0	$0.00	-$319,209
Nickel Cadmium Batteries	0	$0.00	-$1,315,327	0	$0.00	-$1,208,514
Zinc Bromine Batteries	0	$0.00	-$645,650	0	$0.00	-$601,258
Sodium Sulfur Batteries	0	$0.00	-$1,261,471	0	$0.00	-$1,165,999
Lithium-ion Batteries	0	$0.00	-$1,770,442	0	$0.00	-$1,610,927
Vandium Redox Batteries	0	$0.00	-$997,298	0	$0.00	-$911,850

Technology	Discount Rate, 55%		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$154,270
Valve Regulated Lead-Acid Batteries	0	$0.00	-$199,718
Nickel Cadmium Batteries	0	$0.00	-$720,226
Zinc Bromine Batteries	0	$0.00	-$348,253
Sodium Sulfur Batteries	0	$0.00	-$491,729
Lithium-ion Batteries	0	$0.00	-$647,040
Vandium Redox Batteries	0	$0.00	-$521,268

Technology	Electricity Credits: High & Low peak =$.03, Base = $.016		
	Optimal Capacity	**Optimal NPV**	**NPV at 500 Capacity**
Flooded Cell Lead-Acid Batteries	0	$0.00	-$217,246
Valve Regulated Lead-Acid Batteries	0	$0.00	-$275,907
Nickel Cadmium Batteries	0	$0.00	-$948,947
Zinc Bromine Batteries	0	$0.00	-$483,747
Sodium Sulfur Batteries	0	$0.00	-$899,801
Lithium-ion Batteries	0	$0.00	-$1,189,495
Vandium Redox Batteries	0	$0.00	-$704,227

Technology	Price on Carbon, $15			Price on Carbon, $80		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$217,123	0	$0.00	-$217,043
Valve Regulated Lead-Acid Batteries	0	$0.00	-$275,784	0	$0.00	-$275,705
Nickel Cadmium Batteries	0	$0.00	-$948,824	0	$0.00	-$948,745
Zinc Bromine Batteries	0	$0.00	-$483,624	0	$0.00	-$483,545
Sodium Sulfur Batteries	0	$0.00	-$899,678	0	$0.00	-$899,599
Lithium-ion Batteries	0	$0.00	-$1,189,372	0	$0.00	-$1,189,293
Vandium Redox Batteries	0	$0.00	-$704,103	0	$0.00	-$704,024

Technology	Electricity Growth Rate, 0%			Electricity Growth Rate, 10%		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$217,145	0	$0.00	-$217,129
Valve Regulated Lead-Acid Batteries	0	$0.00	-$275,807	0	$0.00	-$275,790
Nickel Cadmium Batteries	0	$0.00	-$948,846	0	$0.00	-$948,830
Zinc Bromine Batteries	0	$0.00	-$483,647	0	$0.00	-$483,630
Sodium Sulfur Batteries	0	$0.00	-$899,701	0	$0.00	-$899,685
Lithium-ion Batteries	0	$0.00	-$1,189,395	0	$0.00	-$1,189,378
Vandium Redox Batteries	0	$0.00	-$704,126	0	$0.00	-$704,110

Technology	Electricity Rates: 0%, Price on Carbon:$15 , Discount Rate: 0%, Electricity Credits: 0			Electricity Rates: 10%, Price on Carbon:$80 , Discount Rate: 55%, Electricity Credits: $.03,$.03,$.016		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$217,145	0	$0.00	-$217,129
Valve Regulated Lead-Acid Batteries	0	$0.00	-$275,807	0	$0.00	-$275,790
Nickel Cadmium Batteries	0	$0.00	-$948,846	0	$0.00	-$948,830
Zinc Bromine Batteries	0	$0.00	-$483,647	0	$0.00	-$483,630
Sodium Sulfur Batteries	0	$0.00	-$899,701	0	$0.00	-$899,685
Lithium-ion Batteries	0	$0.00	-$1,189,395	0	$0.00	-$1,189,378
Vandium Redox Batteries	0	$0.00	-$704,126	0	$0.00	-$704,110

Technology	Electricity Rates: 0%, Price on Carbon:$15 , Discount Rate: 0%,			Electricity Rates: 10%, Price on Carbon:$80 , Discount Rate: 55%,		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$272,882	0	$0.00	-$154,193
Valve Regulated Lead-Acid Batteries	0	$0.00	-$333,715	0	$0.00	-$199,641
Nickel Cadmium Batteries	0	$0.00	-$1,315,313	0	$0.00	-$720,148
Zinc Bromine Batteries	0	$0.00	-$645,635	0	$0.00	-$348,176
Sodium Sulfur Batteries	0	$0.00	-$1,261,457	0	$0.00	-$491,652
Lithium-ion Batteries	0	$0.00	-$1,770,428	0	$0.00	-$646,963
Vandium Redox Batteries	0	$0.00	-$997,284	0	$0.00	-$521,190

Technology	Electricity Rates: 0%, Price on Carbon:$15			Electricity Rates: 10%, Price on Carbon:$80		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0.00	-$217,127	0	$0.00	-$217,032
Valve Regulated Lead-Acid Batteries	0	$0.00	-$275,788	0	$0.00	-$275,693
Nickel Cadmium Batteries	0	$0.00	-$948,828	0	$0.00	-$948,733
Zinc Bromine Batteries	0	$0.00	-$483,628	0	$0.00	-$483,533
Sodium Sulfur Batteries	0	$0.00	-$899,683	0	$0.00	-$899,587
Lithium-ion Batteries	0	$0.00	-$1,189,376	0	$0.00	-$1,189,281
Vandium Redox Batteries	0	$0.00	-$704,108	0	$0.00	-$704,013

Technology Scenario

Technology	100% Round-trip efficiency			Capital Costs reduced 50%		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0	-$169,637.60	0	$0	-$114,588.26
Valve Regulated Lead-Acid Batteries	0	$0	-$211,713.48	0	$0	-$140,078.61
Nickel Cadmium Batteries	0	$0	-$596,377.10	0	$0	-$458,026.98
Zinc Bromine Batteries	0	$0	-$284,574.12	0	$0	-$195,766.87
Sodium Sulfur Batteries	0	$0	-$826,304.96	0	$0	-$734,429.96
Lithium-ion Batteries	0	$0	-$1,082,781.14	0	$0	-$869,857.56
Vandium Redox Batteries	0	$0	-$476,911.74	0	$0	-$355,989.51

Technology	Capital Costs reduced 75%			Capital Costs (-75%) & Effiency (100%)		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0	-$65,007.66	0	$0	-$53,979.70
Valve Regulated Lead-Acid Batteries	0	$0	-$73,912.48	0	$0	-$58,738.13
Nickel Cadmium Batteries	0	$0	-$236,558.05	0	$0	-$160,411.11
Zinc Bromine Batteries	0	$0	-$103,507.81	0	$0	-$79,580.10
Sodium Sulfur Batteries	0	$0	-$653,492.46	0	$0	-$635,992.46
Lithium-ion Batteries	0	$0	-$723,126.44	0	$0	-$702,991.77
Vandium Redox Batteries	0	$0	-$183,619.13	0	$0	-$127,664.50

Technology	100% Round-trip efficiency			Capital Costs reduced 50%		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	0	$0	-$98,395.69	0	$0	-$43,346.34
Valve Regulated Lead-Acid Batteries	0	$0	-$140,471.57	0	$0	-$68,836.69
Nickel Cadmium Batteries	0	$0	-$525,135.18	0	$0	-$386,785.07
Zinc Bromine Batteries	0	$0	-$213,332.21	0	$0	-$124,524.96
Sodium Sulfur Batteries	0	$0	-$755,063.05	0	$0	-$663,188.05
Lithium-ion Batteries	0	$0	-$1,011,539.22	0	$0	-$798,615.65
Vandium Redox Batteries	0	$0	-$405,669.83	0	$0	-$284,747.60

Technology	Capital Costs reduced 75%			Capital Costs (-75%) & Effiency (100%)		
	Optimal Capacity	Optimal NPV	NPV at 500 Capacity	Optimal Capacity	Optimal NPV	NPV at 500 Capacity
Flooded Cell Lead-Acid Batteries	**358**	**$6,871**	$6,234.25	**1299**	**$27,879**	$17,262.22
Valve Regulated Lead-Acid Batteries	**115**	**$1,675**	-$2,670.57	**1078**	**$17,169**	$12,503.78
Nickel Cadmium Batteries	0	$0	-$165,316.13	0	$0	-$89,169.19
Zinc Bromine Batteries	0	$0	-$32,265.90	**115**	**$366**	-$8,338.18
Sodium Sulfur Batteries	0	$0	-$582,250.55	0	$0	-$564,750.55
Lithium-ion Batteries	0	$0	-$651,884.53	0	$0	-$631,749.86
Vandium Redox Batteries	0	$0	-$112,377.22	0	$0	-$56,422.59

With planned future generation at LAHC:	Break-even capacity	Break-even NPV	Optimal Capacity	Optimal NPV
"Dream" Technology	419	$0	115	$1,914