Economic Valuation of Energy Storage Coupled with Photovoltaics: Current Technologies and Future Projections

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Abstract

A practical framework for the economic valuation of current energy storage systems coupled with photovoltaic (PV) systems is presented. The solar-with-storage system's operation is optimized for two different rate schedules: (1) Time-of-use (TOU) for residential systems, and (2) Real-time wholesale rates for centralized generators. Nine storage technologies are considered for PV coupling, including six different battery chemistries, hydrogen electrolysis with a fuel cell, compressed air, and pumped-hydro energy storage. In addition, these technologies are assessed in the capacity of enabling a solar energy generator to provide a set service requirement. Concentrating solar thermal power (CSTP) with thermal storage is presented as a comparison for this final baseload scenario.

Some general insights were gained during the analysis of these technologies. It was discovered that there is a minimum power rating threshold for storage systems in a residential TOU market that is required to capture most of the benefits. This is about 1.5 kW for a 2 kW_P residential PV system. It was found that roundtrip efficiency is extremely important for both TOU and real-time markets, but low self-discharge rates are even more critical in real-time rate schedules. It was also estimated that large storage systems for centralized generation would capture the most revenue with a power rating twice that of the storage capacity (2 hours of discharge). However, due to cost limitations, actual optimal ratios were calculated to be about 3 to 7 hours of discharge for operation in a real-time market.

None of the current technologies considered are able to economically meet the requirements for a residential TOU rate schedule; and only CSTP with thermal storage, pumped-hydro, and potentially compressed air storage are able to offer value in a centralized real-time market or a baseload scenario. Recommendations for future research and development (R&D) on the various storage technologies are given. For many of the electrochemical batteries, the key focus areas include cycle lifetime as well as energy and power costs. Roundtrip efficiency was identified as the weak-point of hydrogen systems; the energy cost of lithium-ion batteries was found to be prohibitively expensive for energy arbitrage applications; and the balance of system (BOS) and power costs were identified as the main focus areas for the larger pumped-hydro and compressed air storage systems.

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To my parents, for their unlimited love and support

and to Cari, for being my home…

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List of Acronyms

AC	Alternating Current
AM1.5G	Air Mass 1.5 Global constant
BOS	Balance of System
CAES	Compressed Air Energy Storage
CAISO	California Independent System Operator
CO2	Carbon Dioxide
CSTP	Concentrating Solar Thermal Power
DC	Direct Current
DNLP	Discrete Non-Linear Program
DoD	Depth-of-Discharge
DOE	Department of Energy
EERE	Energy Efficiency and Renewable Energy laboratory
EIA	Energy Information Administration
GAMS	General Algebraic Modeling System
GHG	Green House Gases
H2	Hydrogen
Insolation	Incident Solar Radiation
IPCC	Intergovernmental Panel on Climate Change
kW/MW	Kilowatt/Megawatt
kWh/MWh	Kilowatt-hour/Megawatt-hour
Li-ion	Lithium-ion
LP	Linear Program
NaS	Sodium Sulfur
NCDC	National Climatic Data Center
NiCd	Nickel Cadmium
NLP	Non-Linear Program
NOAA	National Oceanic and Atmospheric Administration
NPV	Net Present Value
NSRDB	National Solar Radiation Database
O&M	Operation and Maintenance
PCS	Power Control System
PHES	Pumped-Hydro Energy Storage
PQ	Power Quality
PV	Photovoltaic
R&D	Research and Development
SCE	Southern California Edison
SETP	Solar Energy Technologies Program
SNL	Sandia National Laboratories
T&D	Transmission and Distribution
TOD	Time-Of-Day
TOU	Time-Of-Use
VRB	Vanadium Redox Battery
ZnBr	Zinc-Bromide

1. Introduction

The Earth's climate is changing, with the global temperature now poised to rise more than a degree from its historical average, marking the largest deviation in over 10,000 years [1]. It has become apparent that the human processes of green house gas (GHG) emission and deforestation are the largest contributing factors to this unparalleled trend. With GHG emissions already exceeding the worst-case scenario projected by the Intergovernmental Panel on Climate Change (IPCC) [1], immediate action is not only required to mitigate future detrimental effects on human society, it is a moral obligation to the global ecosystem we are a part of. This is the underlying motivating factor for this work.

The following figure is compiled from CO_2 emissions projections by the Energy Information Administration (EIA) [2]; with the residential, commercial, and industrial sectors shown excluding electricity use. It can be seen that the electric power sector is responsible for approximately 40% of all U.S. CO_2 emissions and this does not look likely to change in the near future.

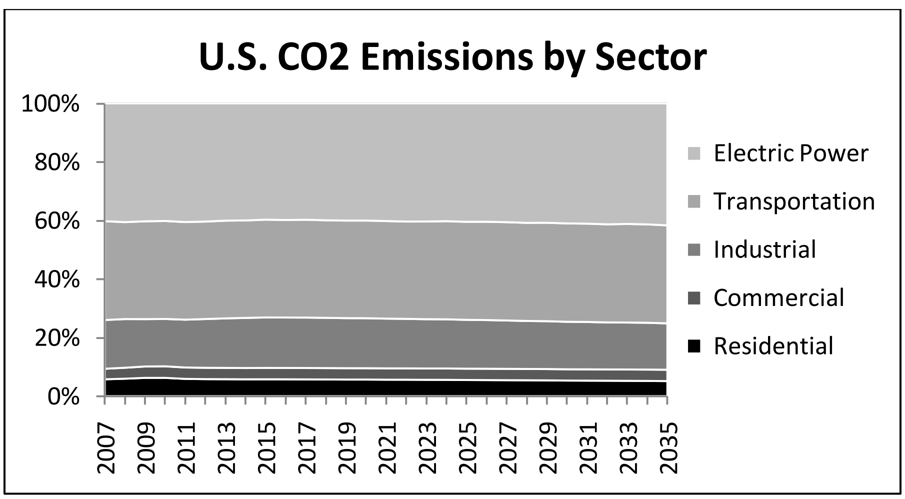

Figure 1.1-1: U.S. Emissions by Sector with Projections to 2035 [2]

Renewable energy technologies are a beacon of hope in this grim situation. However, there are major hurdles to the widespread adoption of many of these technologies to meet the nation's electricity needs; notably, intermittency and cost. The intermittent nature of renewable energy generation arises when the fuel source cannot be controlled directly. For example, solar can only produce energy when the sun is up, and wind turbines can only operate when it is windy. Although this work looks at photovoltaic (PV) solar generation, the principles and methods could be readily expanded to wind, tidal/ocean, or other intermittent generation sources. PV was chosen because it is one of the most rapidly growing renewable energy markets in the world. From an increasing penetration perspective, it becomes prudent to assess various means of controlling the intermittency, while at the same time increasing the value of this energy service. Relevant markets and scales include residential and centralized generation. On a longer time-scale, PV may be asked to provide a set service requirement as renewable energy technologies are required to provide baseload generation. This thesis will look at all three scenarios in turn.

The use of energy storage has the potential to help with both controlling intermittency as well as adding value to the system. In a time-varying electricity market (i.e. time-of-use or real-time pricing), storage can be used to shift generation from periods of low prices (off-peak) to those of higher worth (peak), as recognized by the Department of Energy's (DOE) Energy Efficiency and Renewable Energy (EERE) in the Solar Energy Technologies Program (SETP) Plan:

> Energy storage is an important element of advanced power management systems, as adding storage to a PV system has the potential to increase its value. [3]

Although this benefit may be the economic driving force behind the development and implementation of energy storage, it may also enable significant quantities of renewable generation on the electric grid, as the Power Quality Systems Director for the Power Quality Products Division of S&C Electric Company, Brad Roberts, noted:

> The real benefit [of storage] will come from optimizing the value of wind and solar resources by capturing even more megawatt hours of clean energy to power the world's ever expanding electric grids. [4]

There are several methods for handling the undesirable affects of intermittency (such as demand-side response and/or coupling solar with other generators). This work considers the use of energy storage to control the dispatch of centralized solar generation under the constraint of meeting a specific service requirement.

1.1. Central Questions

Utilizing energy storage with renewable generation, as well as to facilitate electricity grid functions, has been prevalent in recent literature (the reader is referred to many of the works cited in this thesis). Most of this work, however, looks at the benefit gained (economic and environmental) by adding the *concept* of energy storage, independent of current cost and/or performance metrics. For example, Bathurst and Strbac look at the value of adding energy storage to wind farms without considering the costs or performance of a specific storage technology [5]. Their goal is to develop an algorithm to optimize the dispatch of energy storage with wind generation, given both are already available. Another common approach is to explore a purely mathematical framework for the optimization of an unspecified generator with a black-box storage device; like in the work of Bannister and Kaye where they look at a novel method for the rapid optimization of storage systems [6]. Beyond pumped-hydro [7],[8] – see section 2.3.10 for technology description – the author has found little if any analysis assessing the state of current storage technologies in the context of being able to fully capture these benefits. Many of the benefits reported in these studies are not fully realizable with current technologies, or they are limited to niche markets. Valuable insight may be gained by looking at the economic and technological benchmarks that future storage technologies must meet in order to make these benefits accessible to larger markets. The central questions of this work thus become:

1. ***What is the current state of energy storage technologies in being able to capture benefits from a residential TOU electricity rate schedule?***
2. ***What is the current state of energy storage technologies in being able to capture benefits from a wholesale real-time electricity rate schedule?***
3. ***What is the current state of energy storage technologies in enabling centralized generation to meet a specified service requirement?***
4. ***What are the future technological and economic benchmarks for storage to more fully capture these benefits***?

In this work, 'larger markets' are taken to be grid-connected residential PV systems as well as centralized photovoltaic (PV) generation (utility-scale plants) in temporal electricity rate structures. It has also been common practice in recent work to optimize the charge/discharge profile of a storage device for only one day in advance. This is rational in a real-time market because the electricity price forecast accuracy degrades considerably the further into the future it is projected; hence, optimizing a storage profile for a week in advance would not make much sense. However, for residential time-of-use (TOU) rate schedules, the price forecast is known precisely. With this in mind, an optimization method is employed that allows for nocturnal, weekly, or seasonal energy arbitrage (time-shift of energy) to assess any additional utility that may be gained over the traditional daily optimization method for the appropriate markets. However, it is speculated that the added cost and energy losses due to physical limitations of the various storage devices will limit the optimization timeframe to within the realm of real-time pricing forecast error limitations.

This work aims to contribute both a novel means for optimizing energy storage investments as well as offering a snapshot of current storage technologies in the context of being able to enter the energy arbitrage market on a residential as well as a centralized scale. Further insights are offered as to what future energy storage technologies might look like in order to reap these benefits more fully.

2. Background

2.1. Review of Solar Energy

Incident solar radiation (insolation) can be harvested and transformed into a usable energy form by three different processes: thermal capture, the photovoltaic effect, or direct fuel production. The first method has been around since the 7th century B.C., when glass and mirrors were used to concentrate the sun's rays to start fires; and it was incorporated into passive solar building design as early as the 1st century A.D. [9]. The photovoltaic effect was discovered in 1839 by French scientist Edmond Becquerel [9], but it wasn't until the 1950s that modern crystalline silicon PV cells were discovered and then developed primarily for a very specific niche market: the space race [10]. Generating fuels from sunlight, like splitting water to yield hydrogen via artificial photosynthesis, has been the most recent development in capturing the sun's power. The recent work by MIT Professor Daniel Nocera has been very promising in this area [11].

This thesis will focus on the use of energy storage with photovoltaic (PV) generation. The other two solar technologies do not lend themselves to this analysis as readily because (1) solar fuel technologies generate their own storage by the very definition of their process (hence the reason for much of their appeal), and (2) solar thermal technologies have already been relatively successfully integrated with thermal storage. Recent work has been done with integrating a thermal storage medium (usually molten salt) into concentrating solar thermal power (CSTP) systems, both via government demonstration projects [12], as well as promising new research to increase efficiency and decrease cost of this technology [13],[3]. A natural advantage of developing storage for CSTP is the fact that no energy conversion is required for thermal storage. CSTP with thermal storage is used as a comparison for the baseload scenarios looked at in the last sections of this thesis. For PV, however, the energy being generated is in direct current (DC), which cannot be stored directly. Current electric energy storage technologies convert this electricity into another medium that can be stored such as heat (thermal storage), kinetic energy (mechanical storage), electrochemical energy (chemical batteries), or chemical bonds (fuels). The various technologies relevant to this work that exploit these processes are discussed in Section 2.3.

2.2. Review of Energy Storage Markets

There are many different potential markets available for energy storage, both for interfacing with a generation source as well as being used directly on the grid. Energy storage applications can be divided into two general functions: (1) power quality (PQ), and (2) energy arbitrage. This work will focus on the latter, primarily because the PQ market is already showing signs of being exploited [14]. Before the energy storage functions are broken down, definitions of common energy market terms are given.

Power Quality – Can include frequency and voltage regulation as well as backup power in case of outages.

Energy Arbitrage – Involves the storage of energy when the price and/or demand (usually both) is low, and then discharging/selling the energy when the price and/or demand is high.

Load-Following – Is the use of a storage device to match the generation profile of the grid to the rapidly fluctuating demand profile on the end-user side.

Frequency Regulation – Is the use of energy storage to maintain the frequency within the tolerance limits of the generators. The frequency can drop under conditions when demand increases faster than new generation can come online.

Transmission and Distribution (T&D) Deferral – Involves the temporary use of a storage device to allow the existing transmission line to operate for a longer time without being upgraded or replaced by increasing the peak-capacity of the transmission line.

TOU Cost Reduction – Is energy arbitrage on the user side of the meter to shift consumption from periods of high electricity rates to those of lower cost (end-user energy arbitrage).

Energy storage functions can be beneficial when supplied along a variety of locations on the electricity value chain [15].

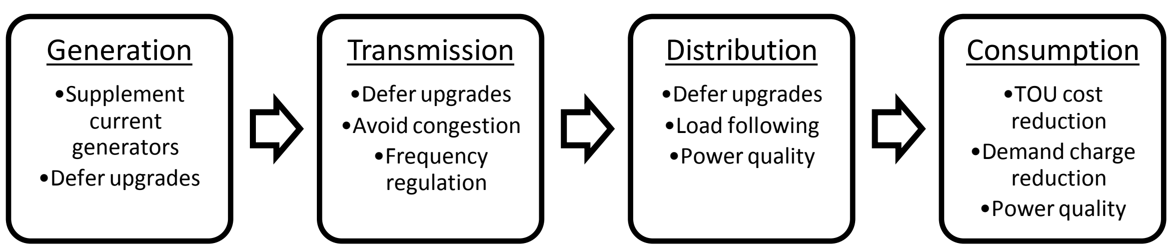

Figure 2.2-1: Potential Energy Storage Benefits Along Electricity Value Chain

The basic functions shown in Figure 2.2-1 are: supplementing existing generation sources (power quality and/or energy arbitrage), deferring upgrades of generators or transmission and distribution (T&D) lines, avoiding congestion in the transmission stage, load following (can be in the generation, distribution, or consumption functions), and several end-user benefits [15]. Everything prior to end-user consumption can be viewed as "utility-scale" or "centralized" applications, whereas the consumption section of the value chain is referred to as "residential-" or "commercial-scale".

In addition to the economic benefits along the value chain, environmental benefits may be realized from the use of energy storage. It is possible to arbitrage energy such that energy from cleaner generators (natural gas) offset the emissions from dirtier sources (coal and oil). However, it has been shown that significant revenue losses can be observed if a storage system is optimized purely for environmental benefit within a real-time pricing market [16]. Of course, if a price on GHG emissions were imposed, optimizing for economic benefits would at least partially include environmental concerns as well. Therefore, it is simplest to think of the optimization procedure as being with respect to perceived economic benefit, which may or may not reflect environmental effects.

Unfortunately, there are significant regulatory barriers that prevent storage technologies from capturing revenue streams from many of these markets. Notably, all of the T&D functions and many of the generation functions do not have a regulatory framework to facilitate integration into their rate base. A recent report by Pike Research LLC stated this problem concisely:

> Major regulatory hurdles must be met before storage can even be considered for use in some markets. According to the newly established Electricity Advisory Council, no cohesive plan exists as to how storage technologies will be incorporated into the grid. In addition, the current system does not credit the value of storage across the entire utility value chain. Generation, transmission and distribution are typically viewed discretely. The resulting challenge is the complete lack of a cost recovery system, and with no clear path for cost reimbursement, most utilities have opted not to invest in energy storage. It is easier for utilities to make investments in conventional approaches to addressing grid instability, such as natural gas spinning reserves, as these investments are sure to be covered by the regulatory rate base. [17]

Another issue that the above excerpt refers to is the fact that a single energy storage device is currently unable to capture revenues from multiple services along the value chain. A report by the DOE's Sandia National Laboratories (SNL) summarizes additional benefits of utilizing storage with renewable generation that are not accounted for in the current regulatory framework:

> Depending on where the storage is located, if it is used in conjunction with bulk renewables resources, then the benefits may also include: 1) avoided/deferred need to build or to purchase other generation capacity, 2) avoided/deferred need to build transmission capacity, 3) avoided transmission access charges, 4) avoided transmission congestion charges, 5) transmission support, and 6) ancillary services. [18]

As mentioned at the beginning of this section, this work focuses on the energy arbitrage market. The primary reason being that the PQ market has key players (ex. Beacon Power Corporation [14]) who have already entered onto the scene; whereas the only major players in the energy arbitrage market are geographically limited (pumped-hydro and compressed air energy storage). Energy arbitrage also offers the unique possibility of enabling baseload/firm generation from intermittent renewable energy sources, which is looked at in Section 4.3.

2.3. Review of Current Energy Storage Technologies

Within the framework of energy arbitrage, as discussed in the previous section, current energy storage technologies are evaluated on their potential to serve this market. The grayed-out region of Figure 2.3-1 indicates several storage technologies that are not appropriate for arbitrage. These include superconducting magnetic energy storage (SMES) systems, flywheels (low- and high-speed), and supercapacitors. The remaining storage technologies that could potentially perform arbitrage services are electrochemical batteries, flow batteries, compressed air energy storage (CAES), and pumped-hydro energy storage (PHES). Another technology which is not listed in the figure, but which is considered in this work, is electrolysis with hydrogen storage and a fuel cell (H2). Each technology considered in the analysis is described briefly in the following sections. First, however, an explanation of the dynamics of energy storage capital cost is given.

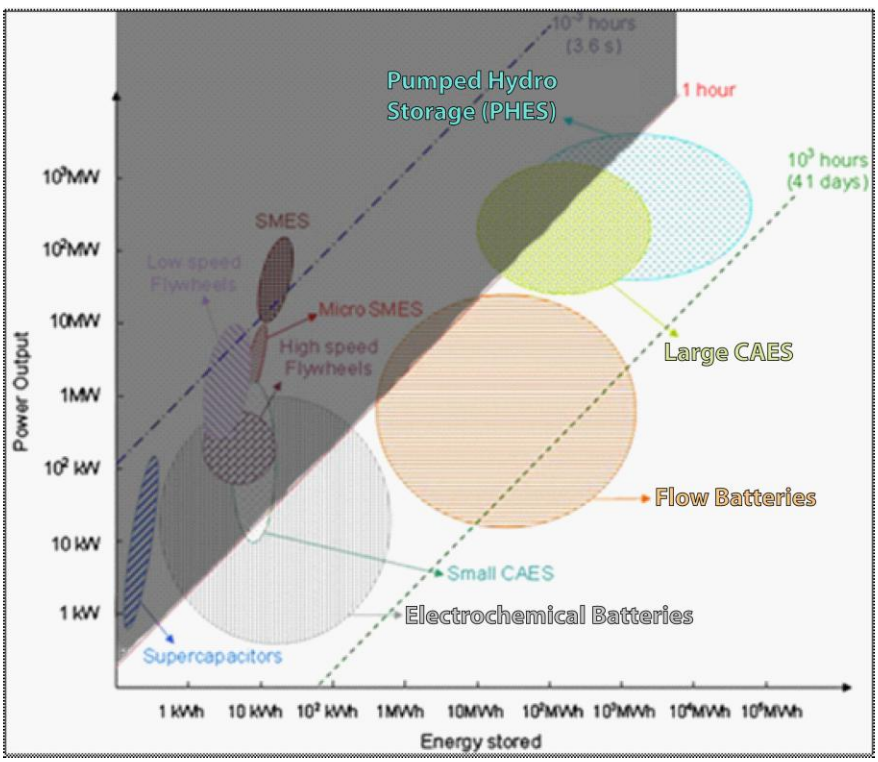

Figure 2.3-1: Feasible Storage Application Ranges [19]

2.3.1. A Note on Storage Capital Cost Estimation

While compiling cost information for this work, it was discovered that estimating the capital cost of a large storage facility can be an area of significant confusion, and is rarely addressed clearly (or even explicitly) in the literature. Hence, some clarifications are made here before the storage technologies are described.

Table 2-1: Power- and Energy-Related Capital Costs

Capital Expenditures	
BOS_P	Power-Related BOS Cost ($/kW)
BOS_E	Energy-Related BOS Cost ($/kWh)
C_P	Power-Related Storage Cost ($/kW)
C_E	Energy-Related Storage Cost ($/kWh)

The balance-of-system (BOS) cost is usually given as per unit power (BOS_P) *or* per unit energy (BOS_E), whereas the unit cost of actual storage device is given both on a power (C_P) and an energy (C_E) basis, as shown in Table 2-1. In addition, the BOS expense is often included in the unit storage costs. The cost of the power control system (PCS) is often included in the capital cost estimate; however, it is kept separate here because of the difference in the PCS lifetime and the total solar-with-storage system lifetime (see Section 3.3.2 for how PCS cost is included). An important distinction in storage system architectures must be addressed here. If a storage device is able to be sized for power and energy independently of one another, then the unit power and energy costs are given as separate components from which the total cost must be obtained by summing over power and energy requirements. If, however, the storage cell has a fixed power/energy ratio, then the costs are given as a complete system cost and either the power or the energy component must be used to find the total capital cost (whichever is higher). For example, if a 1 kW / 1 kWh battery cell cost $100 and the power and energy components cannot be sized independently, then the unit capital cost of this device would be *either* $100/kW *or* $100/kWh, and even if the storage *requirement* were only 1 kW / 0.5 kWh, the battery would still cost $100. The former system architecture will be referred to as a "flexible" system, and the latter as a "fixed" system for convenience.

For flexible systems, the capital cost may be computed as:

Equation 2-1: Total Capital Cost for Flexible Systems

$$Capital = (BOS_P + C_P) \cdot P + (BOS_E + C_E) \cdot E.$$

In this expression, BOS_P is the balance of system cost per unit power ($/kW), BOS_E is the balance of system cost per unit energy ($/kWh), C_P is the storage cost per unit power ($/kW), C_E is the storage cost per unit energy ($/kWh), P is the power rating of the storage device (kW), and E is the energy capacity of the storage device (kWh). This expression can be re-written as:

Equation 2-2: Simplified Total Capital Cost for Flexible Systems

$$Capital = TC_P \cdot P + TC_E \cdot E$$

if the total unit power cost is defined as $TC_P = BOS_P + C_P$, and the total unit energy cost is defined as $TC_E = BOS_E + C_E$.

For the fixed systems, the capital cost must be calculated as:

Equation 2-3: Total Capital Cost of Fixed Systems

$$Capital = \; max[(C_P \cdot P), (C_E \cdot E)] + BOS_P \cdot P + BOS_E \cdot E.$$

In this expression, $max[(C_P \cdot P), (C_E \cdot E)]$ is the maximum of the power and energy costs, respectively. Note that this expression does not lend itself to the simplification shown in Equation 2-2. A summary of these power- and energy-related costs for each technology to be analyzed is shown in Table 2-2 below.

Table 2-2: Storage Capital Cost Summary

Storage Technology	Lead-Acid	Li-Ion	NiCd	NaS	VRB	ZnBr	H2	CAES	PHES
System Architecture	Fix	Fix	Fix	Fix	Flex	Flex	Flex	Flex	Flex
Power-Related ($/kW)									
BOS_P	$0	$0	$0	$20	$0	$0	$0	$0	$0
C_P	$250	$333	$6,020	$1,500	$700	$300	$500	$425	$600
Energy-Related ($/kWh)									
BOS_E	$50	$0	$92	$0	$0	$0	$0	$50	$0
C_E	$150	$1,333	$600	$176	$230	$250	$15	$2	$12

The entries with a zero BOS cost have already included this expense in the C_P or C_E metrics.

Taking a large, 10 MW / 85 MWh, Sodium Sulfur (NaS) battery plant as an example, the distinction between the two system architectures can be illustrated. Using the proper method, where the energy and power components of the battery cell itself are fixed and cannot be sized independently, as shown in Equation 2-3, the upfront capital cost of the system would be:

$$Capital = \; max[(1{,}500 \cdot 10{,}000), (176 \cdot 85{,}000)] + 20 \cdot 10{,}000 = \$15.2 \; M.$$

However, if we assume energy and power are sized independently with the same respective unit costs for each as shown in Equation 2-1, then the capital cost would be nearly twice as much:

$$Capital = \; (20 + 1{,}500) \cdot 10{,}000 + 176 \cdot 85{,}000 = \$30.2 \; M.$$

Note that these capital costs do not include the PCS or fixed operation and maintenance (O&M) costs, which are discussed in Section 3.3.2.

2.3.2. Lead-Acid Batteries

A schematic of the discharge and charge states of an electrochemical battery (not just lead-acid) is shown in Figure 2.3-2 below. For a lead-acid battery, the oldest rechargeable battery chemistry, lead-dioxide serves as the cathode electrode, lead as the anode, and sulfuric acid is used as the electrolyte [20].

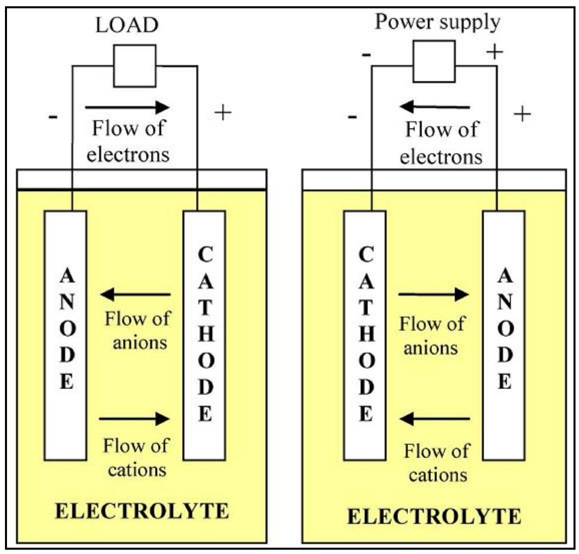

Figure 2.3-2: Discharge (left) and Charge (right) States of an Electrochemical Battery [20]

The main advantages of lead-acid batteries are their low capital and operation costs, and high efficiencies. However, their limited cycle and calendar lifetimes make them much less economical in energy arbitrage applications. These qualitative characteristics are summarized in Table 2-3.

Table 2-3: Lead-Acid Qualitative Characteristics

Advantages	Disadvantages
Low Capital Cost Good Roundtrip Efficiency Low Self-Discharge	Low Cycle Lifetime Low Calendar Lifetime

When available, key cost and performance metrics were obtained from the Sandia National Laboratories (SNL) 2001 report on energy storage characteristics and technologies (reference [21]). However, many other sources were utilized in an attempt to obtain the most recent information, and for technologies not listed in the SNL report. The key parameters for lead-acid batteries are listed in Table 2-4.

Table 2-4: Lead-Acid Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$150/kWh [22]
Power-Related Cost	$250/kW [21]
Balance of System Cost	$50/kWh [21]
Fixed O&M Cost	$1.55/kW-yr [21]
Variable O&M Cost	$0.01/kWh [21]
Roundtrip Efficiency	87.5% [21],[20]
Self-Discharge Rate	2%/month [20]
Cycle Lifetime	~1,500 [20]
Calendar Lifetime	10 years [20]

2.3.3. Lithium-Ion (Li-Ion) Batteries

Li-ion batteries have the same basic electrochemical architecture shown in Figure 2.3-2 above. In this case, the cathode is comprised of a lithiated metal oxide (such as LiCoO2 or LiMO2), the anode is made of graphitic carbon, and the electrolyte is composed of a lithium salt [23]. Li-ion batteries tend to be most beneficial for portable frequency regulation type applications because of their excellent energy density and much higher cycle lifetimes at lower depths-of-discharge (>3,000 at 80% DoD [23]).

Table 2-5: Li-Ion Qualitative Characteristics

Advantages	Disadvantages
Excellent Efficiencies	High Cost
High Energy Density	Low Cycle Lifetime

A summary of the qualitative characteristics is shown above in Table 2-5, and the quantitative metrics are given in Table 2-6.

Table 2-6: Li-Ion Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$1,333/kWh [24],[22]
Power-Related Cost	$333/kW [24]
Balance of System Cost	Included
Fixed O&M Cost	N/A [25]
Variable O&M Cost	N/A [25]
Roundtrip Efficiency	~95% [20]
Self-Discharge Rate	~3%/month [20],[25]
Cycle Lifetime	1,500 [20]
Calendar Lifetime	15 years [26]

2.3.4. Nickel-Cadmium (NiCd) Batteries

As with lead-acid and Li-ion batteries, the electrochemical architecture for NiCd batteries is the same as shown in Figure 2.3-2 above. The NiCd chemistry has been around almost as long as lead-acid batteries. They use nickel hydroxide for the anode material, cadmium hydroxide as the cathode, and an aqueous solution of mostly potassium hydroxide (small amounts of lithium hydroxide) as the electrolyte [25].

Table 2-7: NiCd Qualitative Characteristics

Advantages	Disadvantages
Long Calendar Lifetime	Higher Cost
Reliability	Moderate Efficiencies

A summary of the qualitative characteristics is shown above in Table 2-7, and the quantitative metrics are given in Table 2-8.

Table 2-8: NiCd Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$600/kWh [22]
Power-Related Cost	$6,020/kW [25]
Balance of System Cost	$92/kWh [25]
Fixed O&M Cost	$97/kW-yr [25]
Variable O&M Cost	$0 [25]
Roundtrip Efficiency	74% [20]
Self-Discharge Rate	10%/month [20]
Cycle Lifetime	~2,250 [20]
Calendar Lifetime	17 years [20]

2.3.5. Sodium-Sulfur (NaS) Batteries

Whereas most electrochemical batteries contain solid anodes and cathodes, and a liquid electrolyte; NaS batteries are comprised of liquid sulfur as the anode, liquid sodium as the cathode, and are separated (the "electrolyte") by a solid alumina ceramic [27]. This system architecture is shown in Figure 2.3-3. To maintain proper functioning, the liquid sulfur and sodium are kept at about 300^{0}C. This parasitic heat requirement is responsible for the relatively high self-discharge of ~17% per day [28].

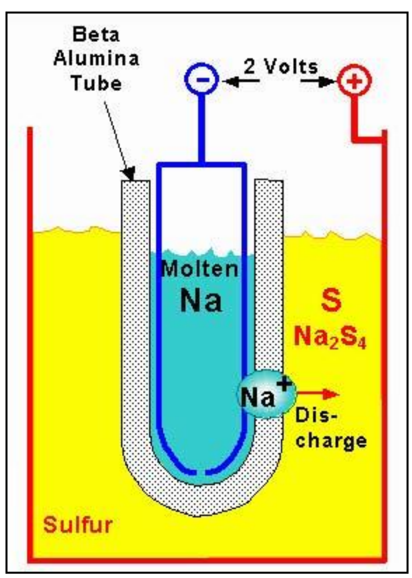

Figure 2.3-3: NaS Schematic [27]

The qualitative and quantitative characteristics are given in Table 2-9 and Table 2-10, respectively.

Table 2-9: NaS Qualitative Characteristics

Advantages	Disadvantages
Good Cycle & Calendar Lifetime	Fairly Expensive Parasitic Energy Requirement

Table 2-10: NaS Quantitative Characteristics

Parameter	Value
Energy-Related Cost	\$176/kWh [29]
Power-Related Cost	\$1,500/kW [29]
Balance of System Cost	\$20/kW [29]
Fixed O&M Cost	\$9/kW-yr [30]
Variable O&M Cost	\$0 [30]
Roundtrip Efficiency	76% [30],[31]
Self-Discharge Rate	~17%/day [28]
Cycle Lifetime	>3,000 [30]
Calendar Lifetime	15 years [30]

2.3.6. Vanadium Redox Flow Batteries (VRB)

A schematic of how a flow battery operates is shown in Figure 2.3-4. A liquid electrolyte is stored in external tanks and is pumped into reaction stacks (fuel cells) that converts the chemical energy into electricity (during discharge) or electricity into chemical energy (during charge) [29]. An advantage of flow batteries over conventional batteries is that the energy capacity (as determined by the volume of electrolyte and size of the storage tanks) can be sized independently from the power rating (as determined by the size of the reaction stacks).

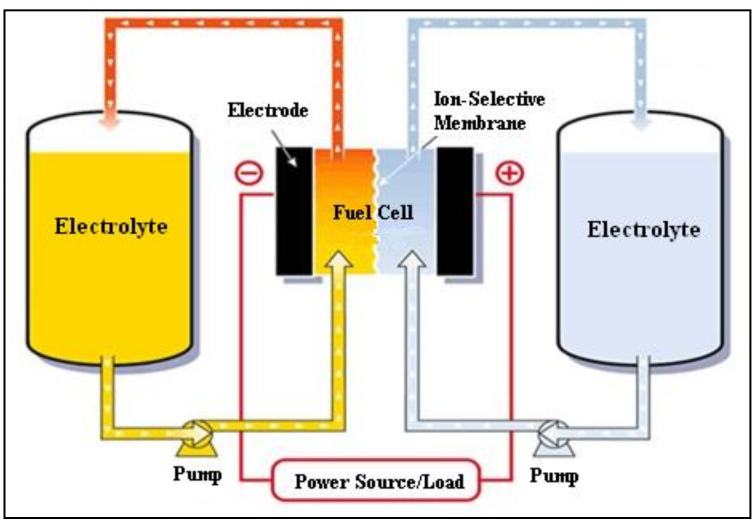

Figure 2.3-4: Flow Battery Schematic [32]

Another advantage is that although the reaction stacks of VRBs require replacement every 1,000 cycles or so, this is only a fraction of the entire system cost (~$375/kW) and most of the system will continue to operate for the lifetime of a PV array [29]. Refer to Table 2-11 for a summary of the qualitative characteristics, and Table 2-12 for the quantitative metrics.

Table 2-11: VRB Qualitative Characteristics

Advantages	Disadvantages
Energy and Power Sized Independently Good Efficiencies Long Lifetime of Electrolyte/Tanks	Mechanical Complexity Moderate Parasitic Losses (due to pumps)

Table 2-12: VRB Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$230/kWh [29]
Power-Related Cost	$700/kW [29]
Balance of System Cost	Included
Fixed O&M Cost	$4/kW-yr [29]
Variable O&M Cost	$0 [29]
Roundtrip Efficiency	85% [29],[33]
Self-Discharge Rate	7.5%/month [31]
Cycle Lifetime	1,250 [29]
Calendar Lifetime	12 years [29]

2.3.7. Zinc-Bromide (ZnBr) Flow Batteries

The operational characteristics of a ZnBr flow battery is the same as shown in Figure 2.3-4. Although the efficiencies are slightly below that of VRB, ZnBr flow batteries have a lower cost and at least one major manufacturing company (Premium Power, located in North Reading, MA) claims unlimited deep cycling capability. The company is very secretive about their metrics, however, and no justifications are given for this claim [24],[34]. Since a source could not be found that states otherwise, Premium Power's numbers were assumed accurate for the purposes of this analysis. A summary of the qualitative and quantitative metrics are given in Table 2-13 and Table 2-14, respectively.

Table 2-13: ZnBr Qualitative Characteristics

Advantages	Disadvantages
Low Cost Excellent Lifetime	Moderate Efficiencies

Table 2-14: ZnBr Quantitative Characteristics

Parameter	Value
Energy-Related Cost	\$250/kWh [24]
Power-Related Cost	\$300/kW [24]
Balance of System Cost	Included
Fixed O&M Cost	N/A [21]
Variable O&M Cost	\$0.004/kWh [34]
Roundtrip Efficiency	75% [35]
Self-Discharge Rate	13.5%/month [31]
Cycle Lifetime	Lifetime [34]
Calendar Lifetime	30 years [34]

2.3.8. Hydrogen Electrolysis with Fuel Cell (H2)

There are three key processes of a hydrogen storage system: electrolysis which uses electricity to produce hydrogen from water, storage of the hydrogen (many different forms/states can be used), and the use of a fuel cell to generate electricity from the stored hydrogen when it is desired. A schematic of how the fuel cell functions is shown in Figure 2.3-5. As with flow batteries, the energy and power ratings can be sized independently for a H2 system. However, the roundtrip efficiency is considerably less than flow batteries.

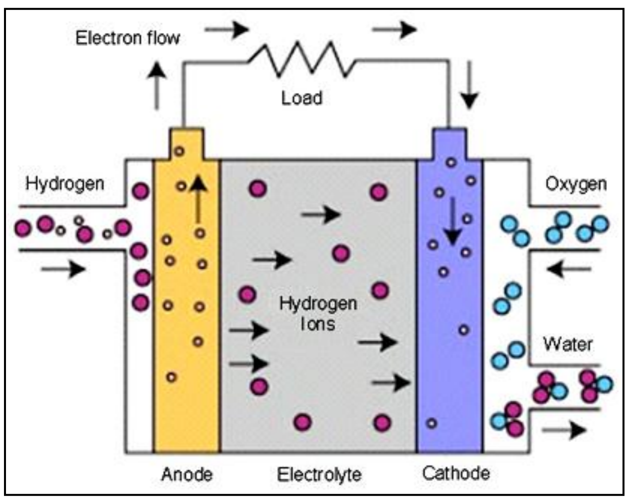

Figure 2.3-5: Hydrogen Fuel Cell Schematic [19]

A summary of the qualitative and quantitative metrics are given in Table 2-15 and Table 2-16, respectively.

Table 2-15: H2 Qualitative Characteristics

Advantages	Disadvantages
Low Energy Cost Good Lifetime	Low Efficiencies O&M Cost Complexity

Table 2-16: H2 Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$15/kWh [21]
Power-Related Cost	$500/kW [21]
Balance of System Cost	Included [21]
Fixed O&M Cost	$10/kW-yr [21]
Variable O&M Cost	$0.01/kWh [21]
Roundtrip Efficiency	59% [21]
Self-Discharge Rate	3%/day [20]
Cycle Lifetime	Lifetime [21]
Calendar Lifetime	17 years [21],[25]

2.3.9. Compressed Air Energy Storage (CAES)

CAES technology has been commercially developed since the late 1970s, but there is only one CAES facility in the U.S., which has been operating since 1991 in McIntosh, Alabama [29]. This is the only storage technology considered which has a fuel cost associated with its operation. In a CAES system, electricity is used to compress air during the charge cycle which is then released, heated in an expansion chamber with natural gas, and used to drive combustion AC turbines during the discharge cycle (see Figure 2.3-6).

The variable cost associated with the use of natural gas during the discharge cycle can be computed from the following relationship:

Equation 2-4: CAES Variable Operation Cost

$$Variable\ Cost\ \left({\$}/_{kWh}\right) = \frac{Fuel\ Cost\ \left({\$}/_{MMBtu}\right) \cdot Heat\ Rate\ \left({}^{Btu}/_{kWh}\right)}{1{,}000{,}000\ \left({}^{Btu}/_{MMBtu}\right)}.$$

Assuming a fuel cost of $3/MMBtu and a heat rate of 4,000 Btu/kWh [29], this equates to a variable O&M of $0.012/kWh. An interesting characteristic of CAES plants is that 2-3 times more energy is released during the discharge cycle than is spent in the compression stage. This is because of the additional energy from the natural gas. A simplification is made in this work by using an “effective” roundtrip efficiency of 85%, which accounts for the use of the fuel in the operational cycle [29].

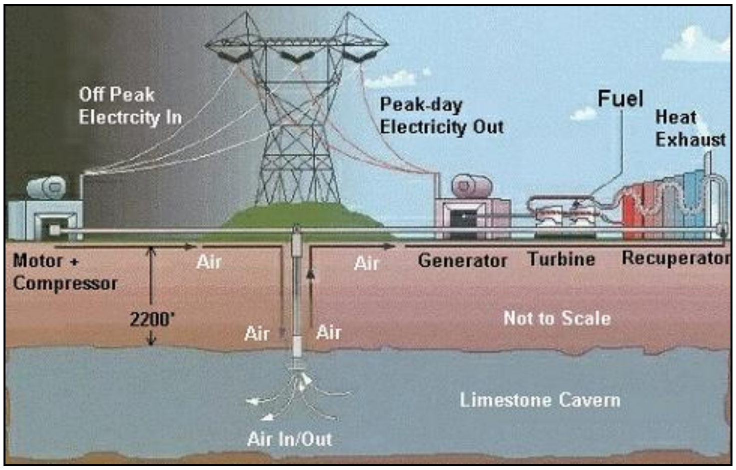

Figure 2.3-6: CAES Schematic [29]

For large CAES plants, it is most economical to store the compressed air in large underground caverns (salt caverns, rock caverns, or porous rock formations) [29]. The costs/metrics listed in this work correspond to CAES in salt caverns. Although somewhat geographically limited, CAES may still be viable for over 80% of the United States [29]. The qualitative and quantitative characteristics of this technology are shown in Table 2-17 and Table 2-18, respectively.

Table 2-17: CAES Qualitative Characteristics

Advantages	Disadvantages
Low Cost Good Efficiencies Excellent Lifetime	Geographically Limited

Table 2-18: CAES Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$2/kWh [29],[21]
Power-Related Cost	$400/kW [29],[21]
Balance of System Cost	$50/kWh [21]
Fixed O&M Cost	$1.42/kW-yr [21]
Variable O&M Cost	$0.012/kWh [29]
Roundtrip Efficiency	85% [29]
Self-Discharge Rate	0% [21]
Cycle Lifetime	Lifetime [21]
Calendar Lifetime	30 years [21]

2.3.10. Pumped-Hydro Energy Storage (PHES)

In PHES, the potential energy contained in an elevated body of water serves as the energy capacity. Generation and pumping can either be accomplished by single-unit reversible pump-turbines, or by separate pumps and generators [21]. Water is pumped from a lower reservoir up to the elevated reservoir during the charge cycle, and is released back down to the lower reservoir during discharge (see Figure 2.3-7).

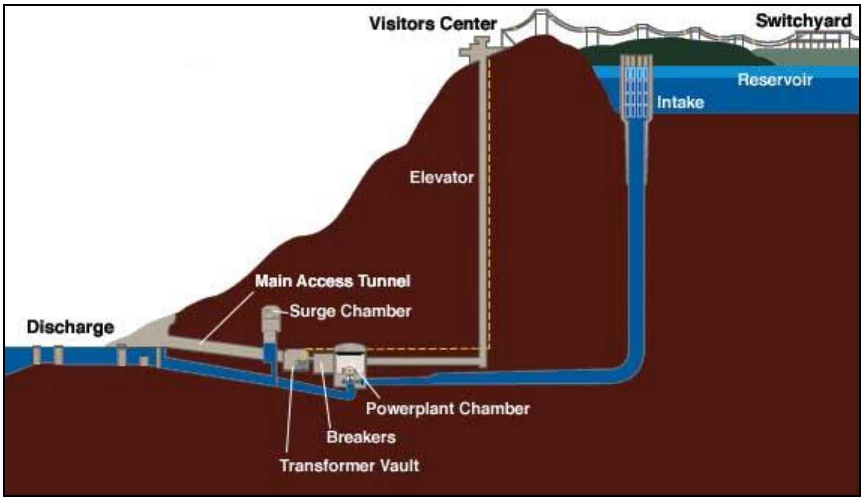

Figure 2.3-7: PHES Schematic [36]

This technology has been in development since the 1920s [21]. The qualitative characteristics are the same as for CAES and are shown in Table 2-19. The quantitative metrics are given in Table 2-20.

Table 2-19: PHES Qualitative Characteristics

Advantages	Disadvantages
Low Cost Good Efficiencies Excellent Lifetime	Geographically Limited

Table 2-20: PHES Quantitative Characteristics

Parameter	Value
Energy-Related Cost	$12/kWh [21]
Power-Related Cost	$600/kW [21]
Balance of System Cost	Included
Fixed O&M Cost	$3.8/kW-yr [21]
Variable O&M Cost	$0.0038/kWh [21]
Roundtrip Efficiency	87% [21]
Self-Discharge Rate	0% [21]
Cycle Lifetime	Lifetime [21]
Calendar Lifetime	30 years [21]

2.4. Description of Case Studies

In order to assess the value of adding energy storage in arbitrage applications, three case studies were chosen within the context of "larger markets". All three case studies are located close to Blythe, California, so that the level of incident solar radiation (insolation) would be consistent throughout. Blythe is also desirable because a local utility company, Southern California Edison (SCE), offers a TOU rate schedule. For the real-time pricing rates an average across the California Independent System Operator's (CAISO) entire region was used. The following subsections describe the relevant regional datasets.

2.4.1. Insolation Data

The insolation data for Blythe, CA, were obtained from the National Solar Radiation Database (NSRDB) as provided by the National Climatic Data Center (NCDC). Richard Perez, at the State University of New York in Albany, resolved high-resolution satellite data (10 km grid-squares) into both global and direct insolation components. Global insolation data are used for the PV simulations because the photovoltaic effect occurs with both direct and diffuse solar radiation, and the direct insolation data are used for the baseload concentrating solar thermal power (CSTP) simulations. This insolation data can be publicly downloaded from the National Oceanic and Atmospheric Administration's (NOAA) website cited here: [37]. In an attempt to simulate the average value of adding storage to a PV system, data from 1997 – 2005 were averaged to obtain a typical year. This insolation dataset, along with the electricity rates described below, is plotted for July 15th in Figure 2.4-1.

Hourly generation was computed from this hourly insolation data by multiplying the insolation for a given hour ($\Phi(\mathrm{h})$ in Wh/m^2) by the peak watt rating of the system ($\mathrm{W_P}$), and dividing by 1,000 W/m^2, the global Air Mass ($\mathrm{AM1.5}$) constant [38]:

Equation 2-5: Solar Energy Generation

$$Generation = \frac{\Phi(h) \cdot W_P}{AM1.5 \cdot 1{,}000}.$$

2.4.2. Pricing Data

The real-time hourly location marginal pricing (LMP) data were obtained from the CAISO public download site listed in the bibliography under this citation: [39]. The pricing dataset for 2008 was used, as this was the most recent complete dataset at the time it was retrieved. Since 2008 was a leap-year, pricing data for February 29th were removed from the dataset so that the timestamp would match the hourly insolation data (which omitted data from the leap-years of 2000 and 2004 before averaging). As seen in Figure 2.4-2, the bulk of wholesale electricity prices are in the range of 1 – 10 ¢/kWh with only a handful of peak-prices on the order of 25 – 40 ¢/kWh. Therefore, the value of energy arbitrage lies within shifting as much generation as possible from the bulk hours to the relatively few peak-price hours. The TOU rate schedule for SCE has both a time-of-day (TOD) and a seasonal variation. These distinctions are shown in Table 2-21. This rate schedule was obtained from the SCE utility company.

Table 2-21: SCE TOU Rate Schedule

Season / TOD	Electricity Price
Winter Off-Peak	17.59 ¢/kWh
Winter Peak	21.24 ¢/kWh
Summer Off-Peak	18.44 ¢/kWh
Summer Peak	36.06 ¢/kWh

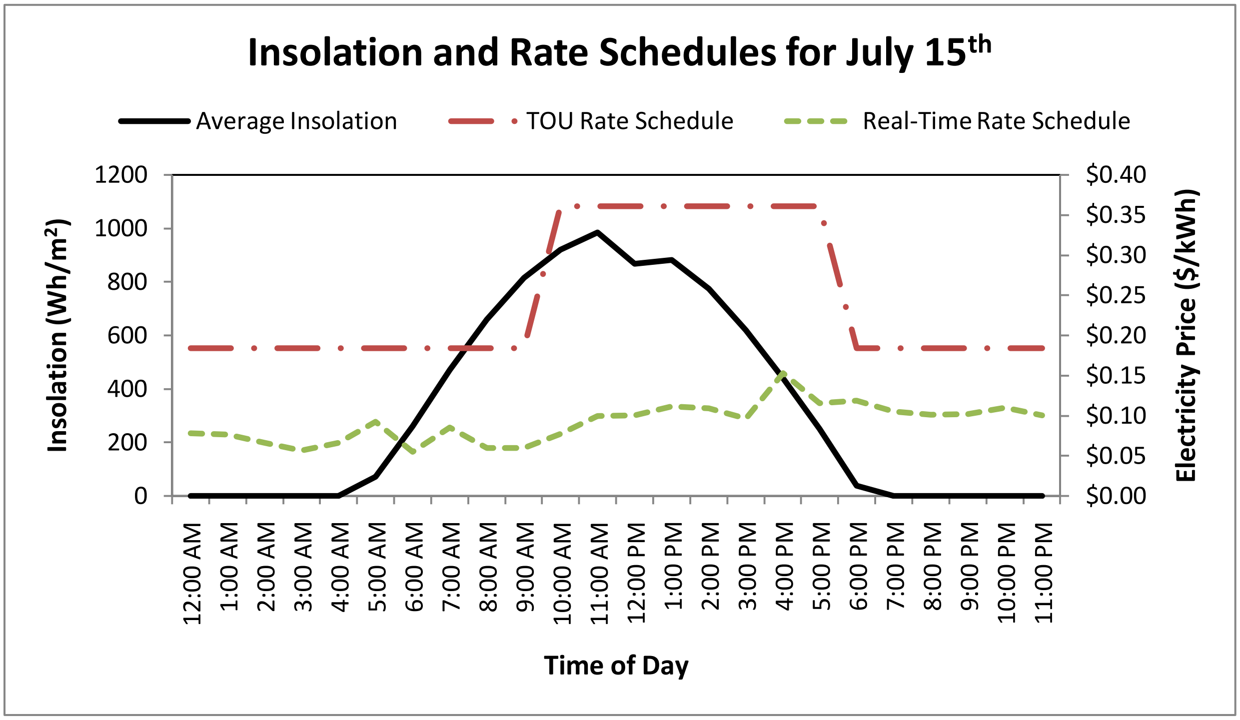

Figure 2.4-1: Insolation and Electricity Pricing Data for July 15th

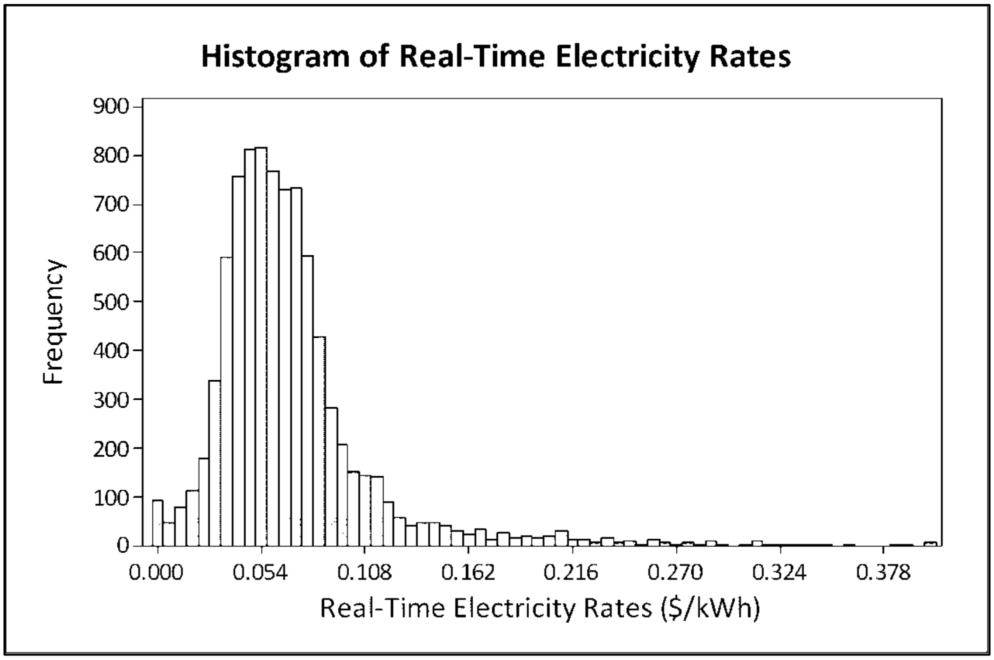

Figure 2.4-2: Real-Time Rate Schedule Histogram

2.4.3. Load Data

For the last case-study, solar-with-storage systems were evaluated within a baseload generation role. This was simulated by requiring the generator to meet a specific demand profile. The demand profile was calculated by scaling CAISO's hourly load by a base system size (10 MW). The hourly system load data were obtained from CAISO's public download site mentioned previously, and can be accessed under this reference: [39].

3. Modeling Methodology

The lifetime cost of a storage device often depends on how it is operated. For example, the frequency and depth to which a storage device is charged and discharged will often dictate the operational lifetime of the device; and therefore the lifetime cost due to the requirement of additional capital purchases. Financial dynamics such as these are why the NPV calculation was kept separate from the optimization procedure. The resulting two-step process is outlined in detail in Section 3.1.1, and the steps themselves are described in Sections 3.3.1 and 3.3.2. In addition, throughout this work the residential and centralized scenarios operating within temporal rate schedules are treated separately from the centralized scenarios operating as baseload generators (meeting a specified service requirement).

As a consequence, this section is divided into four main components: first, the temporal rate schedule scenarios' objective and control variables are presented, and then the same is done for the baseload scenarios. Next, the two steps of the optimization procedure for the temporal scenarios are discussed, followed by the two steps of the centralized baseload scenarios.

3.1. Temporal Rate Schedules

3.1.1. Objective Function

For all the temporal rate schedule scenarios (residential TOU and centralized real-time), the ultimate objective is to maximize is the net present value (NPV) of the storage investment.

The optimization problem can readily be set up as a linear programming (LP) model if the energy and power limits are treated as independent variables. In other words, the storage optimization procedure will vary the energy capacity and power rating of the storage device and calculate the maximum dispatch profile for each configuration. In this manner, the optimization procedure can be set up as a two-step problem; (1) solving for the optimal storage dispatch given electricity prices, certain efficiency limitations, and varying the energy and power constraints on the storage device and (2) calculating the objective function (i.e. NPV) of each storage solution to find the optimal configuration given the financial characteristics. In this respect, the outputs of the first step (dependent variables) become inputs to the second (independent variables). The objective function of step one is to maximize the total revenue observed from the dispatch profile. In step two, this objective function (revenue), along with the corresponding dispatch profile, is used to calculate the NPV of the storage device over the operational lifetime of the PV system.

3.1.2. Control Variables

For the temporal rate schedule scenarios, the dispatch profile is optimized iteratively with the power and energy capacity of the storage device being set at different levels. The control variables that can be fine-tuned by the optimization procedure to maximize revenues are on an hourly basis throughout the entire year. These include the energy being sent to storage, the energy being used directly, and the energy being discharged from storage. The variables that are fixed versus those that can be controlled during this optimization procedure are shown in Table 3-1.

Table 3-1: Fixed and Control Variables - Temporal Rate Schedule Optimization

Fixed Variables	Control Variables
Storage Efficiencies Storage Energy Capacity Storage Power Rating Hourly Generation Hourly Electricity Prices	Hourly Energy Used Hourly Energy Stored Hourly Energy Discharged

3.2. Baseload Generation

3.2.1. Objective Function

For the utility-scale baseload scenario, there are two cases considered: (1) an agreement between the utility and the solar generator in which the generator must dispatch only the requested demand, and (2) an agreement in which the generator must meet the service requirement but may also sell additional generation into the wholesale market. Both cases require the solar-with-storage system to be optimized for meeting the required dispatch profile; therefore, the objective function is to minimize the total cost of the solar-with-storage system. For the first case, the optimization problem ends here because the revenues are set by the dispatch requirement. However, for the second case, the generator has the option of dispatching additional energy above and beyond the service requirement. It is important to note that if the solar-with-storage system were allowed to sell additional energy into the wholesale market, and the goal was to maximize revenues, then there would be no upper-bound on the size of the system (the larger the system, the larger the profits). Therefore, in order to incorporate the costs of the solar-with-storage system, revenues are only maximized within the system size determined by the service requirement optimization procedure. For both cases, this allows assessment of the lifetime cost of a storage device needed to enable meeting a particular service requirement, while minimizing the entire upfront capital cost of the solar-with-storage system. The service requirements are defined by different demand profiles, which are discussed in Section 4.3.

3.2.2. Control Variables

For the first step of the baseload optimization procedure, the fixed variables include the unit costs of the solar-with-storage system, the efficiencies, the required demand profile (service requirement), and a normalized generation profile. The insolation data discussed in Section 2.4.1 was normalized to a 10 MW plant, and the actual generation during the optimization process was scaled by multiplying this profile by a variable factor until the desired output was reached. The control variables make up the system size, including the energy storage capacity and power rating, and the solar multiple (i.e. the previously mentioned factor, which dictates the PV array or CSTP field size). These metrics are summarized in Table 3-2.

Table 3-2: Fixed and Control Variables – Baseload Generation Optimization – Step 1

Fixed Variables	Control Variables
Storage Efficiencies Storage Power Cost Storage Energy Cost Solar Generation Cost Hourly Service Requirement Relative Hourly Generation Profile	Storage Energy Capacity Storage Power Rating Solar Generator Size

Step 2 is the same as that described in Section 3.1.2 for the temporal rate schedules. The energy storage capacity and power rating, as well as the hourly generation determined in the first step, now become the fixed variables shown in Table 3-3.

Table 3-3: Fixed and Control Variables – Baseload Generation Optimization – Step 2

Fixed Variables	Control Variables
Storage Efficiencies Storage Energy Capacity Storage Power Rating Hourly Service Requirement Hourly Generation Hourly Electricity Prices	Hourly Energy Used Hourly Energy Stored Hourly Energy Discharged

3.3. Temporal Rate Schedule Model

3.3.1. Step 1: Storage Dispatch Optimization Model (GAMS)

The inputs and outputs of the LP model are summarized in Table 3-4 below.

Table 3-4: Inputs and Outputs of LP Optimization

Inputs (Parameters)		Outputs (Variables)	
$p(t)$	Price of Electricity ($/kWh)	$discharged(t)$	Energy Discharged from Storage (kWh)
$g(t)$	Electricity Generation (kWh)	$used(t)$	Energy Used Directly (kWh)
η	Roundtrip Efficiency of Storage (%)	$storageLevel(t)$	State of Charge of Storage (kWh)
d	Self-Discharge Rate of Storage (%/hr)	$stored(t)$	Energy Sent to Storage (kWh)
S_P	Storage Power Limit (kW)	$totalR$	Total Revenue (objective function)
S_E	Storage Energy Limit (kWh)		

The total revenue (R), which is the objective function to maximize, can be written as:

Equation 3-1: Revenue Objective Function

$$R = \sum_t \big(discharged(t) + used(t)\big) \cdot p(t)$$

where t represents the hour within the optimization timeframe, $discharged(t)$ is a vector of energy values in hour t that are discharged from the storage device, $used(t)$ is a vector of energy values in hour t that are used directly from the PV system (sent to the load/grid), and $p(t)$ is the price of electricity in hour t. The energy being used can be related to the energy sent to storage, $stored(t)$, in the following constraint:

Equation 3-2: Energy Generation Constraint

$$g(t) = used(t) + stored(t)$$

where $g(t)$ is the energy generated from the PV system in hour t. In other words, the energy generated in a given hour must either be used directly, or sent to storage. The energy being discharged in a given hour is subject to an energy-balance equation that takes into account the state-of-charge, roundtrip efficiency, and the self-discharge rate of the storage device:

Equation 3-3: Energy Discharged Constraint

$$storageLevel(t) = storageLevel(t-1) \cdot (1-d) + stored(t) \cdot \eta - discharged(t).$$

In this constraint, $storageLevel(t)$ is the amount of energy remaining in the storage device after hour t, d is the hourly self-discharge rate of the storage device, and η is the roundtrip efficiency of the storage device. The storage capacity and power limitations must also be imposed as follows:

Equation 3-4: Capacity Limit Constraint

$$storageLevel(t) \leq S_E$$

and

Equation 3-5: Power Limit Constraints

$$discharged(t) \leq S_P$$

$$stored(t) \leq S_P.$$

In these expressions, S_E is the capacity limitation of the storage device in kWh, and S_P is the power rating of the device in kW. Note that this assumes the storage device has the same charge and discharge rate limit.

Storage optimization models often include an explicit constraint that energy may not be charged and discharged at the same time. This is a logical operational restriction; however, implementing it is both inconvenient and unnecessary. Inconvenient because it would transform the model into a non-linear problem (NLP) because of the conditional nature of the constraint (i.e. *If* charging, *then* don't discharge), which is most readily expressed by setting the product of the changed and discharged energy in every hour equal to zero. Unnecessary because the model will never choose to charge and discharge at the same time so long as the objective function is to maximize revenues. This is because there is always an efficiency sacrifice associated with sending energy to the storage device. Therefore, the model would only loose revenues by cycling energy through storage within a single hour, when it could simply use it directly in that hour. This condition has been tested with several different scenarios, and it has been found that the optimal solution never charges and discharges at the same time, even without this constraint explicitly imposed. This constraint was also found to be unnecessary for the two-step optimization process for the baseload generation scenarios, even though the objective function of the first step is system cost, not revenues. This is discussed in section 3.4.1.

In addition to these energy-balance constraints on the operation of storage with the PV system, a lower bound of zero is imposed on each metric:

$$\begin{array}{lcl} discharged(t) & \geq & 0 \\ used(t) & \geq & 0 \\ storageLevel(t) & \geq & 0 \\ stored(t) & \geq & 0. \end{array}$$

The parameters of this optimization problem are constructed in MATLAB, after which they are sent to the General Algebraic Modeling System (GAMS) software package for evaluation (see Appendix I-a for the GAMS code used).

Using this simplified optimization model, it is possible to calculate the absolute maximum value of adding a storage device to a PV system within a time-varying price market. Since the model is linear, GAMS is able to quickly solve for the optimal storage dispatch for an entire year at a time.

3.3.2. Step 2: Storage Financial Model (Excel)

A list of the required inputs for the financial model is shown in Table 3-5 below. For a list of these parameters for each storage technology, please see Section 2.3.

Table 3-5: Financial Inputs

Updated Inputs		Storage Characteristics	
De	First Year Discharged Energy (kWh)	C_E	Capacity Cost ($/kWh)
DoD	Average Depth-of-Discharge (%)	C_P	Power Cost ($/kW)
Cy	Average Cycles per Year (Cycles)	BOS	Balance of System ($/kWh or $/kW)
S_E	Req. Capacity (kWh)	$O\&M_F$	Fixed O&M ($/kW-yr)
S_P	Req. Power (kW)	$O\&M_V$	Variable O&M ($/kWh)
L_{PV}	PV System Lifetime (years)	L_S	Storage Lifetime (Years)
		L_{Cy}	Lifetime at 100% DoD (Cycles)

The parameters in the left column ("Updated Inputs") need to be updated for each specific storage application (except for the PV system lifetime), and the parameters in the right column ("Storage Characteristics") need to be updated for each storage technology. The application specific inputs are determined from the optimization model described in Section 3.3.1.

An important assumption is made for electrochemical batteries, that the actual cycle lifetime of the storage device is proportional to the average depth-of-discharge. The following figure (from Ibrahim, et al. [19]) demonstrates this relationship for lead-acid batteries:

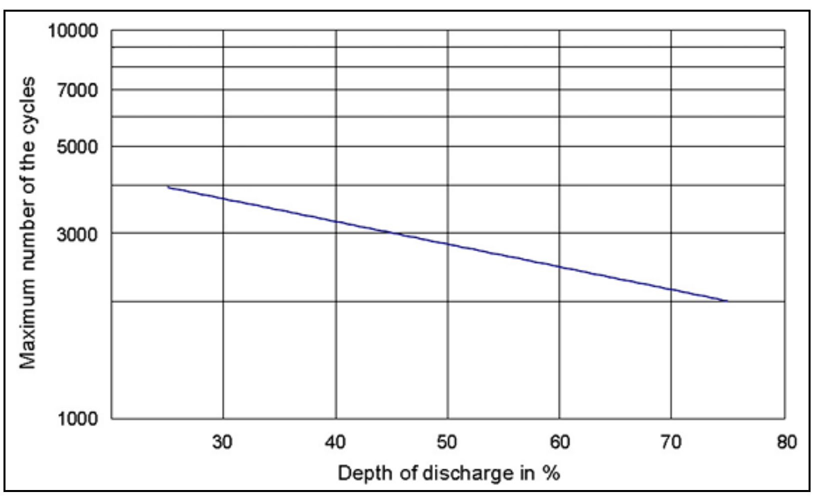

Figure 3.3-1: DoD vs. Cycle Lifetime for Lead-Acid Batteries [19]

Using this relationship and the initial condition of 1,500 cycles at 100% DoD [20], the following extrapolation was made:

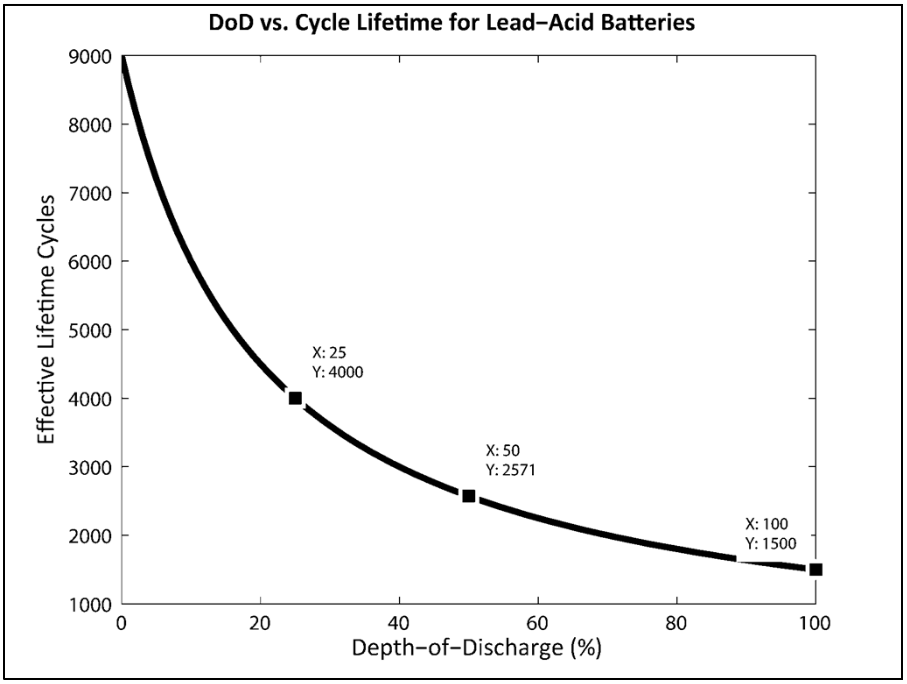

Figure 3.3-2: DoD vs. Cycle Lifetime for Lead-Acid Batteries - Extrapolation

This curve has the general form:

Equation 3-6: Effective Cycle Lifetime

$$EL_{Cy} = \frac{L_{Cy}}{DoD \cdot \left({}^{5}/_{6}\right) + {}^{1}/_{6}}$$

where EL_{Cy} is the effective lifetime cycling capacity of the storage device at a specified average depth-of-discharge (DoD), and L_{Cy} is the cycling lifetime at 100% DoD. Due to the difficulty of obtaining a similar specific relationship for the other storage technologies, this same general form was adapted to the other electrochemical batteries by updating L_{Cy} for each technology. Once the effective lifetime cycling capacity is known, the number of capital purchases required for each storage device can be approximated by:

Equation 3-7: Number of Required Capital Purchases

$$N_C = max\left[\frac{Cy \cdot L_{PV}}{EL_{Cy}}, \frac{L_{PV}}{L_S}\right]$$

where $Cy \cdot L_{PV}$ is the total cycles required of the storage device over the entire PV system lifetime (a system lifetime of 30 years is used for these analyses [40],[41]). Note that each of these ratios should be rounded up to the nearest integer, because only whole capital purchases are allowed (cannot buy half of a device).

The calculation of capital cost per device was described in Section 2.3.1, and given in Equation 2-2 and Equation 2-3.

The power control system (PCS) required for many storage devices to convert the DC output to AC before interfacing with the load is treated as a separate cashflow in this analysis. The basis for this decision is the difference in timescales between the storage device lifetime (which is variable under operational conditions) and the inverter (PCS) lifetime (which is assumed to be constant). The base PCS cost is assumed to be $230/kW for a mature (not first-of-a-kind) 1 MW system [29], and a lifetime of 7 years is used [42], [43]. It has been estimated that the PCS expense scales non-linearly with the system size according to the following relationship [29]:

Equation 3-8: Scaled PCS Cost

$$PCS = PCS_{base} \cdot \left(\frac{S_P}{1{,}000}\right)^{-0.2}$$

where PCS_{base} is the base PCS cost of $230/kW, and S_P is the power rating of the storage device in kW.

The operation and maintenance (O&M) expenses are assessed on a yearly basis. There are two types of O&M costs: fixed ($O\&M_F$) and variable ($O\&M_V$). Fixed O&M costs are in units of $/kW per year, and are based on the total power rating of the storage system. Variable O&M costs are in $/kWh of cycled energy through the system. For any given year, the O&M expense can be calculated as:

Equation 3-9: O&M Cost

$$O\&M(y) = O\&M_F \cdot S_p + O\&M_V \cdot \sum_{t=1}^{8760} discharged(t)$$

where $O\&M(y)$is the annual O&M cost, S_p is the storage power rating, and the summation of $discharged(t)$ is the total energy discharged from the storage device over the entire year.

The financial model must also consider the time value of money. This was accomplished by discounting the cashflows on an annual basis by a rate consistent with the investor's perceived return on similar-risk investments. For this work, a rate of 10% was assumed [44]. The NPV of the storage investment then becomes:

Equation 3-10: NPV Calculation

$$NPV = -Capital_0 + \sum_{y=1}^{T} \frac{F_y}{(1 + r_D)^y}$$

where $Capital_0$ is the initial capital investment in year zero (see Section 2.3.1), T is the lifetime of the solar generator in years, F_y is the net cashflow at the end of year y, and r_D is the appropriate discount rate. F_y is assessed for each year by the following relationship:

Equation 3-11: Annual Cashflow Relationship

$$F_y = Savings(y) - \left(O\&M(y) + Capital(y) + PCS(y)\right)$$

where $Savings(y)$ is the amount of money saved annually by the addition of the storage device, $Capital(y)$ is the storage device replacement cost each year (this is equal to zero for years in which the storage device does not need replacement, see Section 2.3.1 for the calculations), and $PCS(y)$ is the power control system replacement cost (also equal to zero for years in which the PCS does not need replacement). An illustrative example of the cashflows generated by the Excel financial model is given in Appendix II for a fictitious lead-acid battery configuration.

3.4. Baseload Generation Optimization Model

For the baseload scenario, the storage financial model is exactly the same as that described in 3.3.2, and will not be repeated here. This section describes the differences of the system size and storage dispatch models from the model described in the previous section for temporal rate schedules.

3.4.1. Step 1: System Size Optimization (GAMS)

Table 3-6: Inputs and Outputs of System Size LP Optimization

Inputs (Parameters)		Outputs (Variables)	
$d(t)$	Service Requirement Profile (kWh)	S_P	Storage Power Rating (kW)
$g(t)$	Electricity Generation (kWh)	S_E	Storage Energy Capacity (kWh)
η	Roundtrip Efficiency of Storage (%)	M	Generation Multiple (unitless)
d	Self-Discharge Rate of Storage (%/hr)		
P_{cost}	Storage Power Cost ($/kW)		
T_{cost}	Turbine Power Cost ($/kW)		
E_{cost}	Storage Energy Cost ($/kWh)		
PV_{cost}	PV Generation Cost ($/kWp)		
$CSTP_{cost}$	CSTP Field Cost ($/kWp)		

The system size optimization model has all of the same operational constraints as the model described in 3.3.1. The main differences lie in the additional constraint of meeting the service requirement, $d(t)$, and with the objective function. As discussed in section 3.2.1, , the objective function is to minimize the total cost of the solar-with-storage system, while still being able to meet the service requirement. For a PV-with-storage system, the service constraint can be defined as:

Equation 3-12: PV Service Requirement Constraint

$$discharged(t) + used(t) \geq d(t)$$

and for a CSTP-with-storage system, this is written as:

Equation 3-13: CSTP Service Requirement Constraint

$$turbineOutput(t) \geq d(t).$$

The objective function to minimize for a PV system (the total upfront cost of the solar-with-storage system) can be written as:

Equation 3-14: PV System Size Optimization Objective Function

$$Cost = P_{cost} \cdot S_P + E_{cost} \cdot S_E + PV_{cost} \cdot M \cdot 10{,}000$$

where P_{cost} is the unit power cost of the storage device, S_P is the power rating of the storage device, E_{cost} is the unit energy cost of the storage device, S_E is the energy capacity of the storage device, PV_{cost} is the unit cost of the PV array, and M is the generation multiple. For CSTP systems, this is written as:

Equation 3-15: CSTP System Size Optimization Objective Function

$$Cost = T_{cost} \cdot T_{power} + E_{cost} \cdot S_E + CSTP_{cost} \cdot M \cdot 10{,}000$$

where T_{cost} is the unit cost of the turbine, T_{power} is the power rating of the turbine, and $CSTP_{cost}$ is the unit cost of the concentrating solar field. The factor of 10,000 is to scale the solar multiple up to the 10 MW generation profile it was calculated with. The unit costs of the PV system (PV_{cost}), CSTP field ($CSTP_{cost}$), and CSTP turbine (T_{cost}) are shown in Table 3-7 along with their references.

Table 3-7: Solar Generation Unit Costs

Metric	Value
PV_{cost}	\$3,500/kW [45]
$CSTP_{cost}$	\$2,381/kW [46]
T_{cost}	\$560/kW [46]

As with the LP model for optimizing revenues (section 3.3.1), the explicit inclusion of the restriction on charging and discharging at the same time is unnecessary. Since the first step of the optimization procedure is allowed to shunt energy (throw it away instead of sell it or send it to storage), the model may always choose this instead of charging and discharging at the same time. Whether or not it actually does is irrelevant – the point is that after the service requirement is met, excess energy will never increase the size/cost of the total system, because it can always be thrown away for free. Therefore, the resulting size/cost will always be for the smallest system capable of meeting the service requirement. The concern thus becomes whether or not the system is *too* small to function realistically in a real-life application. In other words, is the shunting of energy a prerequisite of the system's operation, such as would be the case if the solar field generated more energy than could be dispatched with the given storage size and power constraints? Indeed, if the model converged on such an infeasible solution, one of two outcomes would occur within the second optimization step described below: (1) There would be no solution to the optimization given the system size constraints in the first step, or (2) the system would charge and discharge at the same time in an attempt to shunt energy, even though the objective function is to maximize revenue. Both of these cases are simple to verify, and they have been for all of the baseload scenarios without a single violation.

The GAMS code used for this first optimization step for a PV system and a CSTP system is shown in Appendix I-b and I-d, respectively.

3.4.2. Step 2: Storage Dispatch Optimization Model (GAMS)

This optimization model is the same as that described for the temporal rate schedules in 3.3.1, except for the additional constraint of meeting the service requirement. This constraint is shown in Equation 3-12 and Equation 3-13 for PV and CSTP systems, respectively. This optimization code can be found in Appendix I-c and I-e, for a PV and CSTP system, respectively.

3.5. Integration of Models (MATLAB)

MATLAB was used as the interlacing web (or glue) for all the separate components; tying together the different optimization steps, input files, financial models, and processing the results for graphic display. The simulations were divided into two main groups: the temporal rate schedule scenarios, and the baseload generation scenarios. The function of the MATLAB code within each one of these groups was to organize the inputs and outputs of all the relevant optimization and financial models. Since these functions are not vital to the methodology of this thesis, details are not presented here. The reader is referred to Appendix III for the temporal rate schedule code and Appendix IV for the baseload generation code.

3.6. Model Limitations

An important limitation of the scenarios discussed in this thesis lies in the underlying assumption that the storage device is only able to be charged from the PV array. This is not an unreasonable assumption (as outlined below), but does eliminate the option of charging the storage device from the grid during low-demand hours (when the price of electricity is the lowest), and discharging this additional energy during the peak-hours. This potentially offers an additional revenue stream for a storage device, but is not considered in this work because:

- In the near-term, there are currently no regulations or interconnection standards for a device that would be both consuming and producing large amounts of energy, whereas PV with storage acting solely as a generator is able to be integrated into the system today.
- Allowing the storage device to charge from the grid eliminates the need for a generation source which, in this case, negates the positive environmental and social benefits of utilizing PV.
- At higher levels of penetration, even if the PV system is utilized to offset emissions from marginal generators (gas peakers), charging the storage device when the price is low would increase the demand for baseload generation (coal) or increase firing of marginal generators (gas). Again, this would mitigate the positive benefits of utilizing PV.

Another important limitation of this optimization procedure is the non-inclusion of cycle control of the storage device. A potentially useful strategy could be to oversize the storage device but limit the depth-of-discharge, or even the total number of cycles, such that the operational lifetime of the storage device is prolonged and thereby decreasing the total cost of the device. To include these parameters into the optimization would require a discrete nonlinear model (DNLP) because of the discontinuous response of lifetime cost with respect to number of cycles vs. calendar lifetime as mentioned in the introduction of Section 3. Using such a DNLP model would make it very challenging to achieve convergence on a unique optimal solution.

4. Model Results – Case Studies (CA)

Three scenarios are analyzed for each of the 9 identified storage technologies. All scenarios are located close to Blythe, CA, which has very good insolation as well as the desired rate schedules. For each of the temporal rate schedule cases, an optimal storage capacity and power rating was identified along with the corresponding net present value (NPV) of the storage investment. A summary of these metrics can be seen in Table 4-1. For many of the storage technologies, a zero NPV is reported. For the temporal rate schedule scenarios, this means that the investment of any storage size/power would result in a negative return on investment, and therefore no investment should be made (i.e. money is lost over the lifetime of the system with that particular storage investment). Note that the residential scenarios are in units of kW, kWh, and dollars; whereas the centralized results are reported as MW, MWh, and millions of dollars. Also, negative NPV values are shown in parenthesis.

Thermal storage is only applicable for CSTP systems within the baseload generation scenario. Results are summarized for two specific service requirement profiles for the baseload scenarios. The first service requirement is a base case scenario such that all storage technologies may be compared over providing a common service. This common service requires the solar-with-storage system to provide load-matching between the hours of 9:00 am and 9:00 pm (12 hours). The second service requirement profile is optimized to maximize the return on investment (or minimize cost) for each storage technology. For these scenarios, a negative NPV means that adding storage to meet that specific service requirement would subtract from the total return on investment of the system as a whole. Note that this does *not* mean that the system as a whole is not a desirable investment. To determine this, the financials of the entire solar-with-storage system would have to be assessed over the lifetime of the project, which is out of the scope of this thesis. It should be noted that the “power” rating for CSTP with thermal storage refers to the turbine size, not the thermal storage power rating.

Table 4-1: Summary of Results with Current Technologies

	Lead-Acid	Li-Ion	NiCd	NaS	VRB	ZnBr	H2	CAES	PHES	Thermal
Residential TOU										
Power (kW)	0	0	0	0	0	0	0	0	0.5	N/A
Energy (kWh)	0	0	0	0	0	0	0	0	12	N/A
NPV ($)	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$3.89	N/A
Centralized Real-Time										
Power (MW)	0	0	0	0	0	0	0	6.00	8.00	N/A
Energy (MWh)	0	0	0	0	0	0	0	22.00	60.00	N/A
NPV (M$)	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.328	$0.897	N/A
Centralized Baseload										
Base Case										
Start Hour	9 am	9 am	9 am	9 am	9 am	9 am	9 am	9 am	9 am	9 am
Duration	12 hr	12 hr	12 hr	12 hr	12 hr	12 hr	12 hr	12 hr	12 hr	12 hr
Power (MW)	9.15	9.15	9.15	9.15	9.15	9.15	9.88	9.15	9.15	10.00
Energy (MWh)	52.79	37.46	41.59	52.15	52.20	49.63	162.01	131.39	132.25	125.61
Field Size (MWp)	25.08	27.16	28.56	28.42	25.47	27.24	29.09	23.60	23.34	13.11
NPV (M$)	($49.58)	($392)	($212)	($32.8)	($39.2)	($14.03)	($12.39)	($5.76)	($1.03)	$2.21
Optimum Case										
Start Hour	N/A	N/A	9 am	9 am	9 am	9 am	9 am	8 am	8 am	11 am
Duration	N/A	N/A	6 hr	6 hr	6 hr	6 hr	6 hr	7 hr	8 hr	7 hr
Power (MW)	0	0	2.69	2.85	3.17	3.08	3.06	4.46	3.86	10.00
Energy (MWh)	0	0	7.68	14.69	18.73	18.08	16.56	31.98	31.86	63.52
Field Size (MWp)	0	0	12.99	12.38	11.40	11.62	12.13	12.83	14.71	7.75
NPV (M$)	0	0	($41.50)	($7.38)	($9.56)	($4.47)	($2.18)	($0.598)	$0.273	$3.34

4.1. Residential Time-of-Use (TOU) Pricing

First, it is helpful to take a look at the effects of roundtrip and self-discharge efficiencies on the total possible revenue gains in a TOU rate schedule. This is shown in Figure 4.1-1. There is a surprising drop in revenue down to ~20% with even a slight increase in self-discharge rate. This turns out to be an ideal case which would not be feasible in practical application. This is demonstrated in the storage dispatch profile shown in Figure 4.1-2.

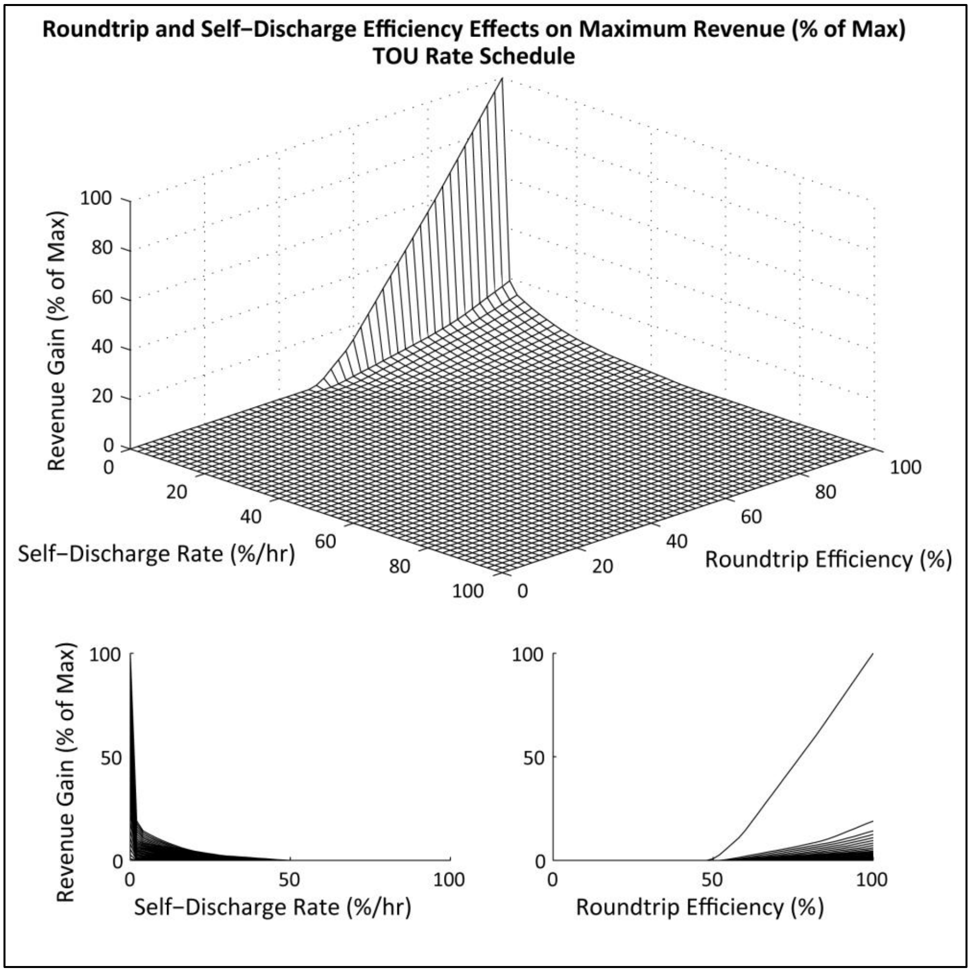

Figure 4.1-1: TOU – Efficiencies vs. Revenue Gain

This ideal case is storing all of the energy generated in the winter months and discharging all of it during the first summer peak-price hours. The energy requirement for such a dispatch profile is approximately 1.6 MWh. The power requirement to discharge all of this stored energy within the peak summer hours is much more reasonable at approximately 3.5 kW (since there are 688 summer peak hours in this TOU schedule). This energy requirement is most likely not feasible for a residential storage installation, and even if it were, the costs of such a storage device would far outweigh the revenue gain of $400 per year. However, this offers some interesting insight as to the potential for a very low-cost per kWh storage device with nearly no self-discharge (similar to pumped-hydro). Further insight may be gained if this ideal case is removed.

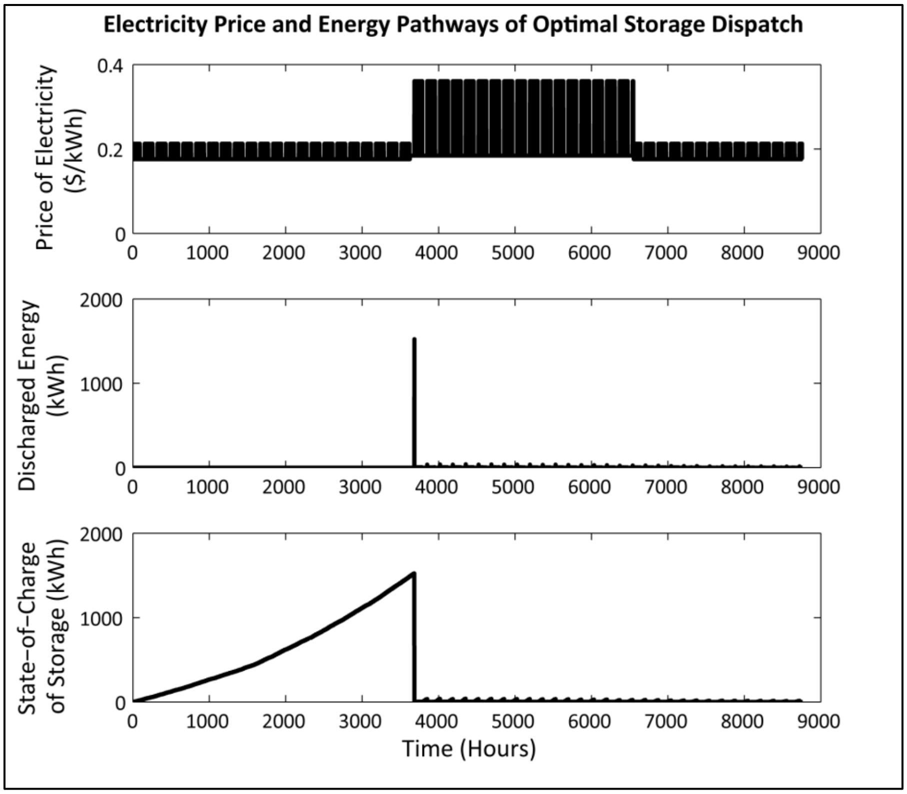

Figure 4.1-2: Residential System – TOU – Ideal Storage Dispatch Profile

When this ideal case is not considered in the solution space, the effect of self-discharge is much more subdued in a TOU rate structure, as shown in Figure 4.1-3. Another interesting observation from this figure is that roundtrip efficiency appears to be even more important in a TOU rate schedule than a real-time market (see Section 4.2). Also, the two efficiency components are almost identically influential on observed revenues (without the ideal case). Hence, *it is expected that storage devices within a TOU market will be able to afford larger self-discharge rate sacrifices than in a real-time market.* This is because of the repeated daily price cycles in TOU rate schedules.

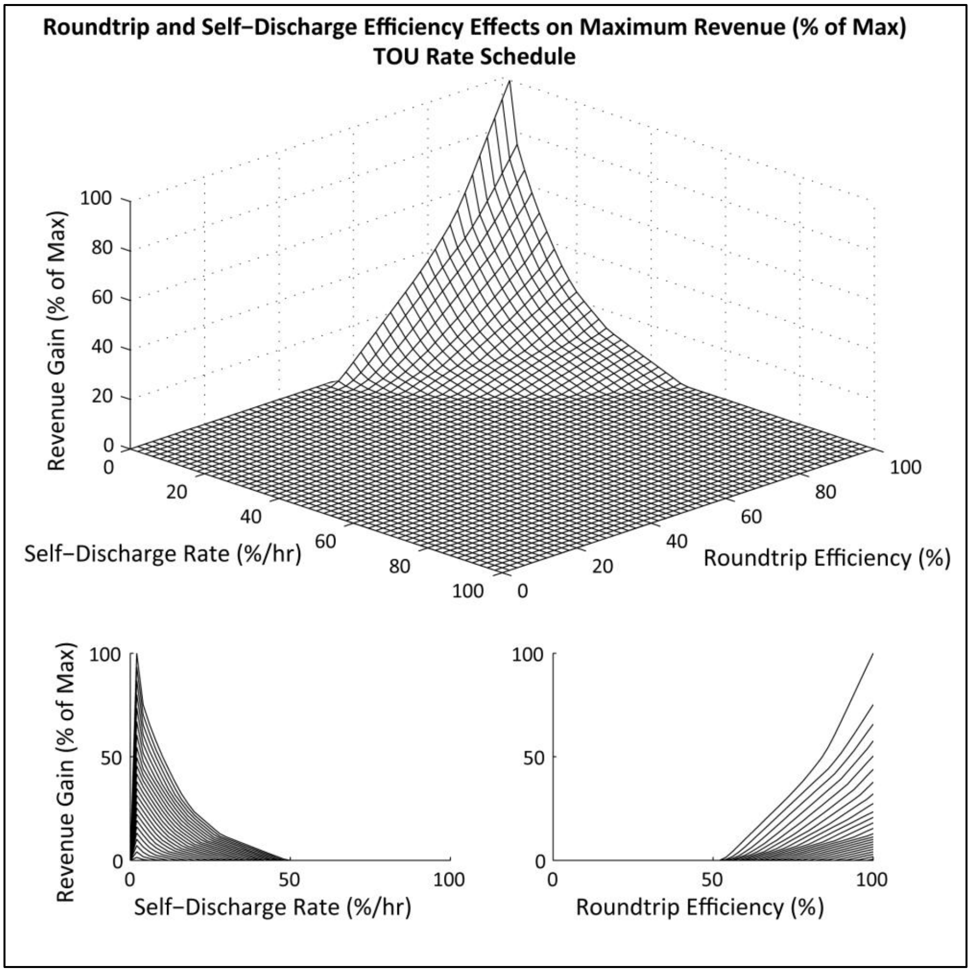

Figure 4.1-3: TOU – Efficiencies vs. Revenue Gain with Ideal Case Removed

Figure 4.1-4 below demonstrates the effects of storage energy capacity and power rating on revenue in a TOU pricing market.

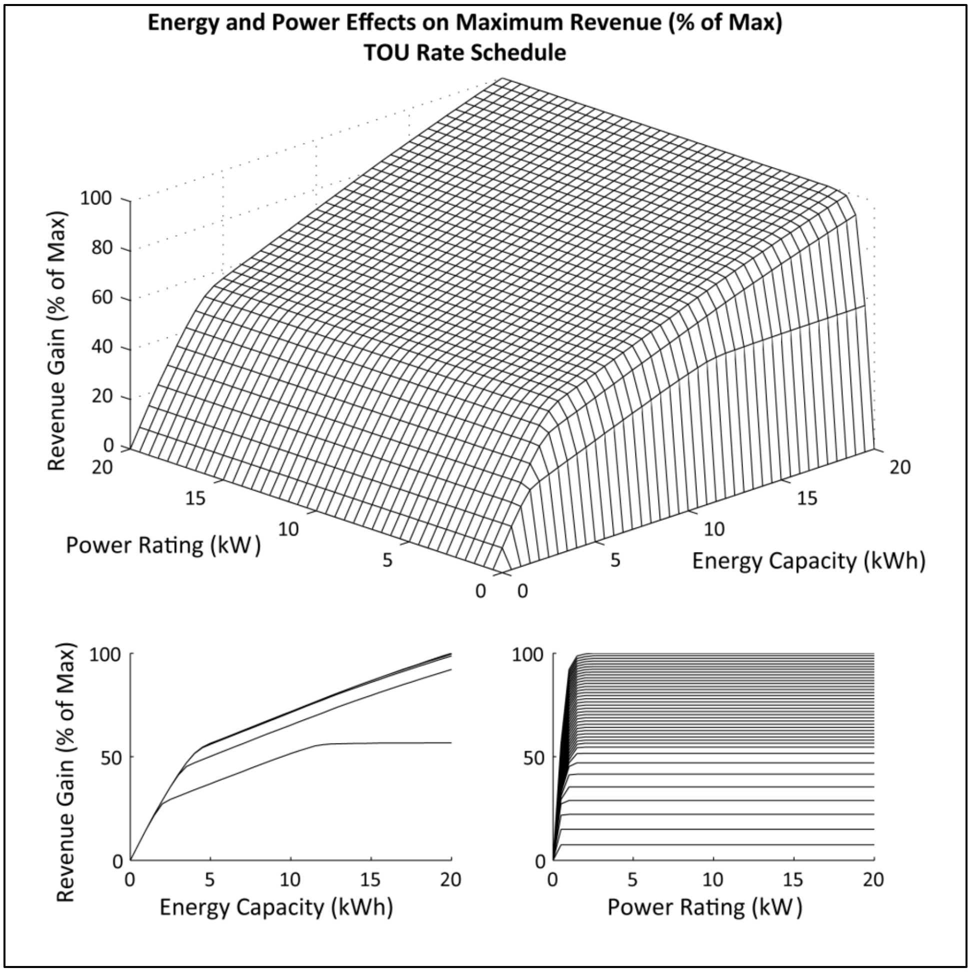

Figure 4.1-4: TOU – Storage Size vs. Revenue Gain

In a TOU rate schedule, increasing the power rating of a storage device hits saturation very quickly with respect to increased revenues. This is because the energy discharge profile can be spread out among many peak pricing hours (decreasing the power requirement) without sacrificing revenues. This is perhaps illustrated best by looking at the optimized dispatch profile for a TOU market. The dispatch profiles shown in Figure 4.1-5 represent a residential 2 kW_P PV system with a 15 kWh / 2 kW hypothetical storage device with perfect efficiency over a period of three days in the summer. As this energy profile indicates, if the power rating of the storage device were increased, all the stored energy would be discharged within the first peak price hour each day and no added revenue benefits would be observed (except via self-discharge savings, if applicable). Hence, *there is a minimum power rating required to discharge all the stored energy within the peak price period, beyond which there is very little additional revenue gained. This threshold is observed to be around 1.5 kW for a 2 kW_P residential system*

<u>in a TOU rate schedule</u>. The reader should note that if the ideal case is feasible (1.6 MWh of storage capacity with no self-discharge), then this threshold is increased to ~3.5 kW.

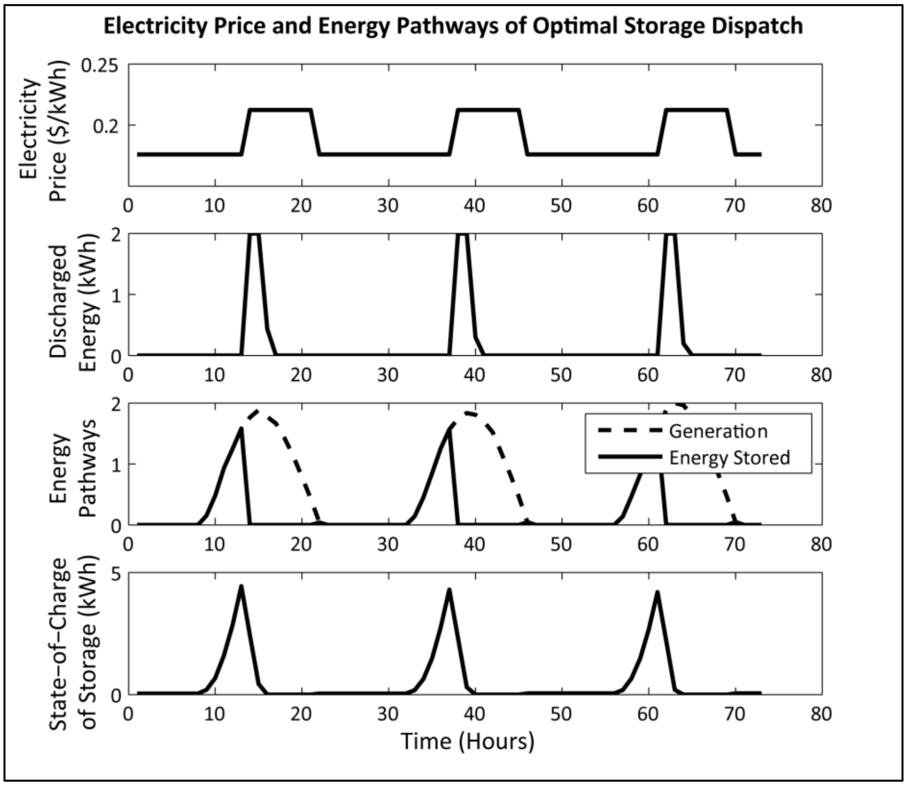

Figure 4.1-5: Residential System – TOU – Optimal Storage Dispatch Example

4.1.1. Lead-Acid Batteries

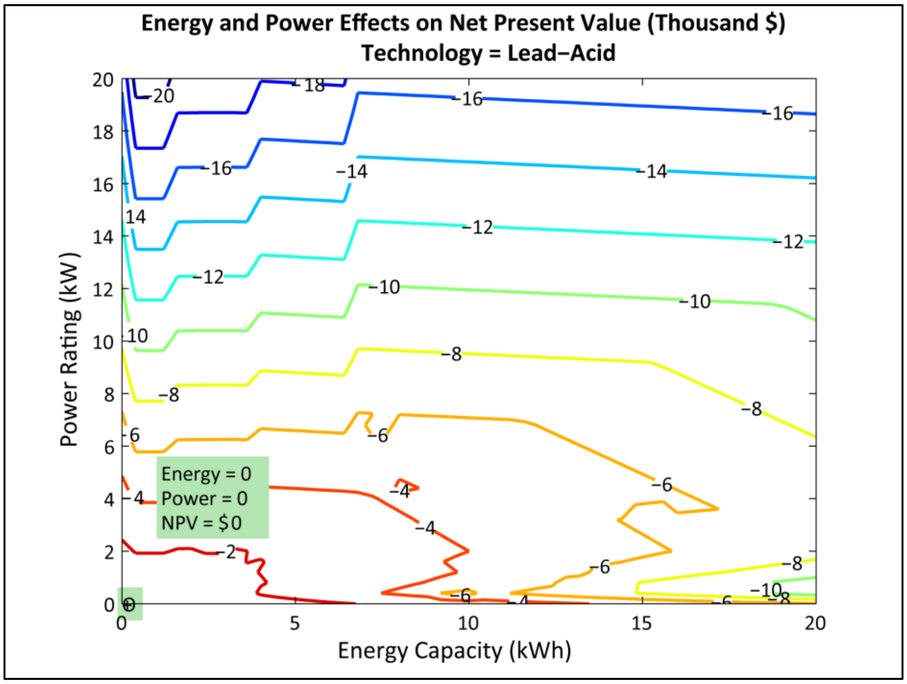

Figure 4.1-6: Residential System – TOU – Lead-Acid – Storage Size vs. NPV

For lead-acid batteries, it should first be noted that the lifetime costs in a residential TOU rate schedule outweigh the economic benefits gained, as illustrated by the maximum NPV of zero in Figure 4.1-6. This suggests that it would be unwise for a residential customer to invest in a lead-acid battery storage system, no matter what power or capacity, if they are in a TOU pricing contract.

The irregular behavior observed in Figure 4.1-6 is an artifact of the interplay between increasing savings as storage size is increased, and the cost of the storage which is dependent on the specific operational conditions. For example, a larger storage device might actually have a lower lifetime cost because it is utilized less-frequently and therefore does not need to be replaced as often. This is a common phenomena observed for the other electrochemical batteries as well. It is especially apparent with lead-acid battery technologies, which have a relatively low cycle lifetime and are therefore highly sensitive to changes in operational conditions.

4.1.2. Lithium-Ion (Li-Ion) Batteries

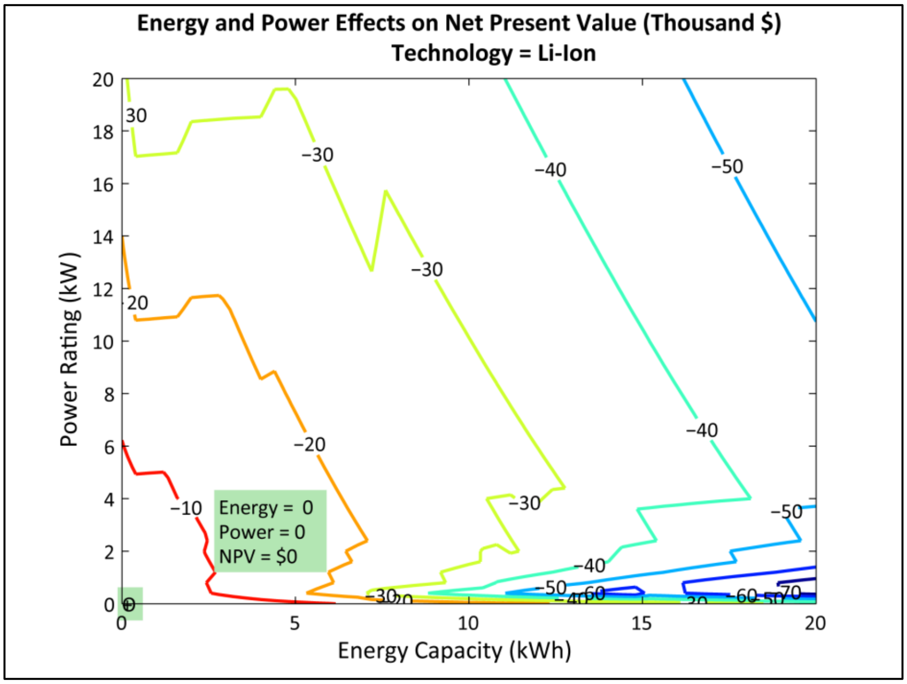

Figure 4.1-7: Residential System – TOU – Li-Ion – Storage Size vs. NPV

As seen in Figure 4.1-7, Li-ion batteries are very poorly suited for energy arbitrage applications due to their high unit energy cost. These batteries are likely to enter into the power quality market well before they are used for any sort of energy arbitrage service. Like lead-acid, the lifetime cost of Li-ion batteries is highly dependent on their operational conditions; hence, irregular contours are observed in the NPV surface.

4.1.3. Nickel-Cadmium (NiCd) Batteries

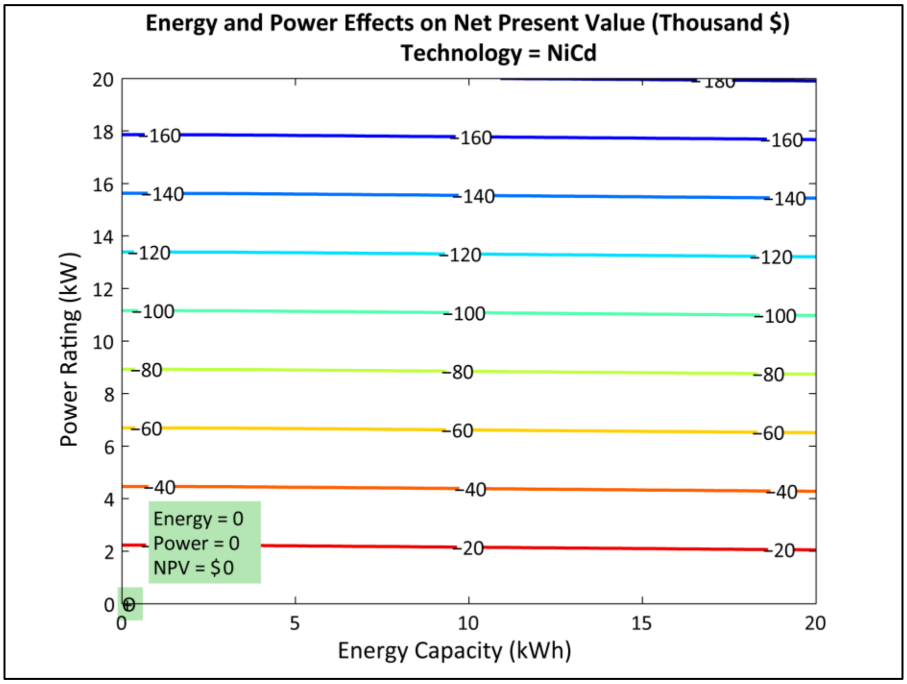

Figure 4.1-8: Residential System – TOU – NiCd – Storage Size vs. NPV

Figure 4.1-8 also shows that it would be undesirable to invest in NiCd as a storage solution for a residential PV system in a TOU schedule. Notice that, because of the very high unit power cost, an increase in power rating dominates the NPV surface, whereas increasing the energy capacity has almost no effect. The contours are uniform because the cycle lifetime of NiCd batteries in this application is not a limiting factor.

4.1.4. Sodium-Sulfur (NaS) Batteries

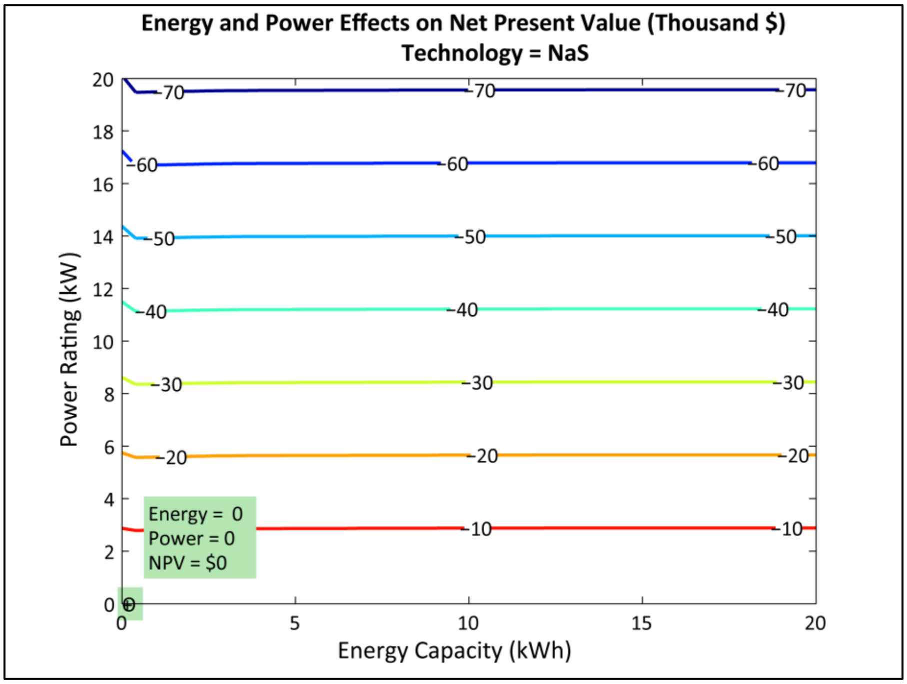

Figure 4.1-9: Residential System – TOU – NaS – Storage Size vs. NPV

Similar to NiCd, NaS batteries have a high system lifetime (and therefore do not need to be replaced often) and a high unit power cost. Hence, the power rating almost entirely dictates the NPV of the storage investment. Although a bit less expensive than NiCd, it would still be undesirable to invest in a residential NaS storage system.

4.1.5. Vanadium Redox Flow Batteries (VRB)

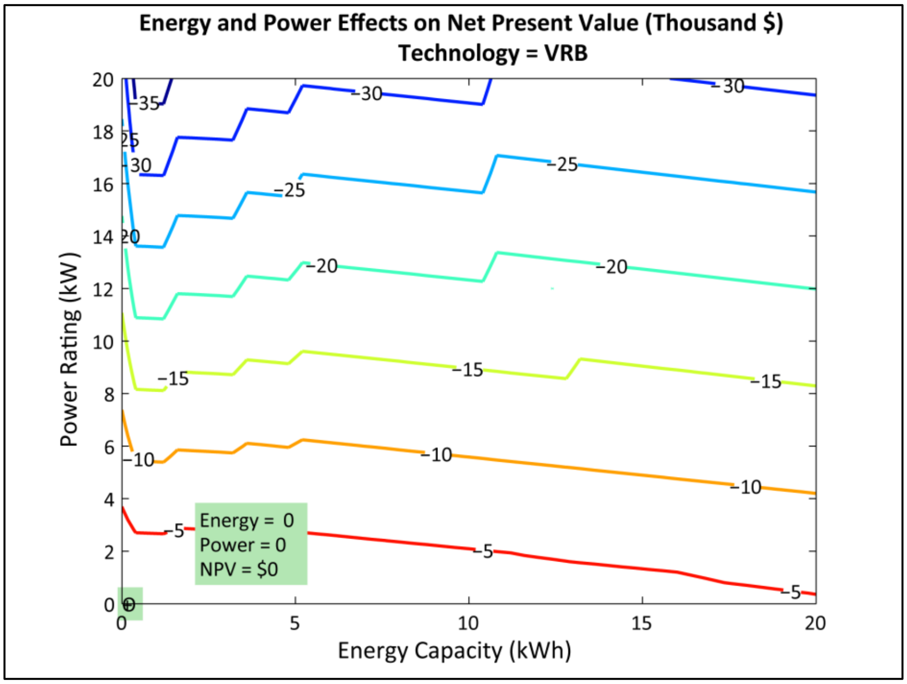

Figure 4.1-10: Residential System – TOU – VRB – Storage Size vs. NPV

VRB batteries have a rather poor cycle lifetime, but only the battery stacks (sometimes referred to as the "fuel cell") need replacement every thousand cycles or so. Hence, the "steps" in NPV shown in Figure 4.1-10 are frequent, but relatively small in magnitude. Still, these results suggest that VRB storage is not suited for residential TOU systems.

4.1.6. Zinc-Bromide (ZnBr) Flow Batteries

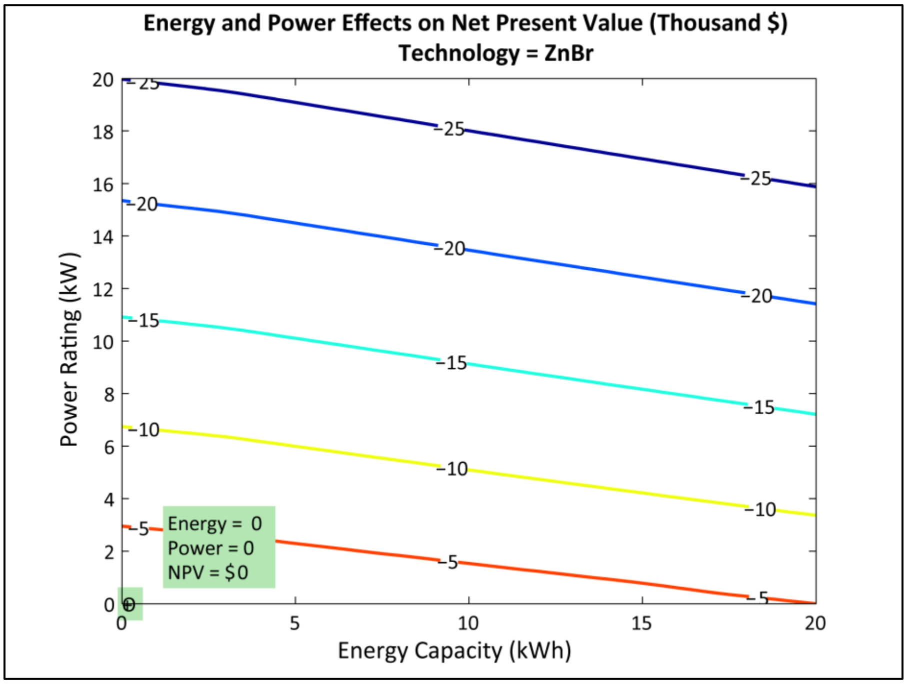

Figure 4.1-11: Residential System – TOU – ZnBr – Storage Size vs. NPV

The unlimited cycle lifetime of ZnBr flow batteries result in the smooth contours of Figure 4.1-11 (the lifetime cost is not dependent on how it is operated). Here again, however, ZnBr is too expensive for the benefits in a residential TOU schedule to recoup. The capital cost (especially energy-related) would have to come down significantly before this technology would be able to offer any value in this market.

4.1.7. Hydrogen Electrolysis with Fuel Cell (H2)

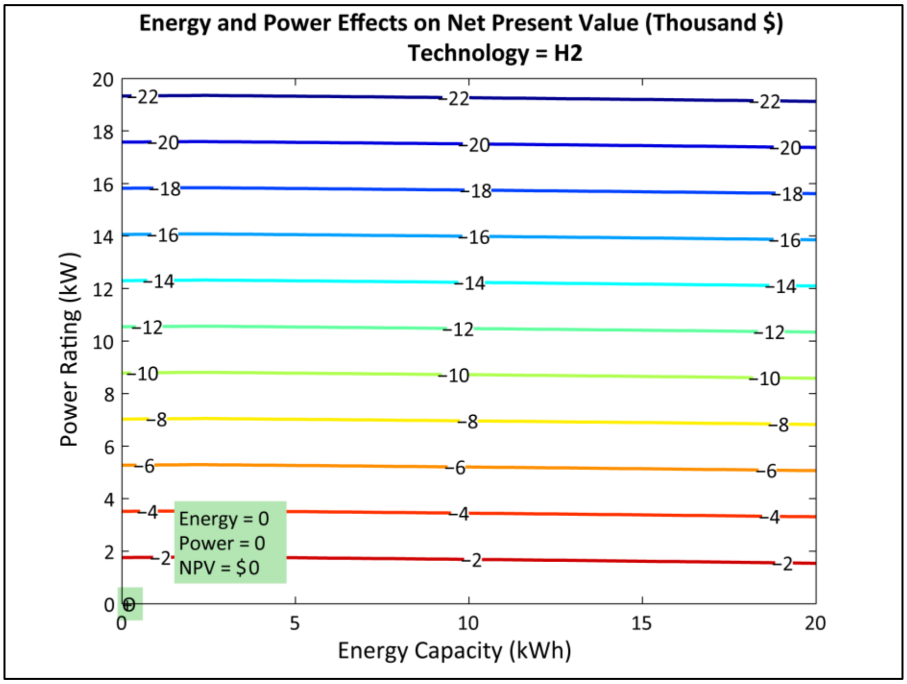

Figure 4.1-12: Residential System – TOU – H2 – Storage Size vs. NPV

Almost all of the capital cost of a H2 system is power related; and since the revenues of a storage system in a TOU rate schedule only increase with increased energy capacity (after a minimum power rating is met), the NPV is drastically affected by an increase in power. Essentially, as the power rating is increased, the cost of the system goes up considerably without any increase in revenues, which causes the NPV to plummet. If the roundtrip efficiency of an H2 system were increased, a high-energy/low-power storage system may become attractive for this application.

4.1.8. Compressed Air Energy Storage (CAES)

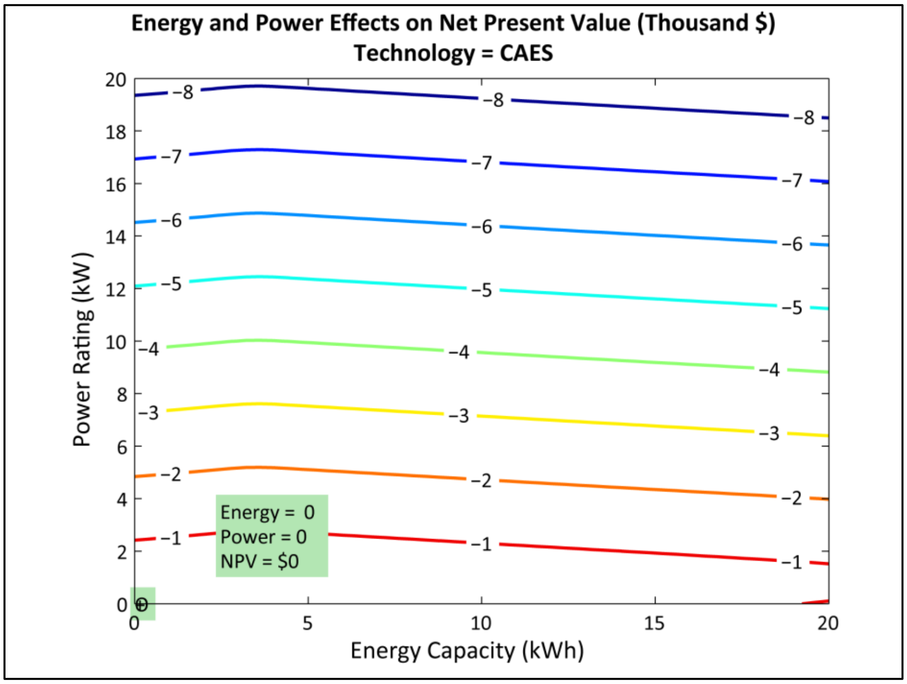

Figure 4.1-13: Residential System – TOU – CAES – Storage Size vs. NPV

Although not on a residential scale, the characteristics of CAES are not terribly suited for this type of storage service. If a micro-CAES system could emulate similar costs and performance as the large scale installations, this could potentially be a desirable storage technology for TOU residential scenarios.

4.1.9. Pumped-Hydro Energy Storage (PHES)

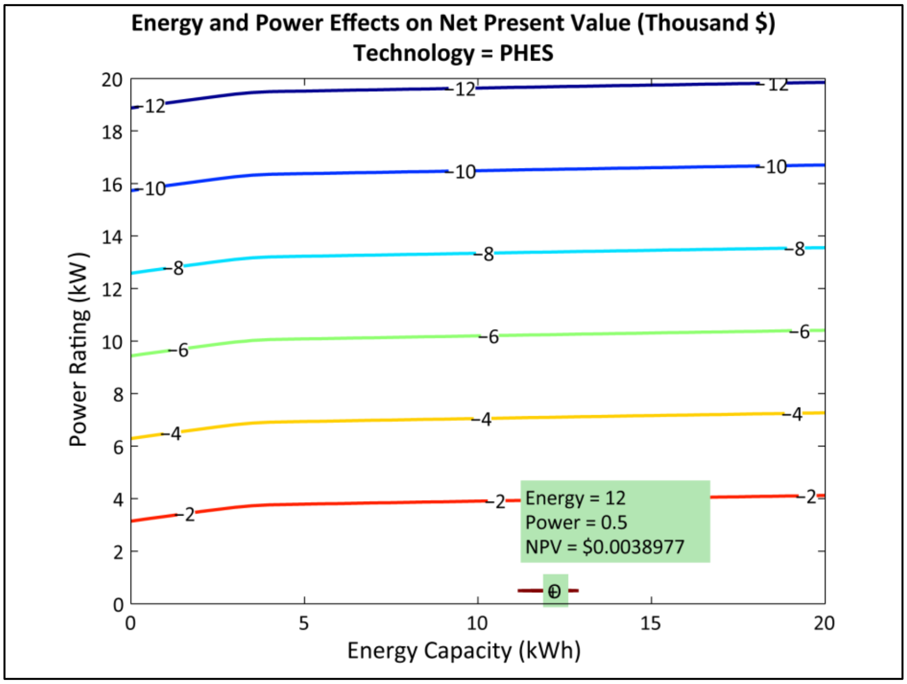

Figure 4.1-14: Residential System – TOU – PHES – Storage Size vs. NPV

Similarly, although PHES is not currently available on a scale which would be useful for residential applications, it is interesting to note that if it were able to be scaled down, the performance characteristics of PHES could be attractive for residential systems on a TOU rate schedule. Specifically, the low cost per unit energy ($/kWh), zero self-discharge, good roundtrip efficiency, no DC-AC conversion requirement, and high cycle and calendar lifetimes, are key characteristics for this scenario. Although the NPV of this hypothetical micro-PHES system is only ~$4, if the capital cost came down (and it were feasible to implement) this may be an attractive option for this scenario.

4.2. Centralized Generation with Real-Time Pricing

Similar to the TOU market, there is an ideal dispatch profile that can be captured when the storage device has zero self-discharge. This profile is shown in Figure 4.2-1. Again, this is completely unrealistic in actual operation; not only because of energy and power limitations of the storage device like in the residential scenario, but due to system limitations of the power grid as well (energy/power requirement of 7,000 MWh/MW, respectively). In addition, anything other than a perfect pricing forecast would completely undermine this dispatch strategy.

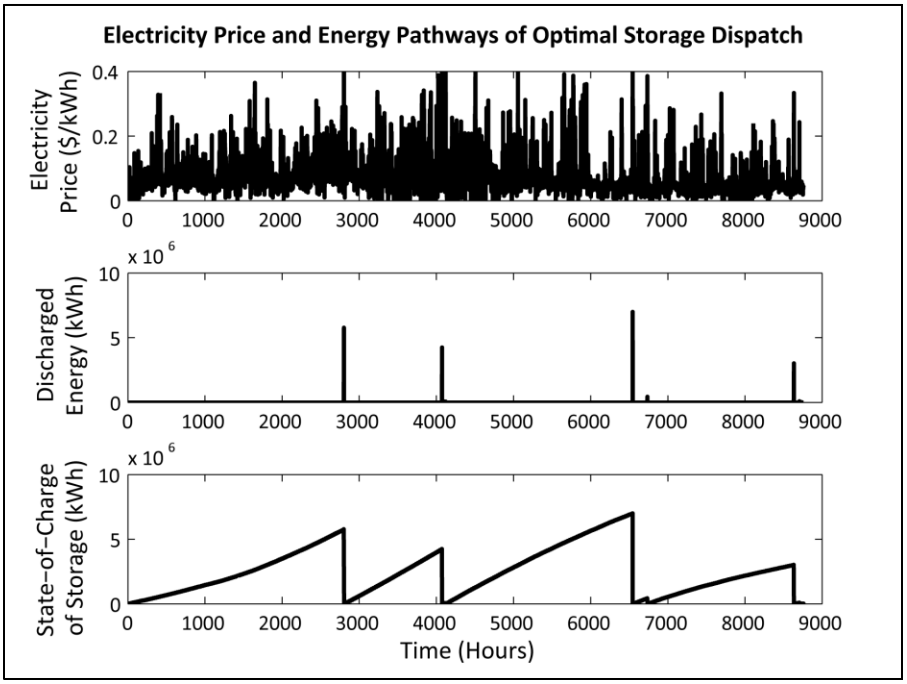

Figure 4.2-1: Central Generation – Real-Time – Ideal Storage Dispatch Profile

Hence, like in the previous section, this ideal dispatch case is removed from the solution space. The following is a plot of the remaining roundtrip and self-discharge efficiency effects on revenue for a real-time market.

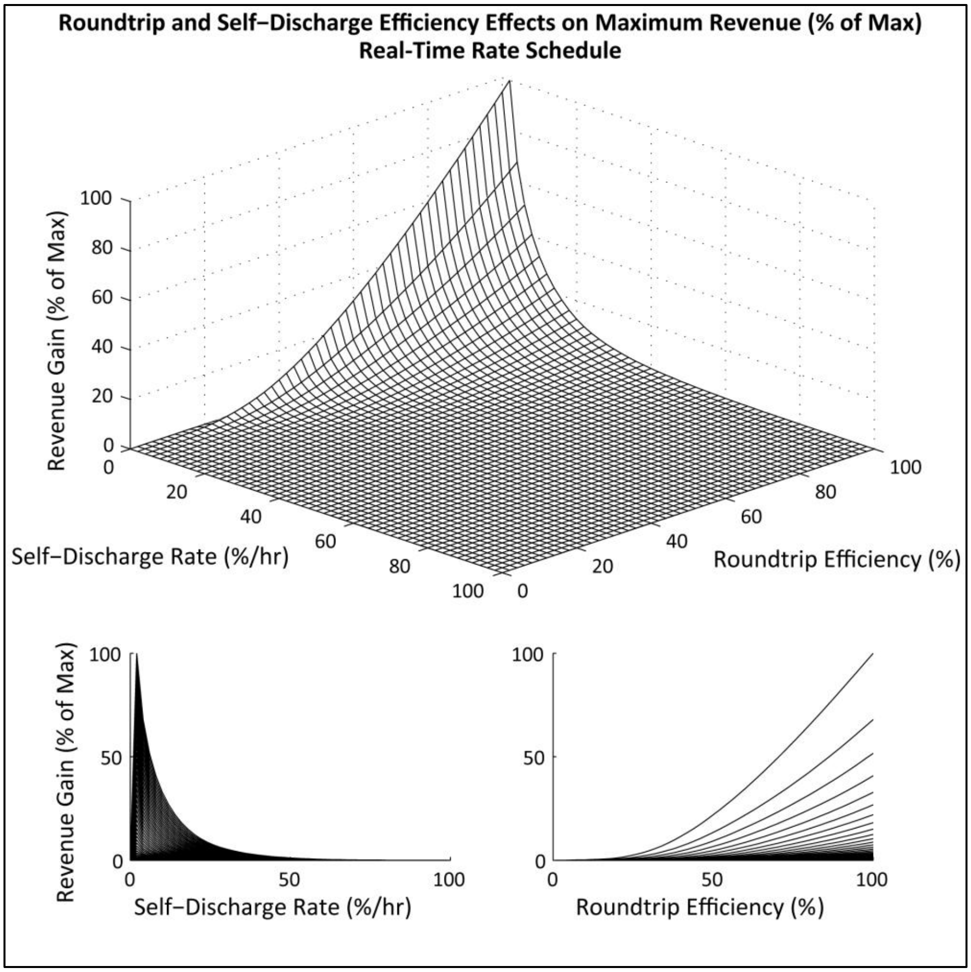

Figure 4.2-2: Real-Time – Efficiencies vs. Revenue Gain with Ideal Case Removed

An important observation from this figure is that both high roundtrip efficiencies and low self-discharge rates are extremely important with regard to recapturing revenue from energy arbitrage in a real-time market, but self-discharge is even more critical. Revenue streams are nearly cut in half going from a 2%/hour – 6%/hour self-discharge rate, confirming that technologies such as flywheels (with an hourly discharge anywhere from 18-200% [47]) are not appropriate for this market. Realistically, with the inclusion of forecast error, self-discharge should not be higher than a single percent per hour, and roundtrip efficiency should be at least in the high 80% range in order to capture most of the benefits in the real-time market. These are ballpark numbers given only from observations of the data presented here. The actual efficiency tolerances are dependent on the storage technologies' capital cost and the revenues obtainable within a specific market, among other factors.

The next figure (Figure 4.2-3) shows the influence of storage size, both energy capacity and power rating, on maximum revenue attainable in a real-time market.

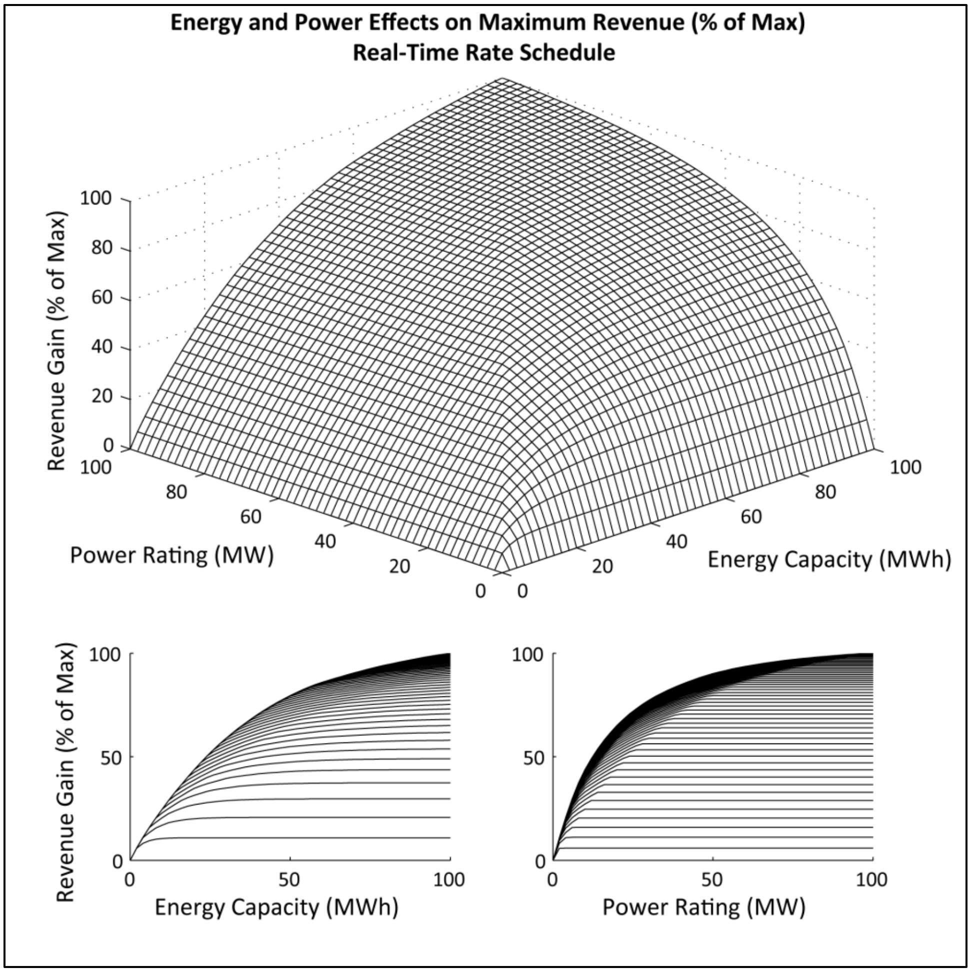

Figure 4.2-3: Real-Time – Storage Size vs. Revenue Gain

Maximum revenue does not attain saturation nearly as quickly as in the TOU market, because in a real-time market revenue is determined by discharging all of the generated energy within a handful of hours. Hence, as energy and power capacity increases, more energy is available to be discharged during these peak hours, and revenue continues to go up. Realistically, the cost associated with increasing capacity and power will outweigh the diminishing returns seen in the revenues. Therefore, it is most helpful to look at the *rate* at which revenue increases with respect to increasing capacity and power limits. It is evident from Figure 4.2-3 that revenue initially increases fastest as the power limit is increased. However, it is important to note that an increase in power (ex. 20 MW) will only have a sizeable benefit on revenue if the energy capacity is at least twice as big (ex. 40 MWh). Hence, *for a given energy storage capacity, it is desirable to be able to fully discharge within ~2 hours to capture most of the benefits in a real-time market.*

4.2.1. Lead-Acid Batteries

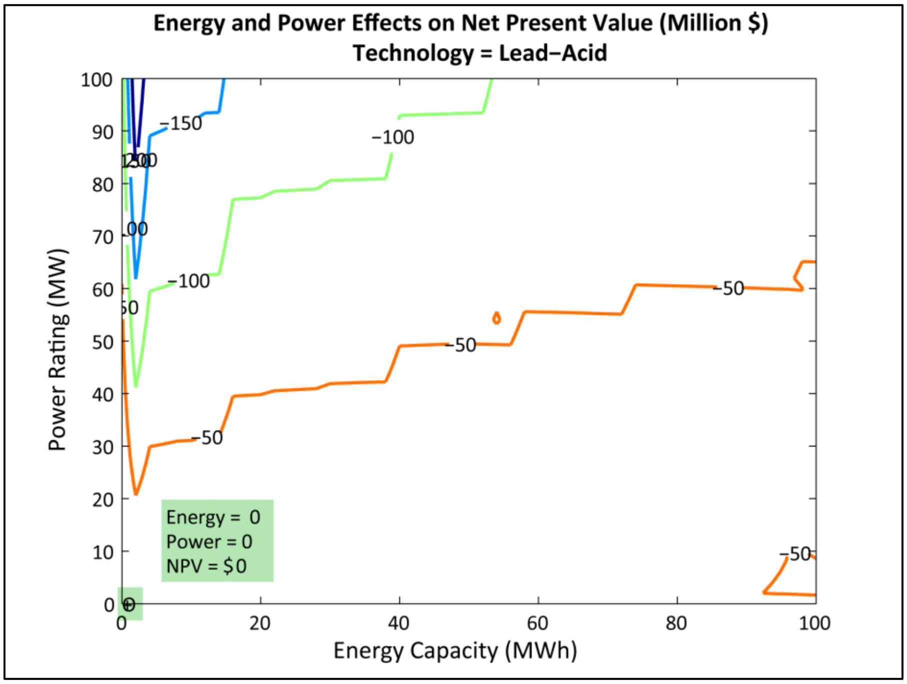

Figure 4.2-4: Central Generation – Real-Time – Lead-Acid – Storage Size vs. NPV

As with the TOU scenario, the limited cycle lifetime of lead-acid batteries makes the NPV very sensitive to operational characteristics. The stair-step behavior of NPV with respect to energy capacity is a direct result of crossing a cycle lifetime threshold for which an additional lead-acid battery pack must be purchased. For example, a 32 MW lead-acid battery bank is cycled less-frequently when the energy capacity is 20 MWh as compared to 15 MWh. This decrease in lifetime cycles results in one less capital purchase requirement; hence there is a threshold that is crossed which abruptly changes the NPV. Like the TOU scenario, lead-acid batteries are not a wise choice for this market.

4.2.2. Lithium-Ion (Li-Ion) Batteries

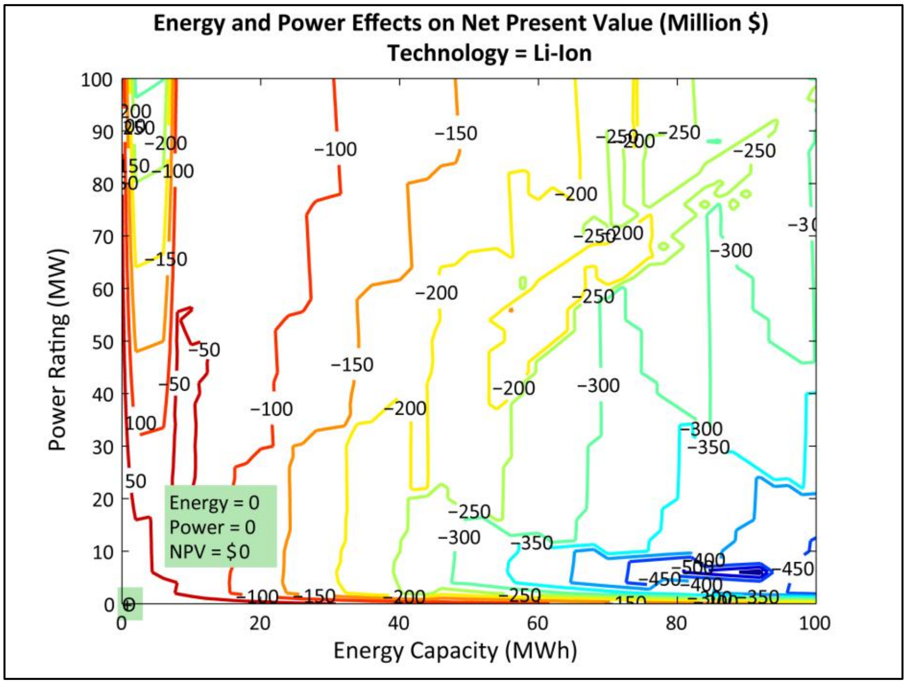

Figure 4.2-5: Central Generation – Real-Time – Li-Ion – Storage Size vs. NPV

Li-ion batteries are the only storage technology analyzed where the cost per unit energy is larger than the cost per unit power (and by a factor of 4!). This intuitively makes Li-ion suited more for power applications than energy arbitrage, which is verified in Figure 4.2-5. Also, because of the high dependence of capital cost on operational characteristics, the NPV surface appears almost to be random except for the general trend of decreasing return on investment with an increase in energy capacity. Hence, any storage system that utilizes Li-ion batteries should be well designed and tailored to the specific operational constraints and capabilities of this storage technology. Regardless, it may prove very difficult to accurately predict the return on investment for this technology in providing any energy arbitrage services.

4.2.3. Nickel-Cadmium (NiCd) Batteries

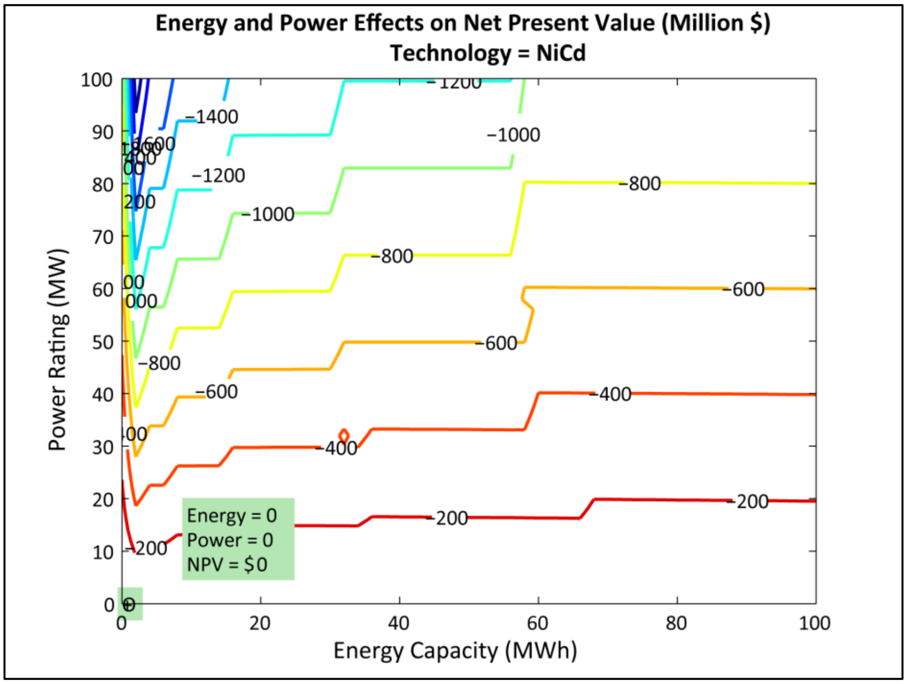

Figure 4.2-6: Central Generation – Real-Time – NiCd – Storage Size vs. NPV

In contrast to the residential TOU scenario, centralized generation requires the NiCd battery pack to be operated in such a way that multiple replacements are possible. This is represented by the stair-step effect in Figure 4.2-6. It is evident that NiCd batteries are not economically viable for this market.

4.2.4. Sodium-Sulfur (NaS) Batteries

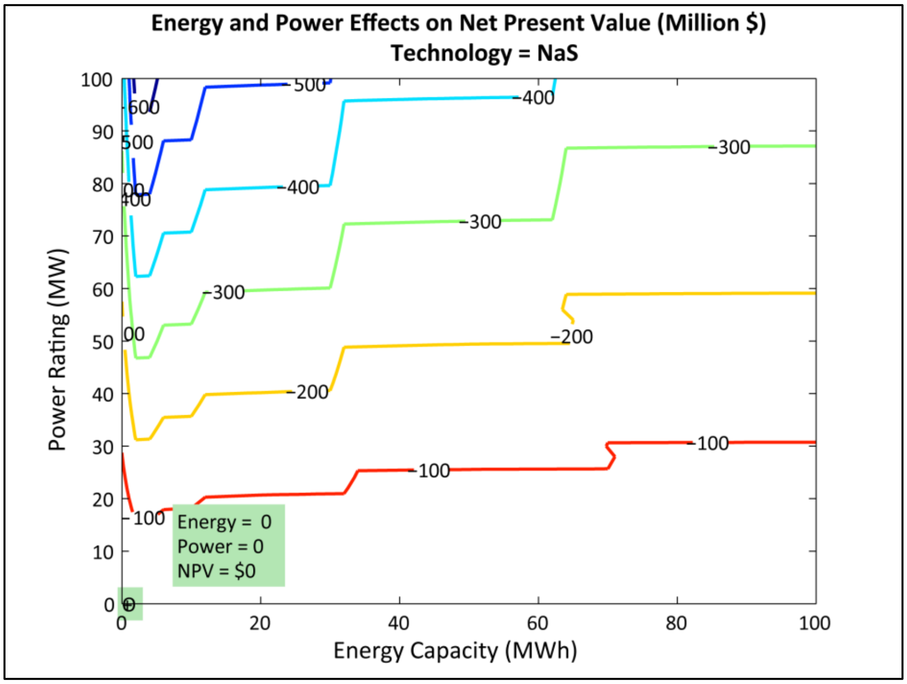

Figure 4.2-7: Central Generation – Real-Time – NaS – Storage Size vs. NPV

NaS batteries show very similar characteristics as NiCd batteries except the capital cost is significantly lower, and therefore the NPV is greater for comparable battery sizes. Even so, this technology is not suitable for real-time markets on this scale.

4.2.5. Vanadium Redox Flow Batteries (VRB)

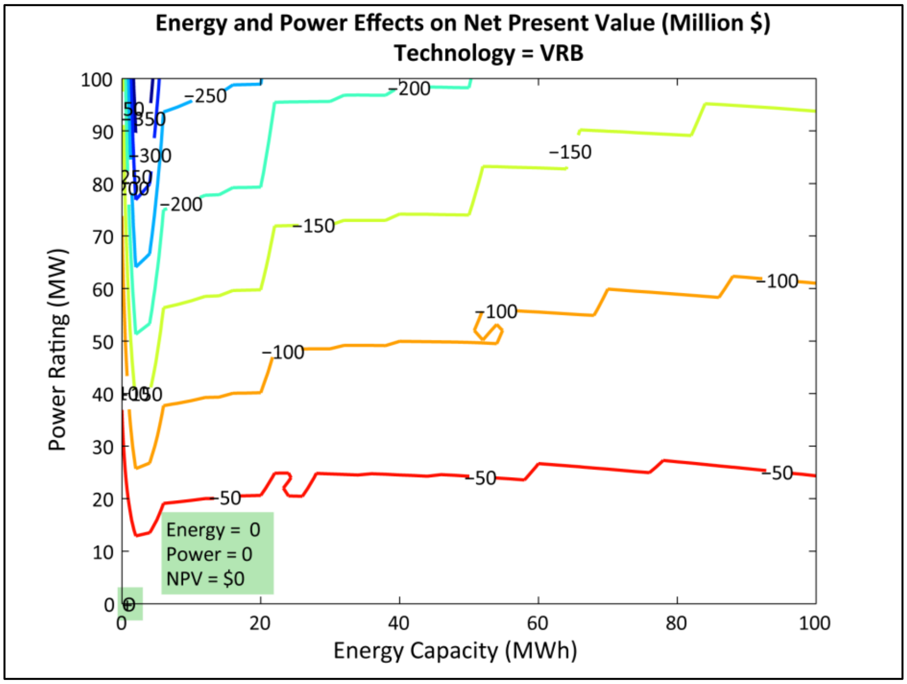

Figure 4.2-8: Central Generation – Real-Time – VRB – Storage Size vs. NPV

The unit power cost of VRBs is about half that of NaS, but the cycle lifetime is about half as well. Therefore, Figure 4.2-8 represents a very irregular NPV surface with losses being about half of those reported for NaS battery systems. Still, this technology is a long way from being lucrative in a real-time market.

4.2.6. Zinc-Bromide (ZnBr) Flow Batteries

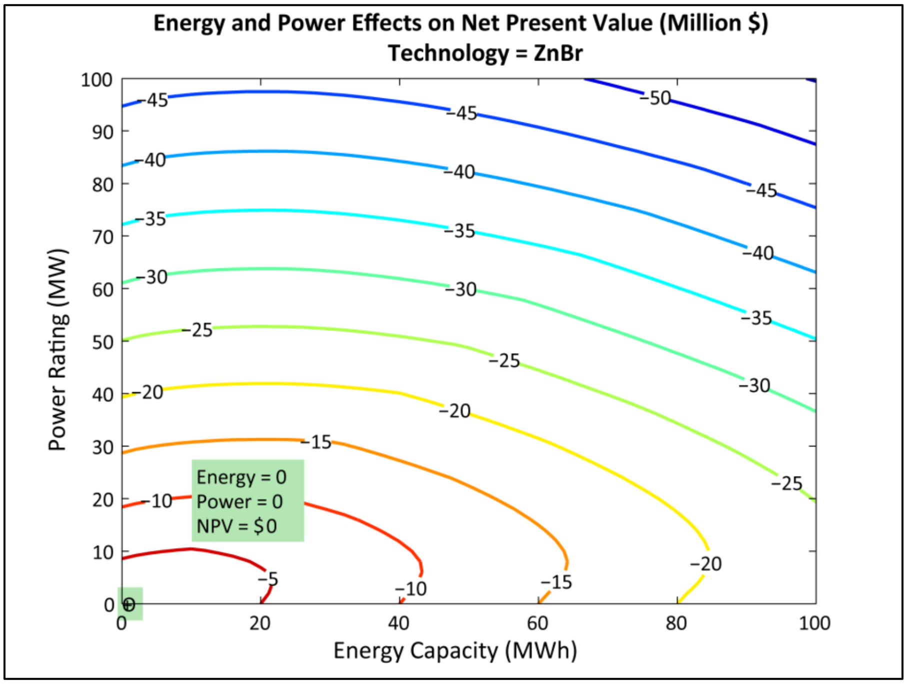

Figure 4.2-9: Central Generation – Real-Time – ZnBr – Storage Size vs. NPV

The unlimited cycle lifetime of ZnBr flow batteries result in a very smooth NPV response surface, as shown in Figure 4.2-9. It appears as though capital cost improvements could make this technology attractive for this market, but further analysis shows that the unit energy cost would have to come down by a factor of 5, and the power cost cut in half before a positive NPV is observed. Hence, this technology is still a long way from becoming attractive for this application.

4.2.7. Hydrogen Electrolysis with Fuel Cell (H2)

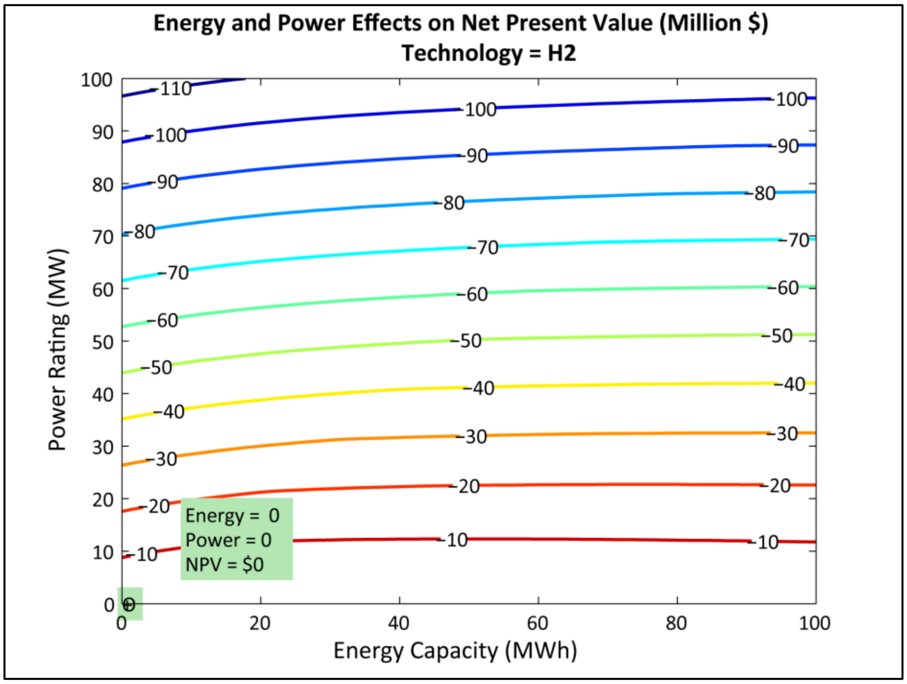

Figure 4.2-10: Central Generation – Real-Time – H2 – Storage Size vs. NPV

Many of the characteristics of H2 systems are very attractive for the energy arbitrage market, including the low cost per unit energy and unlimited cycle lifetime. However, the roundtrip efficiency is too low, and the cost per unit power is too high to currently be viable. Additional benefit could be gained if the roundtrip efficiency and the calendar lifetime were increased. Due to discounting, however, even at 85% system efficiency and a 30 year lifetime, the power cost would have to decrease by over half to about $200/kW before the NPV becomes positive. This emphasizes the importance of decreasing the *capital* expenditure of storage systems – not just the lifetime costs.

4.2.8. Compressed Air Energy Storage (CAES)

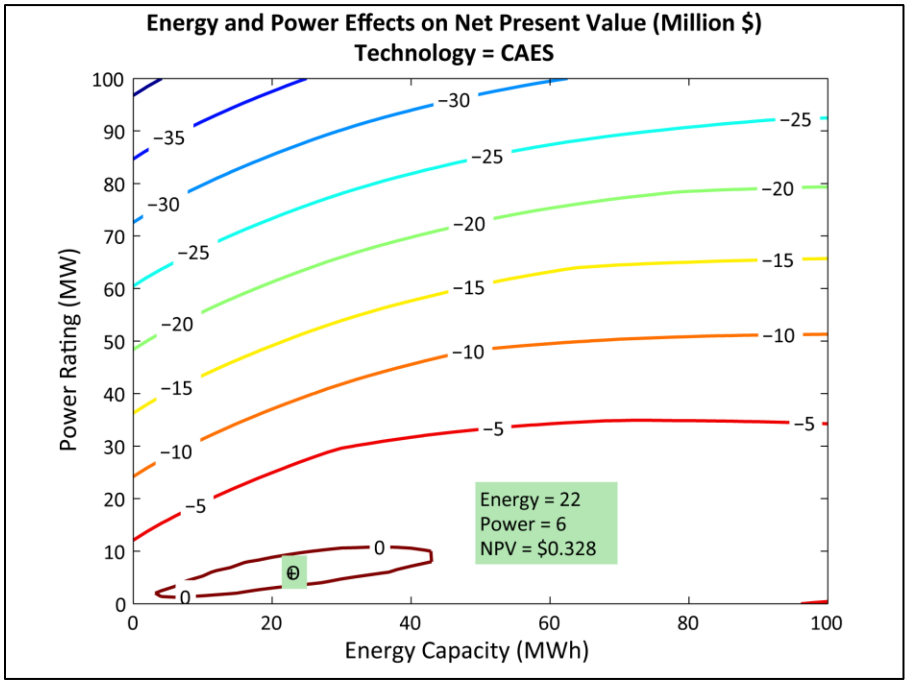

Figure 4.2-11: Central Generation – Real-Time – CAES – Storage Size vs. NPV

CAES is one of two technologies that actually show to be economically viable in a real-time market (PHES being the other – discussed in the next section). There is a rather limited range of options that would observe a positive return on the investment, from 5 MWh at 2-3 MW up to 40 MWh at 10 MW. The maximum return for this particular rate schedule is about $330k, which is obtained with a 22 MWh system rated at 6 MW.

When considering CAES it should also be noted that there are some emissions associated with its operation. The turbines consume about 4,000 Btu/kWh of natural gas [29], which at a CO_2 emission rate of 117,000 pounds per Billion Btu [48], equates to about half a pound of CO_2 per kWh. For the above system configuration of 22 MWh at a rated power of 6 MW, there are about 3.12 Million pounds of CO_2 emitted each year from natural gas use. However, compared to an average natural gas plant which emits about 1.1 pounds of CO_2 per kWh [49], the entire solar-with-CAES system has about 6.5 times less CO_2 emissions than a natural gas plant providing the same generation service.

4.2.9. Pumped-Hydro Energy Storage (PHES)

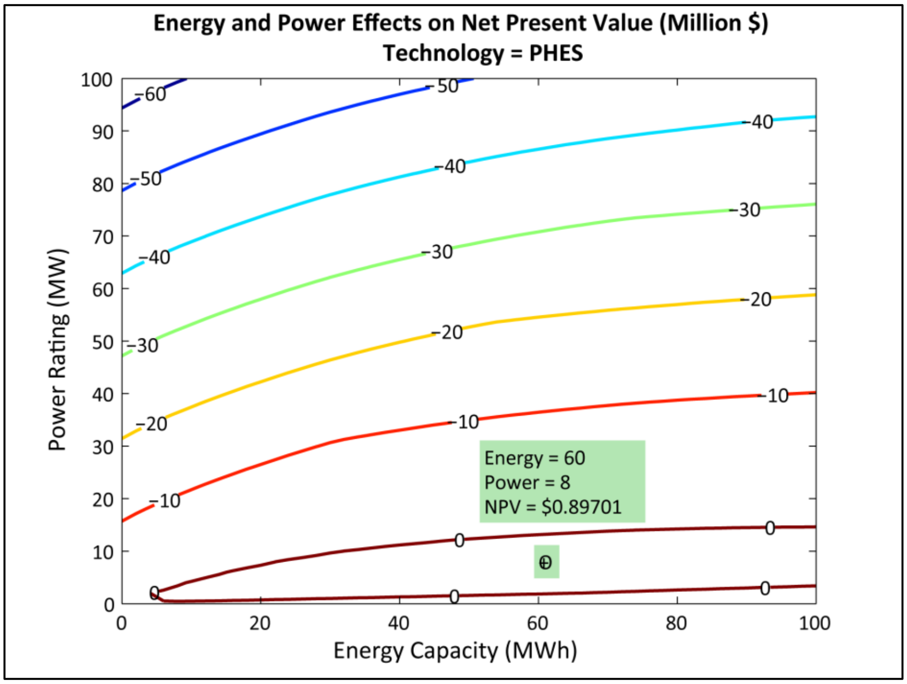

Figure 4.2-12: Central Generation – Real-Time – PHES – Storage Size vs. NPV

PHES is the only other technology considered in this work that demonstrates a positive NPV. The range for which this is attainable is even larger than for CAES systems, as seen in Figure 4.2-12. The low cost per unit energy capacity extends the possible system configurations past the 100 MWh limit of the plot. However, the maximum is observed with a 60 MWh system with a power rating of 8 MW, which is estimated to give a net return of almost $900k.

4.3. Centralized Generation as Baseload

In addition to the NPV evaluations for different service requirements, a sensitivity analysis is performed for all the storage technologies except CSTP with thermal. This is done by holding all characteristics of the storage device constant for the 9am – 9pm service requirement configuration, and then varying each key cost and performance metric while measuring its effect on NPV.

CSTP with thermal storage will be used as a comparison for PV-with-storage systems within the role of providing a set demand profile (service requirement). As shown in Table 4-1, each storage technology is fist assessed on its capacity to provide a 12 hour service requirement starting at 9am each day of the year. Thermal storage offers a $2.21 Million return on investment while providing this service. In other words, the savings attainable from utilizing thermal storage – even while being required to meet this service requirement – outweighs the costs by a present value of about $2 Million over the lifetime of the system. Figure 4.3-1 shows the lifetime net present value (NPV) of the thermal energy storage investment evaluated for many different service requirement demand profiles. All demand profiles have a peak demand of 10 MW. The hour in which the service requirement begins, and the duration of the daily service requirement are varied. For CSTP with thermal storage, a ~$3.3 Million return on investment is made possible if the system is allowed to sell the excess energy into the wholesale real-time market and if the service requirement starts at 11:00am every day and lasts for 7 hours (through 5:00pm).

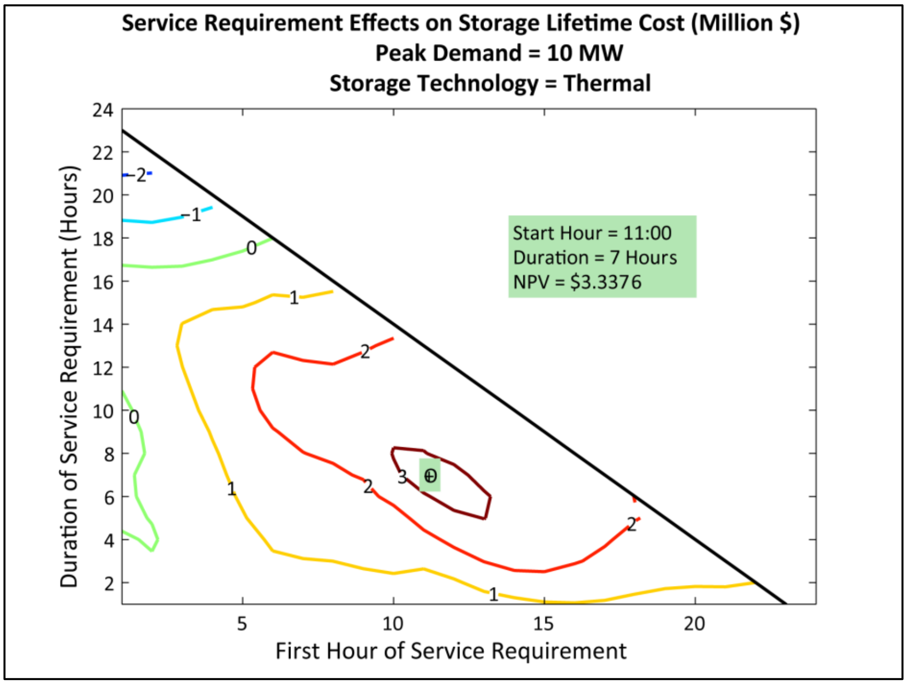

Figure 4.3-1: Baseload Generation – CSTP – Thermal – Optimized Dispatch

A sample demand profile with these characteristics is shown in Figure 4.3-2 along with the CSTP turbine output and real-time electricity price profiles for July 15th. Note that the generator is allowed to sell additional energy into the real-time market at the high price points (4:00pm in this case). If the generator is not allowed to discharge this additional energy, there would be many days in which the system is oversized for the service requirement (because the system must be designed to meet the peak demand periods), and it would be forced to shunt (waste) the extra energy. With this particular service requirement, the annual revenues would be limited to $1.44 Million (dictated by the service requirement), and an amount of ~$560,000 is lost from shunted energy. For many service requirement profiles, this actually results in lower revenues than a completely non-dispatchable system without storage. Hence, no additional revenue exists as an incentive to add the storage device. It is worth noting, however, that a valid possibility may be to couple the solar-with-storage system with a small peaker generator (such as a natural gas turbine). This would allow the solar-with-storage system to be sized for the average demand, and the peaker would only be operated during peak demand periods. The analysis of this configuration is beyond the scope of this thesis, but should be looked at in future work.

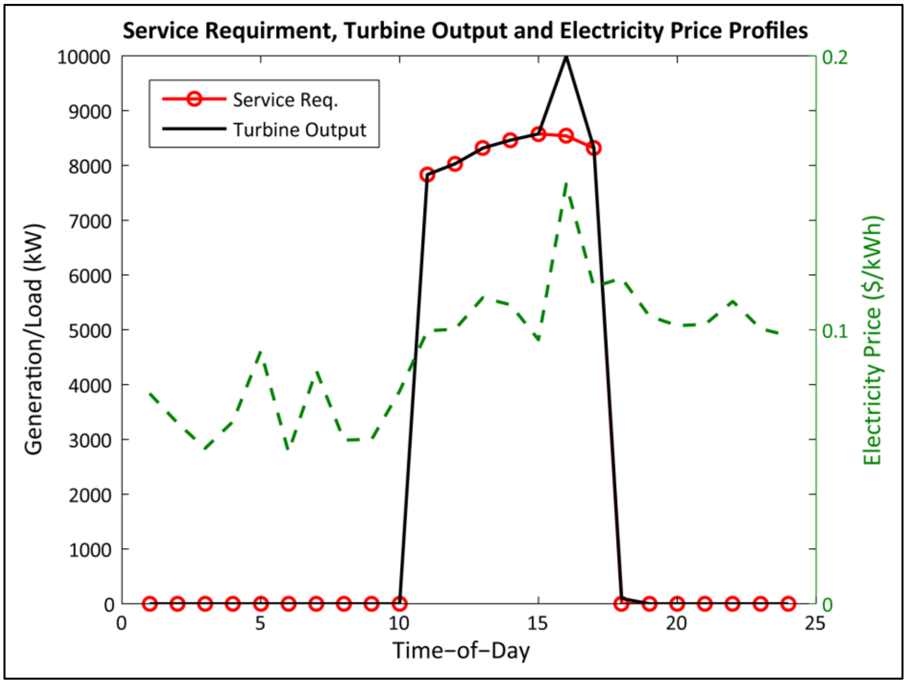

Figure 4.3-2: Baseload Service Requirement and Dispatch Profiles

Figure 4.3-3 shows the NPV of the thermal storage investment for the scenario in which the turbine output is limited to producing the required service profile. Under these restrictions there are no service profiles that would be favorable for adding storage. This does not mean the system as a whole would not provide a positive return on investment. Rather, this indicates that under these service restrictions, the investment value would decrease by the NPV amount shown in Figure 4.3-3 because of the added cost of the required thermal storage. For example, the service requirement mentioned above starting at 11:00am, and lasting for 7 hours each day, would subtract a total lifetime amount of ~$2 Million from the total system investment. Since this restricted service requirement does not result in a favorable return on investment for thermal storage, it is safe to conclude that all the other storage technologies would show an even worse NPV under these conditions. Therefore, this exercise is not repeated for the other technologies, and all the other service requirement plots assume excess energy can be sold into the real-time market.

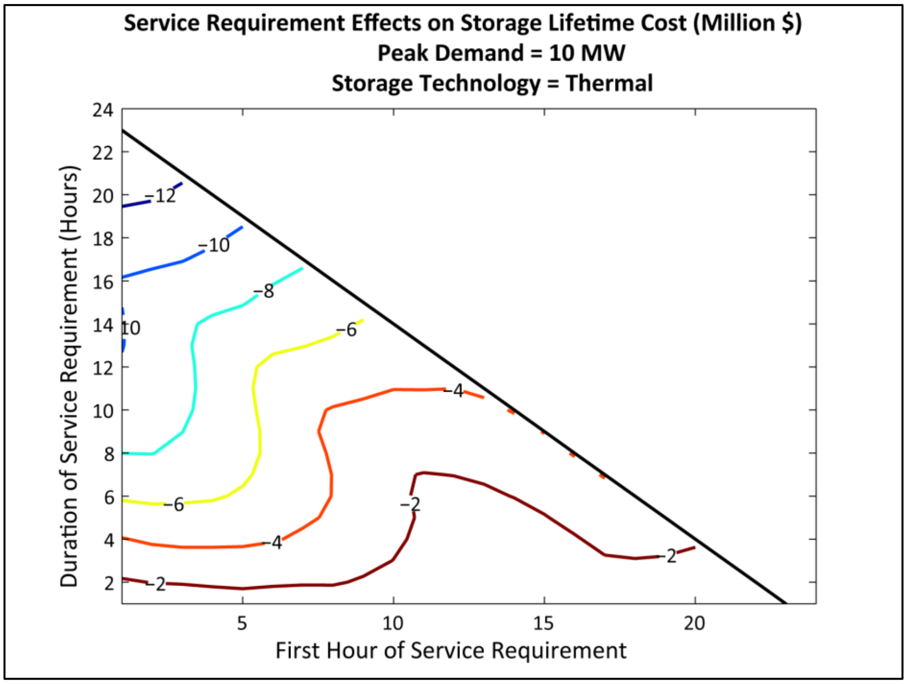

Figure 4.3-3: Baseload Generation – CSTP – Thermal – Restricted Dispatch

4.3.1. Lead-Acid Batteries

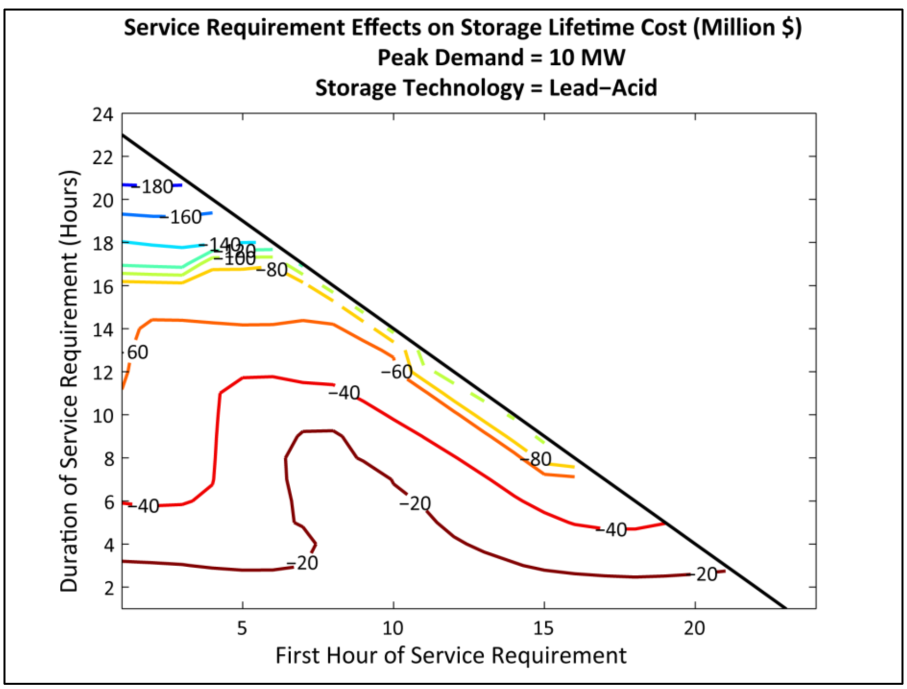

Figure 4.3-4: Baseload Generation – PV – Lead-Acid – Optimized Dispatch

As seen in Figure 4.3-4 above, lead-acid batteries are too expensive over the lifetime of a PV system to provide a positive return for any of the service requirement profiles. In addition, the lifetime cost of using lead-acid batteries to satisfy the base case 9am – 9pm service profile is ~$49.6 Million. This is about 55% of the cost of the PV array required for such a system.

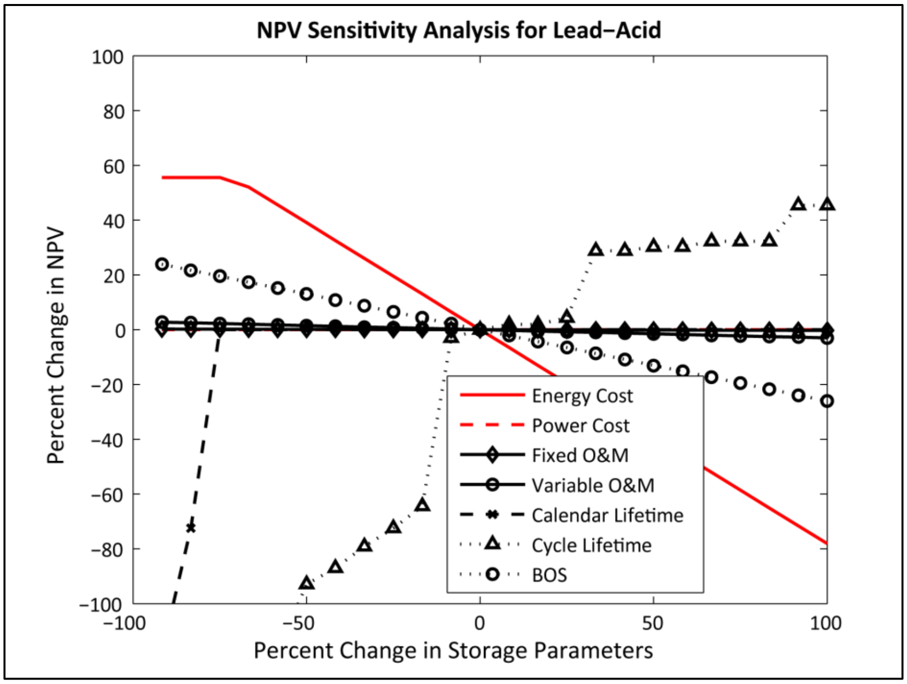

Figure 4.3-5: Baseload Generation – PV – Lead-Acid – NPV Sensitivities

For lead-acid batteries, the two metrics that have the most potential for influencing NPV are the unit energy cost and the cycle lifetime, as seen in Figure 4.3-5. If the energy cost is reduced by 30% ($100/kWh) and the cycle lifetime is increased by 30% (2,000 cycles at 100% DOD), not only is the NPV of the storage investment increased by 36%, but the total installed cost of the solar-with-storage system is decreased by ~3%. This is because the service requirement may be met with a smaller solar field by increasing the size of the battery bank, resulting in an overall lower capital cost. If the energy cost is reduced by 66% to $50/kWh, and the cycle lifetime is increased by a factor of ~4 to 6,150, then the NPV of the storage investment is increased by 68%, and the total cost is reduced by 7.8%. If these dramatic improvements in energy cost and cycle lifetime are achieved, then the BOS cost and energy cost become equally important, and the cycle lifetime is no longer a limiting factor. Therefore, the continued decrease of the $/kWh capital cost of the lead-acid battery becomes the most important area to focus on once a cycle lifetime of ~6,000 is achieved.

4.3.2. Lithium-Ion (Li-Ion) Batteries

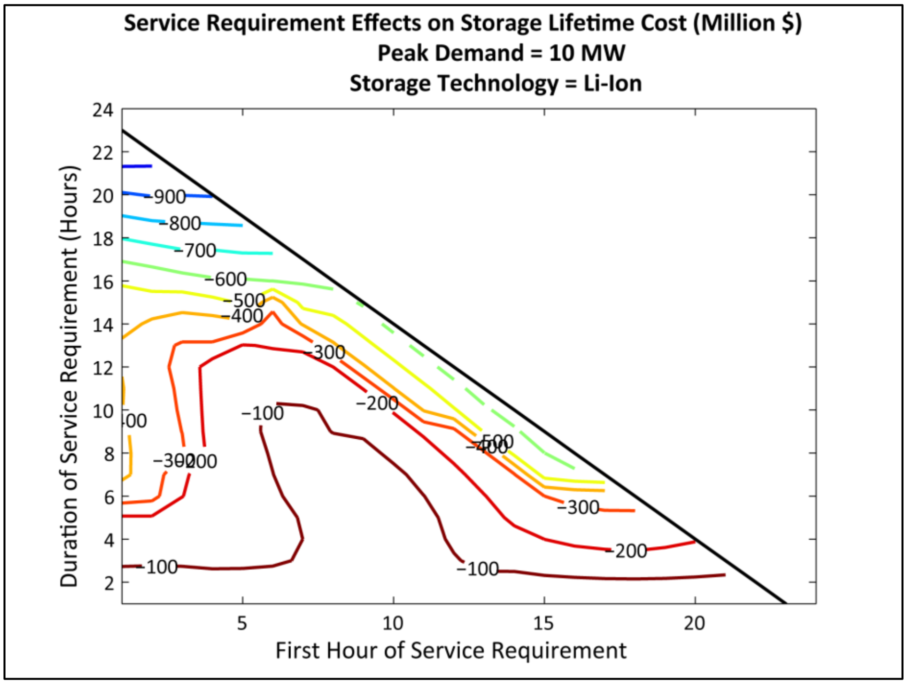

Figure 4.3-6: Baseload Generation – PV – Li-Ion – Optimized Dispatch

Li-Ion batteries are an entirely unreasonable choice for the energy arbitrage required for meeting any service requirement. The lifetime cost of Li-ion batteries to meet the 9am – 9pm demand profile is an astounding $392 Million – approximately 4 times greater than the cost of the PV array for such a system.

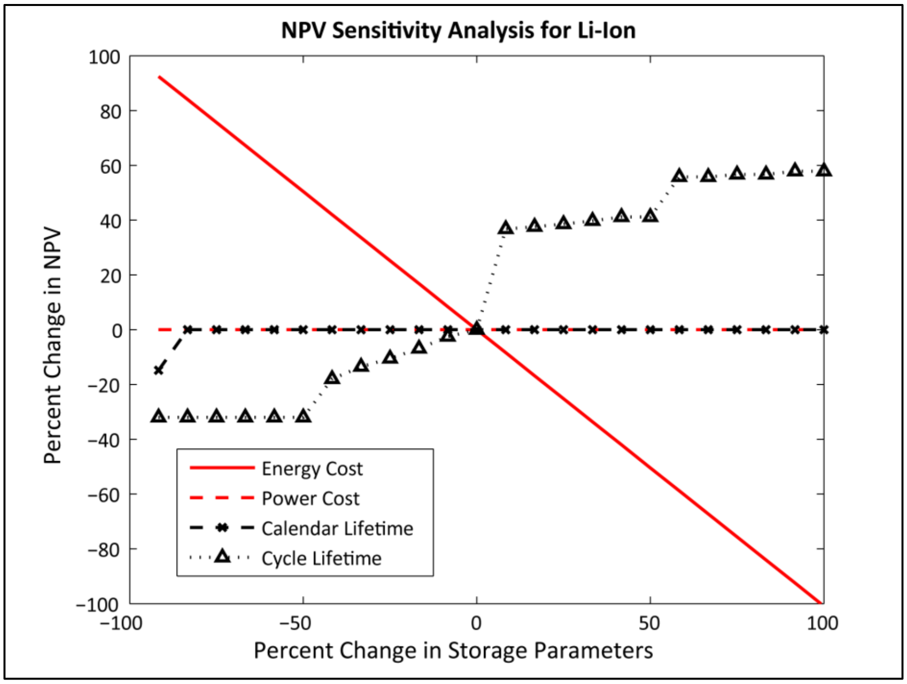

Figure 4.3-7: Baseload Generation – PV – Li-Ion – NPV Sensitivities

Although still not suitable for energy arbitrage, the investment in Li-Ion batteries for this particular service requirement could be increased by a dramatic 37% for only a 1% increase in cycle lifetime from 1,500 to 1,520. This is too close to the assumed value of 1,500 cycles to be claimed different; therefore, it is speculated that an NPV of -$247.8 for Li-ion batteries is achievable. This is still ~2.5 times more expensive than the capital cost of the PV array and would be a very bad investment. A cycle lifetime of ~11,400 would be required to eliminate this as a significant factor for NPV, which would then make the reduction of the unit energy cost the sole focus area. Overall, the unit energy cost dwarfs all the other components, making a reduction in this metric critical for any positive investment effects. There is a 1:1 relationship between the unit energy cost and NPV, where a 1% reduction in the energy cost results in a 1% increase in NPV (assuming all other parameters are held constant, and the operation of the storage device does not change). Since Li-ion has a fixed architecture, and the energy cost is so high, the unit power cost is never a limiting factor for the storage NPV, and is therefore shown at null in Figure 4.3-7.

4.3.3. Nickel-Cadmium (NiCd) Batteries

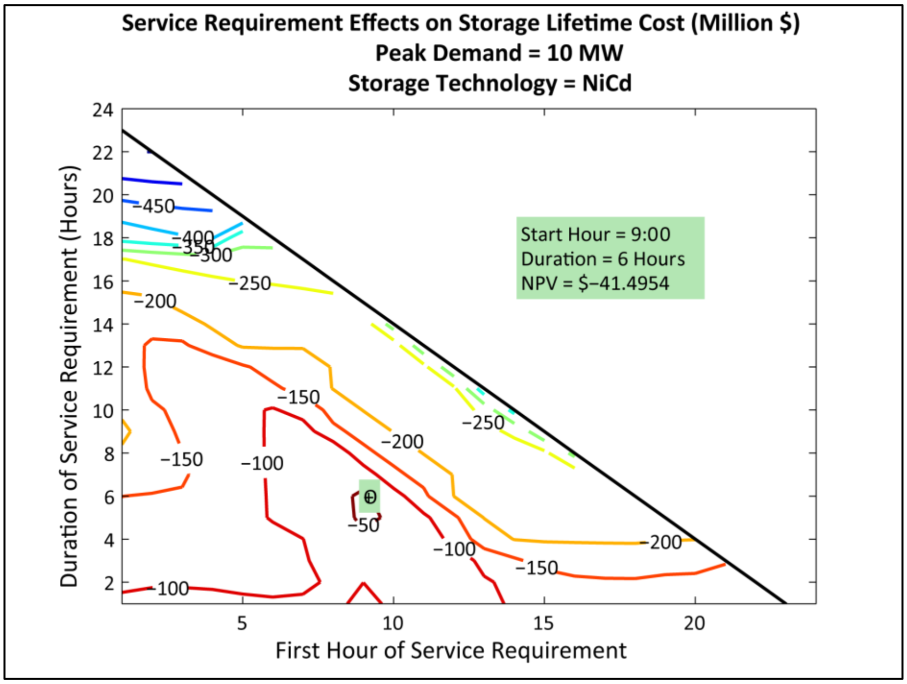

Figure 4.3-8: Baseload Generation – PV – NiCd – Optimized Dispatch

Similar to Li-Ion, NiCd batteries are very poorly suited for the energy arbitrage required to meet a demand profile. The lifetime cost of a NiCd battery bank to meet the 9am – 9pm service requirement is approximately $212 Million, which is about two times greater than the cost of the PV array for such a system. However, if the system is required to meet a 6-hour demand profile starting at 9am instead, then the lifetime cost of the NiCd battery bank would be about 80% that of the PV array ($41.5 Million).

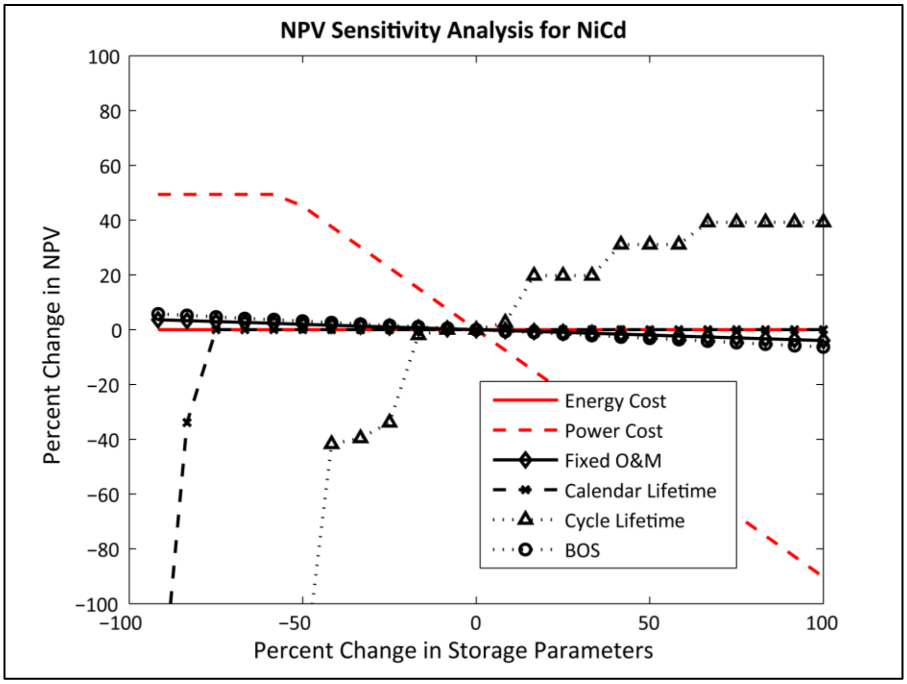

Figure 4.3-9: Baseload Generation – PV – NiCd – NPV Sensitivities

The very high unit power cost of NiCd is the primary area of concern. If this could be reduced by ~57% to \$2,700/kW, then the total capital cost would come down by 17%, the storage NPV would increase by 50%, and the cycle lifetime would become the limiting factor. The cycle lifetime would have to be increased by a factor of 4 (to 9,200 cycles) before fixed O&M and BOS become of concern.

4.3.4. Sodium-Sulfur (NaS) Batteries

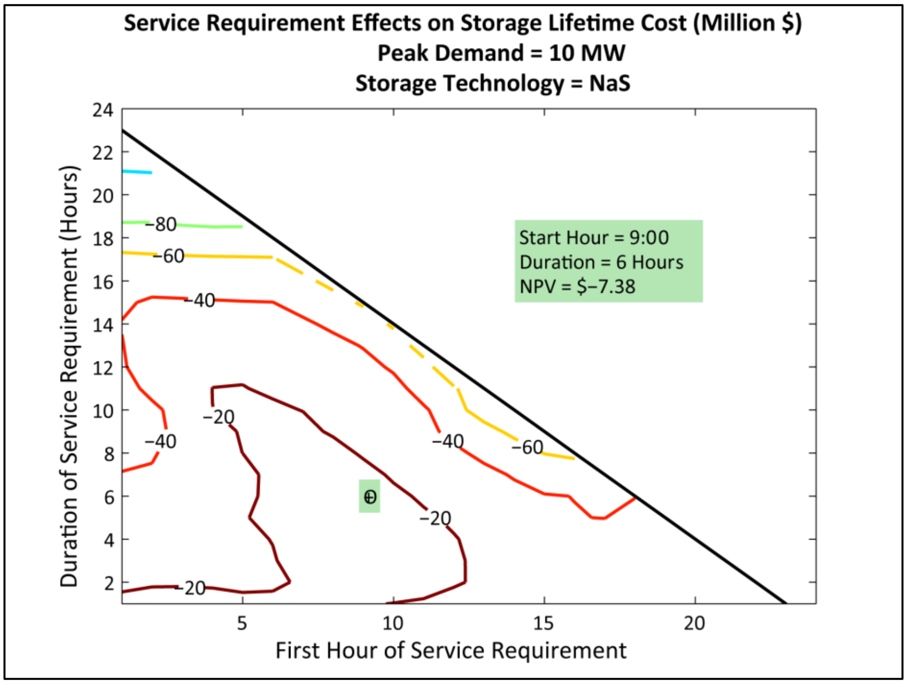

Figure 4.3-10: Baseload Generation – PV – NaS – Optimized Dispatch

Other than flow batteries, NaS batteries are the most promising electrochemical battery architecture for energy arbitrage analyzed in this work. This is mostly attributed to their high cycle and calendar lifetimes, which limits the number of capital expenditures (replacements) that are required over the PV system's lifetime. Although the lifetime cost of NaS to provide the 12 hour service requirement is $32.8 Million, this reduces to ~$7 Million if the demand profile is limited to 6 hours, starting at 9am.

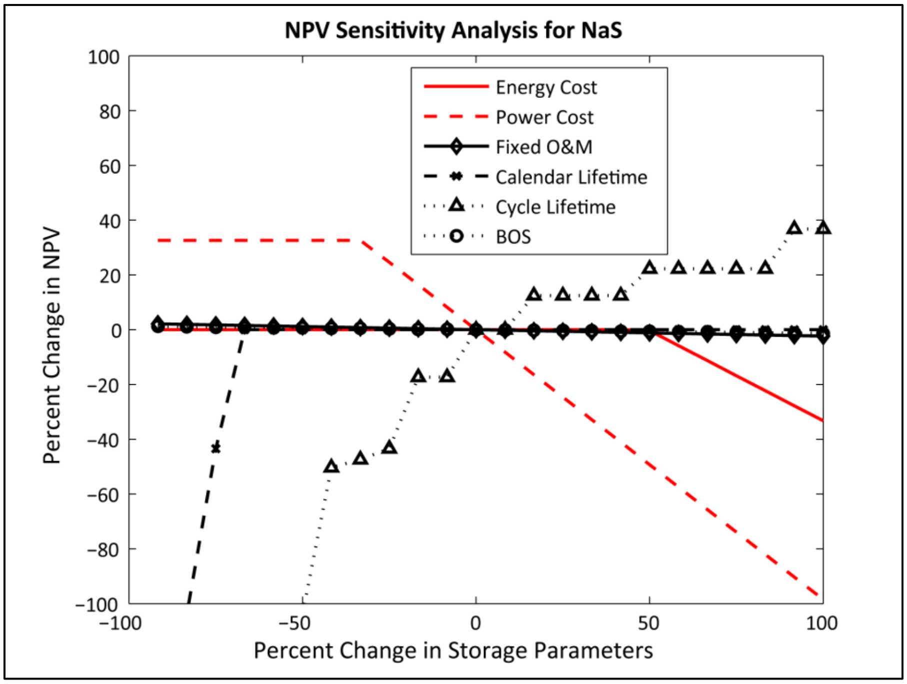

Figure 4.3-11: Baseload Generation – PV – NaS – NPV Sensitivities

As seen in Figure 4.3-11, the unit power cost has the most potential for improving the storage investment. If this metric were decreased by 1/3 to $1,000/kW, it would have a directly proportional affect on NPV – increasing it by 33% – and the cycle lifetime would become the primary focus area. The cycle lifetime would have to be increased by ~67% to 8,750 cycles before O&M and the unit costs become of concern again. Unfortunately, even if these improvements were made, NaS would still be more expensive over the lifetime of a PV system than the available benefits under the constraint of meeting any of the service requirements.

4.3.5. Vanadium Redox Flow Batteries (VRB)

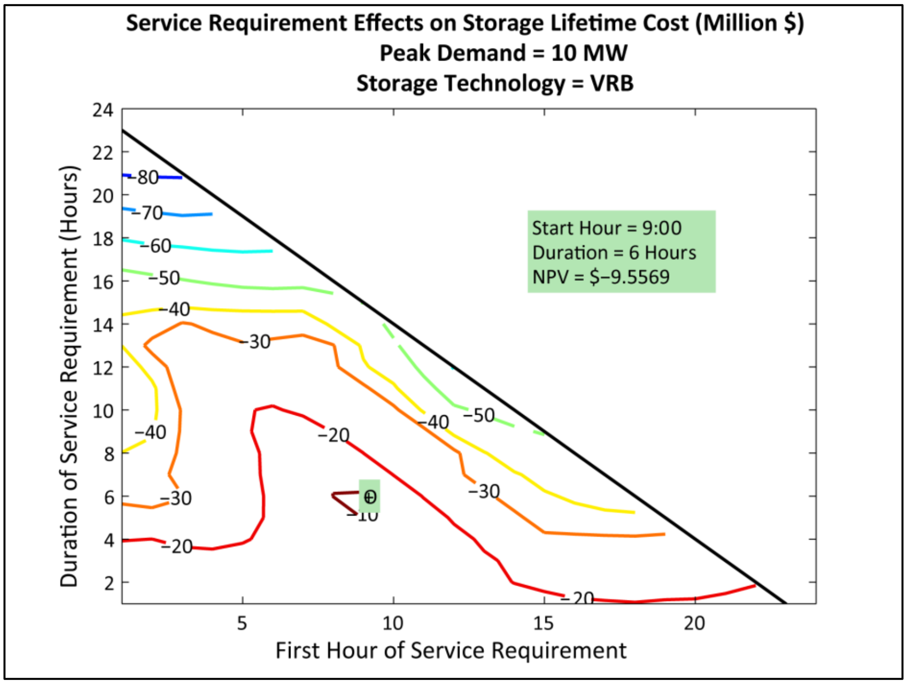

Figure 4.3-12: Baseload Generation – PV – VRB – Optimized Dispatch

Similar to NaS, but a bit more expensive, VRB would add significant cost to a PV system required to meet a service demand profile. The lifetime cost of meeting the 12 hour service requirement is $39.2 Million, whereas the 9am/6 hour service profile has a $9.5 Million price tag.

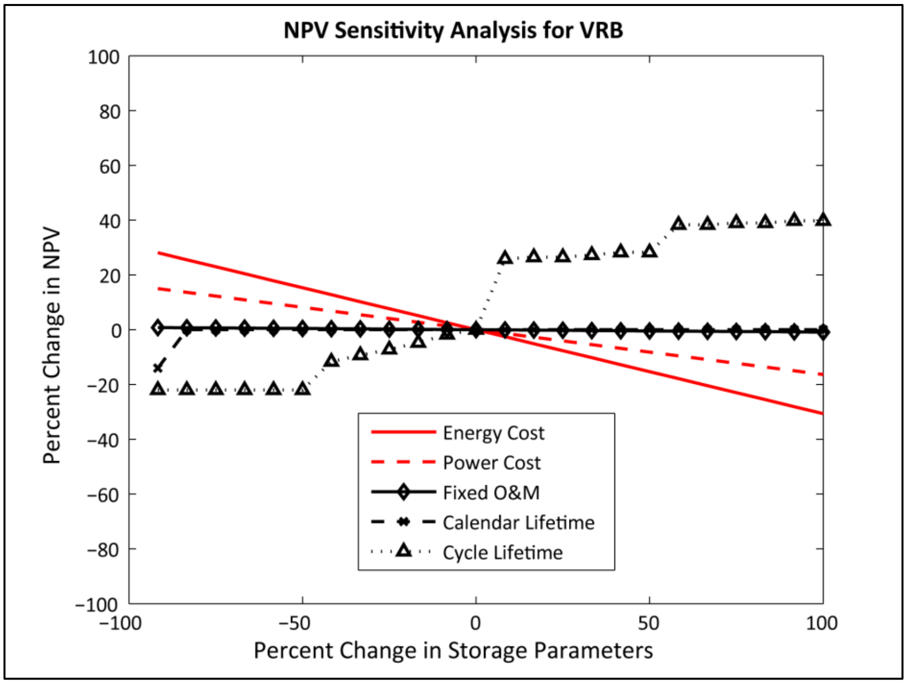

Figure 4.3-13: Baseload Generation – PV – VRB – NPV Sensitivities

If the cycle lifetime of VRB were increased by an unlikely 80% to 6,300 cycles, then the NPV would increase by over 55% and the unit energy and power costs become the sole metrics needing significant improvement. Even with this improvement, however, VRB is still far too costly for this type of energy arbitrage service.

4.3.6. Zinc-Bromide (ZnBr) Flow Batteries

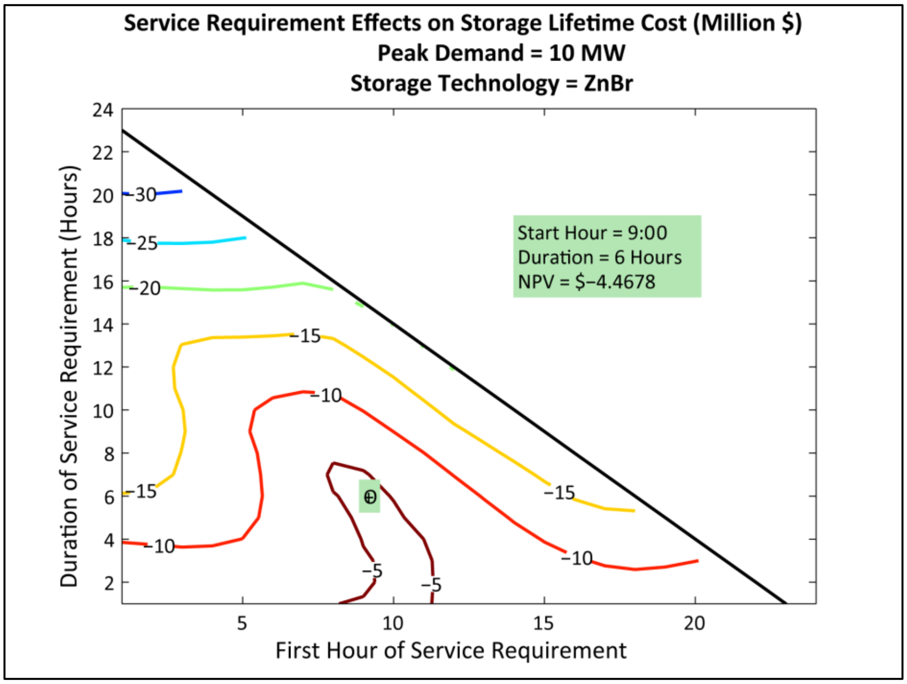

Figure 4.3-14: Baseload Generation – PV – ZnBr – Optimized Dispatch

ZnBr is the most promising electrochemical storage architecture for meeting the high energy arbitrage service requirements. The lifetime cost of meeting the 12 hour demand profile ~$14 Million, but for the 9am/6 hour profile, this is reduced to only ~4.5 Million. This technology is still a significant added cost to the project investment, but perhaps not out of the question with the proper incentives.

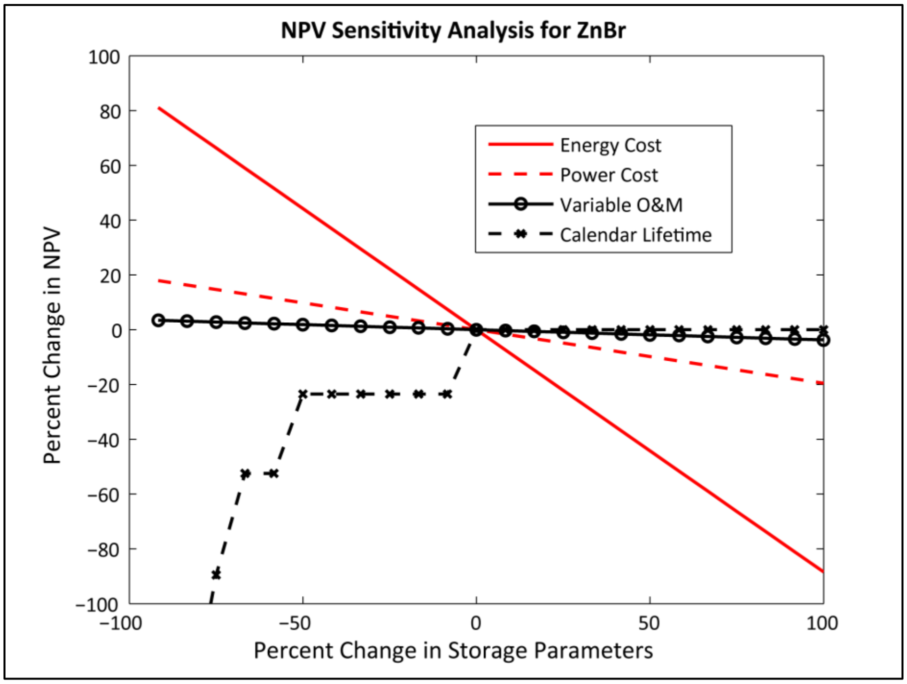

Figure 4.3-15: Baseload Generation – PV – ZnBr – NPV Sensitivities

The unit energy cost dominates the NPV for this technology. If this metric were decreased by 50% to \$125/kWh, the NPV would improve by about 37%. This unit cost of energy would have to come down to about \$20/kWh – an order of magnitude less – before the unit power cost becomes a limiting factor.

4.3.7. Hydrogen Electrolysis with Fuel Cell (H2)

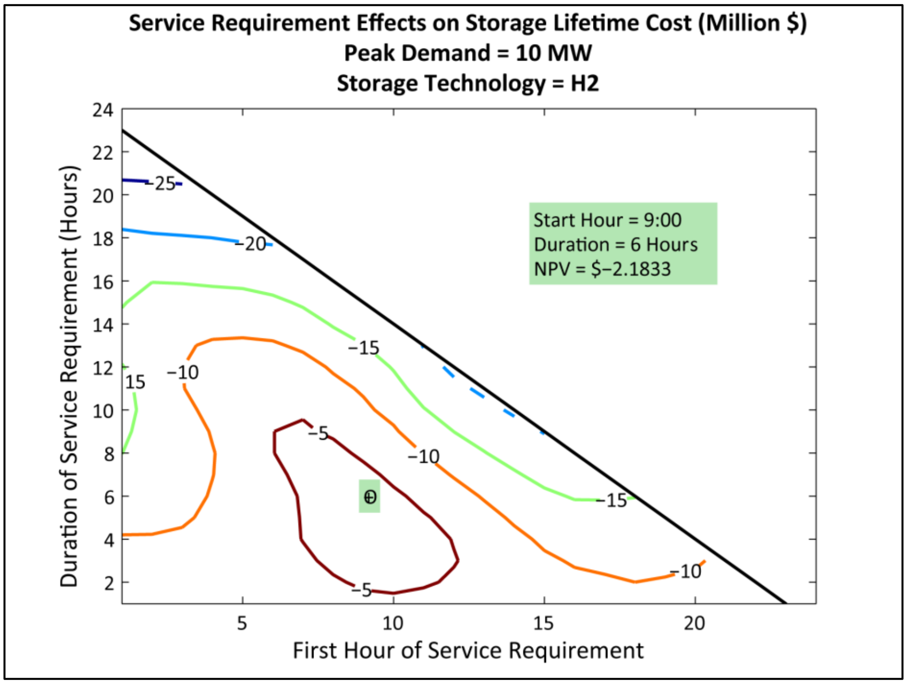

Figure 4.3-16: Baseload Generation – PV – H2 – Optimized Dispatch

H2 systems have some very promising characteristics for energy arbitrage applications. Notably, the unlimited cycle lifetime and low cost per kWh. Reducing the unit power cost appears to offer the most benefit for the storage investment, as shown in Figure 4.3-17.

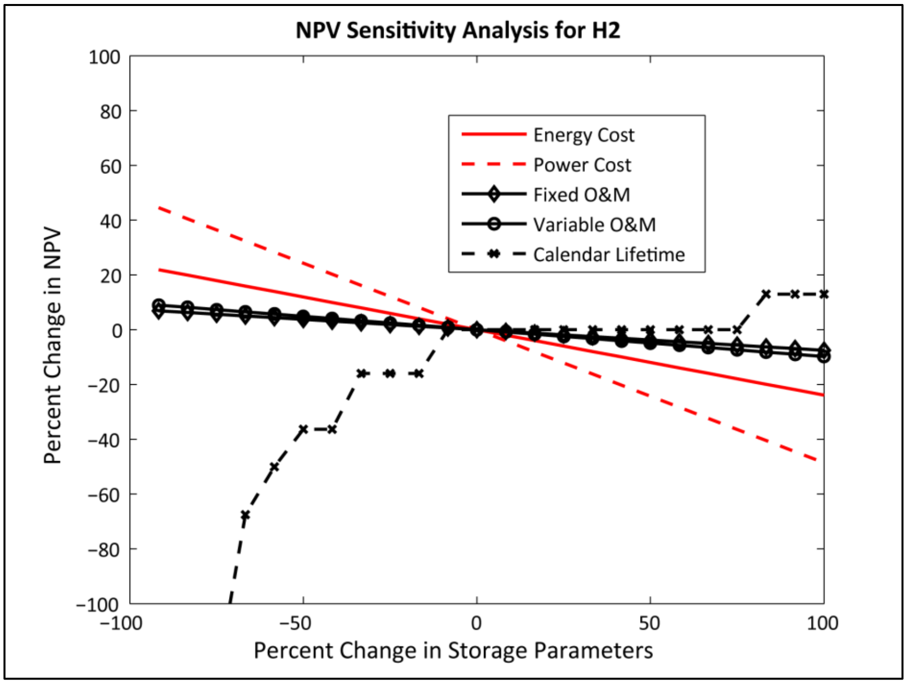

Figure 4.3-17: Baseload Generation – PV – H2 – NPV Sensitivities

However, hydrogen has the lowest roundtrip efficiency of all the storage technologies considered in this work. So, before looking at the benefits gained from decreasing the cost per unit power, an increase in roundtrip efficiency is considered. If this efficiency is increased from 59% to 85%, then the storage NPV increases by 40% and the total capital cost of the solar-with-storage system decreases by 17%. Without such an efficiency improvement, reducing the unit power cost by half – to $250/kW – would only increase the storage NPV by 20%, and reduce the capital cost by ~2.5%. Hence, improvement of roundtrip efficiency should be the primary focus area for H2 systems when coupled with PV.

4.3.8. Compressed Air Energy Storage (CAES)

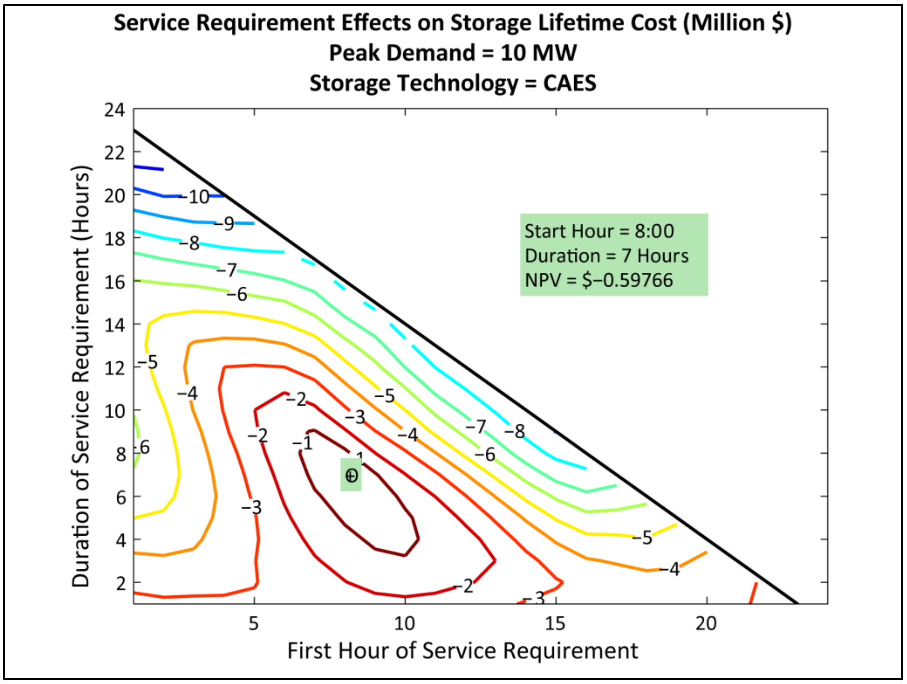

Figure 4.3-18: Baseload Generation – PV – CAES – Optimized Dispatch

Though often considered to be geographically limited due to the requirement of natural salt or rock caverns (to keep the $/kWh down), CAES may actually be viable for over 80% of the United States [29] and the economics are very promising for energy arbitrage services. The lifetime cost to meet the 12 hour service requirement is almost $5 Million, but as it can be seen in Figure 4.3-18, the NPV increases to about -$600k for an 8am/7 hour demand profile.

The emissions rate for the 12 hour service requirement is about 7.52 Million pounds of CO_2 per year, which is reduced to 2.26 Million pounds for the 8am / 7 hour service requirement. This is about 7 times less than the emissions of a comparably-sized natural gas plant for the 12 hour service requirement, and nearly 13 times less for the 8am / 7 hour requirement. Although it is not likely that natural gas would be used for a baseload-type generation service, the emissions from a baseload coal plant are about twice that of natural gas [49].

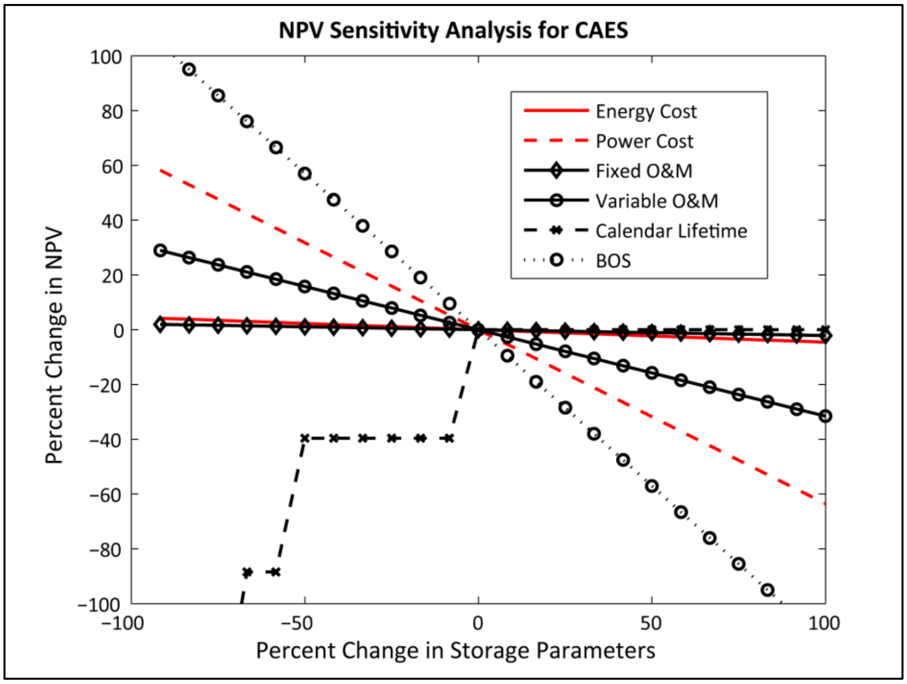

Figure 4.3-19: Baseload Generation – PV – CAES – NPV Sensitivities

The value of CAES is only limited by the BOS (energy-related) and unit power cost. Although improved manufacturing processes could potentially lower the BOS expense, this is unlikely to decrease by very much because of labor costs. It is interesting to note, however, that other metrics could be compromised if it meant bringing down the BOS cost. For example, the unit cost of energy (the storage medium) could be increased if the BOS were decreased. If it were possible to lower the unit power cost by 37.5% to $250/kW, and decrease the BOS expense by 70% to $15/kWh, then CAES actually shows a positive NPV while meeting the 9am – 9pm service requirement. However, these are very aggressive improvements which are unlikely to be realized in the near future. On the other hand, if the unit power cost and the BOS expense were each decreased by 20% to $325/kW and $40/kWh, respectively, then the 8am/7 hour service requirement would offer a positive NPV for CAES. If these improvements are met for either of these two scenarios, then the variable O&M (natural gas fuel cost) becomes a factor.

4.3.9. Pumped-Hydro Energy Storage (PHES)

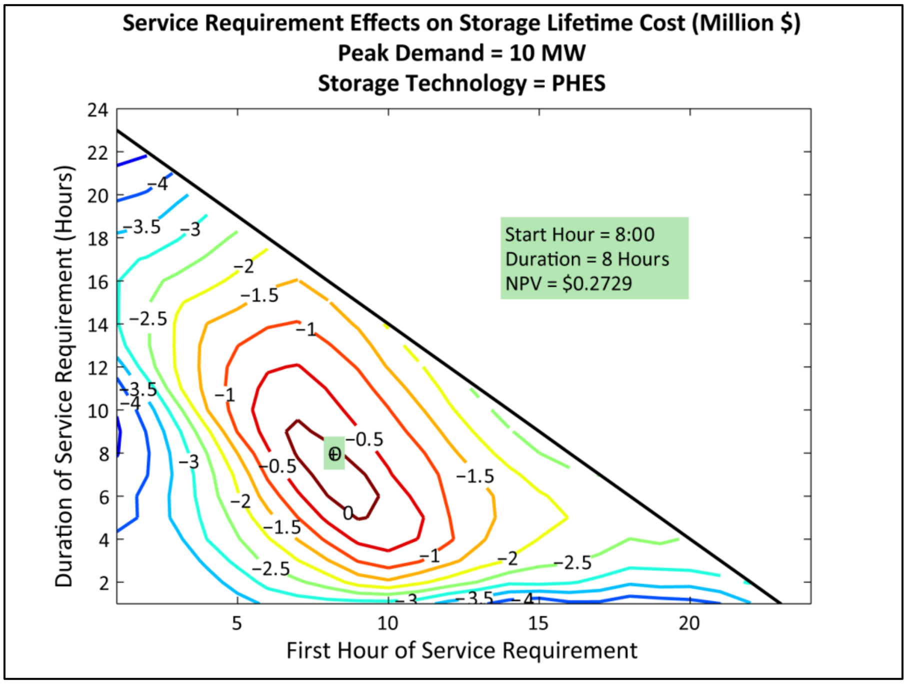

Figure 4.3-20: Baseload Generation – PV – PHES – Optimized Dispatch

Similar to CAES, but even more favorable, PHES boasts a $1 Million cost for the 12 hour service requirement and a positive NPV for an 8am/8 hour profile. However, PHES is much more geographically limited than CAES due to the need for two bodies of water at different elevations.

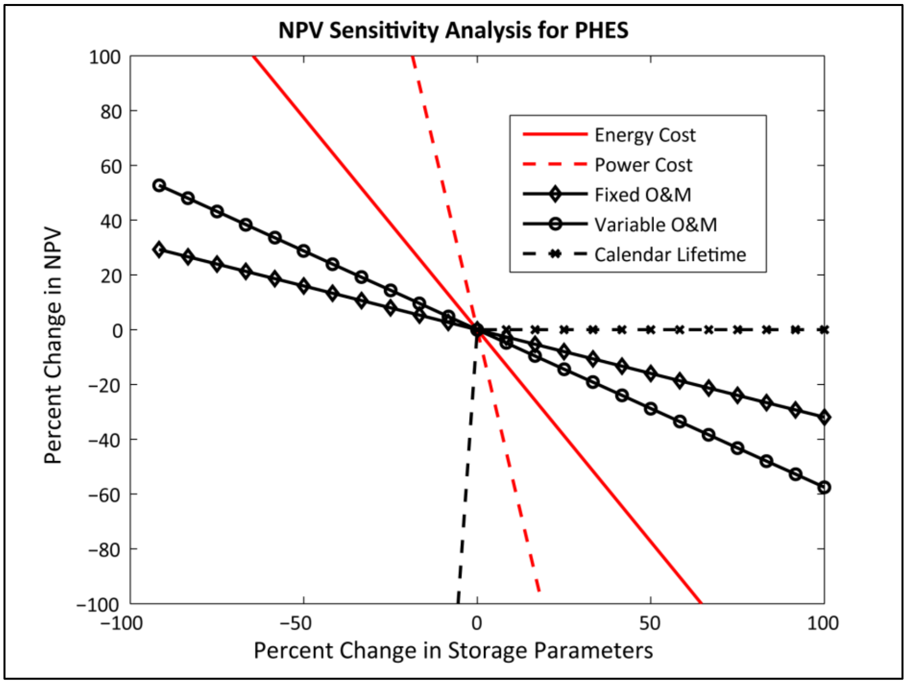

Figure 4.3-21: Baseload Generation – PV – PHES – NPV Sensitivities

The characteristics of PHES are very well suited for enabling PV to match a service requirement. If the unit power cost were decreased by 20% to \$480/kW, then even a slight decrease in power, energy, fixed O&M, or variable O&M costs dramatically increases the return on investment. This can be seen in Figure 4.3-22. Hence, the first priority is a decrease in the unit power cost (cost of the hydraulic turbines/pumps); after which, improvements in all other key parameters become fair game.

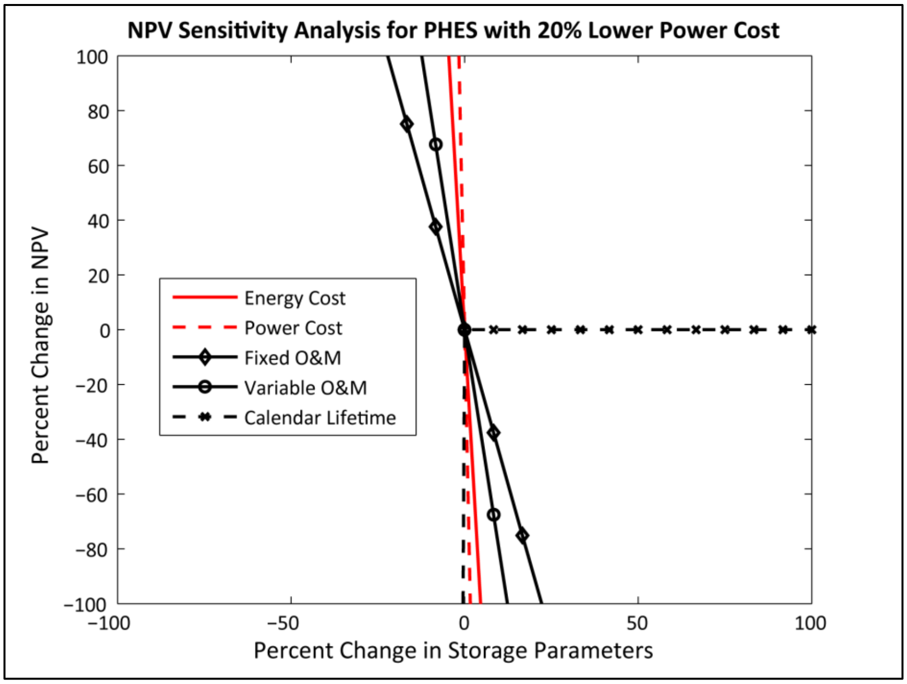

Figure 4.3-22: Baseload Generation – PV – PHES – NPV Sensitivities with Lower Power Cost

5. Conclusions

This thesis looked at the current state of energy storage technologies for the purpose of providing various energy arbitrage services for both residential and centralized PV generators. Two different electricity pricing schedules – TOU and real-time – were included in the analysis. The TOU rate schedule was chosen because it is the only time-varying electricity pricing scheme available for residential customers. Real-time rates were used because this is the time-varying rate schedule that a centralized generator has the option of selling into. Only time-varying pricing schedules were looked at for this work because the value of energy arbitrage only arises when there is a temporal component to the value of electricity; that is, unless dispatchable energy is specifically incentivized. These rate schedules also represent a sizable share of the energy wholesale and retail markets, and thus allow the assessment of energy storage outside of niche applications.

Net present value (NPV) is used as the economic evaluator for each storage technology serving the various roles. NPV assesses the costs and benefits of the storage technology serving a particular function over the lifetime of the project.

In response to the central questions, it was found that most current energy storage technologies are very poorly suited for economically capturing the benefits associated with energy arbitrage in these larger markets (both residential and centralized). For use with PV, the most economic technology is pumped-hydro, which is inherently limited in its market penetration potential due to geographic restrictions. For meeting a service requirement, thermal storage used in conjunction with CSTP should be looked into further. Although thermal storage shows very favorable economic characteristics, the cost of the CSTP plant is likely to undermine this benefit. CAES is perhaps the most promising energy storage technology for use with PV in an energy arbitrage service. The financials are only slightly less desirable than pumped-hydro, and the geographic limitation is much less than commonly viewed. The Electric Power Research Institute shows that over 80% of the United States has geological formations which are favorable for underground storage [29]. As mentioned in Section 5.4, CAES also has the potential to act as a co-generation plant with PV because of the use of gas turbines in the discharge cycle. It is for these reasons that the author chose to rank CAES as number one for energy arbitrage services with PV generation, even though PHES shows a larger NPV. The rankings of all the storage technologies, except for thermal which cannot be used with PV, are shown below in Table 5-1.

Table 5-1: Summary of Current Market Viability and Future Recommendations

Storage Technology	Rank	Market Viability	Recommendations
CAES	**1**	Centralized real-time	R&D on BOS and power cost.
PHES	**2**	Centralized real-time/baseload	R&D on power cost.
H2	**3**	None	Needs R&D on roundtrip efficiency and power cost.
ZnBr	**4**	None	Needs significant R&D on energy cost.
NaS	**5**	None	Needs significant R&D on power cost and cycle lifetime.
VRB	**6**	None	Needs significant R&D on cycle lifetime, and energy and power costs.
Lead-Acid	**7**	None	Needs break-through R&D on cycle lifetime and energy cost.
NiCd	**8**	None	Needs break-through R&D on power cost and cycle lifetime.
Li-Ion	**9**	None	Energy cost prohibitive for arbitrage markets.

Improvements in cost and performance of these technologies may not be enough for them to enter these larger energy arbitrage markets. Alternative regulations to allow energy storage to receive benefits from multiple revenue streams should be aggressively pursued. In addition, the unpredictable effects that limited cycle lifetimes have on the investment of these storage solutions could prove to be very problematic when investors are considering these options. Other means to reduce the risk associated with purchasing a storage device should be looked at as well. For example, offering a calendar-lifetime guarantee, regardless of cycling or other operational conditions.

It is also worth noting that the baseload generation results suggest that a 6-hour service requirement starting at 9am is the most favorable demand profile for many of the storage technologies. This may be useful information when designing/scheduling other generators to operate in conjunction with solar as penetration of renewable energy technologies increases.

5.1. Residential TOU

For a TOU rate schedule, there is a minimum power rating required to discharge all the stored energy within the peak price period, beyond which there is very little additional revenue gained. For storage systems on a kWh scale and non-trivial self-discharge rates, this threshold is observed to be around 1.5 kW for a 2 kW_P residential system. If a storage device meets this power threshold, the addition of 1 kWh of capacity increases the annual revenue by ~$19 up to 3.5 kWh (a present value of $180 over 30 years with a 10% discount rate), after which the incremental revenue increase reduces to ~$4 (present value of $38).

Currently, none of the storage technologies considered in this work are able to economically capture these benefits in a residential TOU rate schedule. Of the technologies available to be scaled down to residential applications, H2 systems appear to hold the most promise – pending significant improvement in roundtrip efficiency and unit power cost. Residential-scale flow batteries may also be an option for this market if costs come down considerably. Although not feasible on a kW scale, the characteristics of PHES are attractive for this market, including the low cost per unit energy and high cycle and calendar lifetimes. Electrochemical batteries are simply too expensive and do not have the required cycle lifetime to be viable in this application.

5.2. Centralized Real-Time

For centralized generation in a real-time market, a low self-discharge rate and high roundtrip efficiency are both extremely important to capture the benefits of energy arbitrage. Available revenues are reduced by 50% going from a 2%/hour to a 6%/hour self-discharge rate. Also, for every 1% reduction in roundtrip efficiency (in the range of 100% to 70%), there is approximately a 1.7% reduction in available revenues. In addition, for a given energy storage capacity it is desirable to be able to fully discharge within ~2 hours to maximize the benefits in this market.

When assessing each storage technology for centralized generation, only PHES and CAES are currently viable. Both of these energy storage systems are geographically limited, and therefore have a restricted market potential, although much less so for CAES.

5.3. Centralized Baseload

For the baseload scenario (providing a service requirement), CSTP with thermal storage was compared with PV and the other storage technologies. The results show that thermal storage with CSTP is by far the most economic choice when adapting a solar generator to meet a service requirement. In addition, the flexibility of allowing the generator to sell excess energy into the real-time market is a prerequisite for capturing enough benefit to offset the cost of storage (even for thermal). If decreasing the required solar field size is of importance, then very large energy and power capacities are needed. Thermal, PHES, and possibly CAES are the only candidates among current technologies for meeting these requirements.

5.4. Future Work

The work done here can be built upon in several ways. First, the key storage parameters will always be able to be updated to most accurately reflect current market conditions. An inherent challenge of financial modeling is to capture the moving cost target as accurately as possible. Along these lines, a more comprehensive uncertainty analysis, expanding on the NPV sensitivities presented here, would offer valuable information for future R&D recommendations.

The methodology may be improved by accounting for the operational characteristics of the storage device within the optimization algorithm. Utilizing metrics such as number of charge/discharge cycles as control variables would offer a new dimension of operational flexibility which may result in a more favorable storage configuration. However, the inclusion of these variables will significantly complicate the optimization model by transforming it into a DNLP. If convergence can be achieved, this could offer some interesting insights as to the cost-benefit tradeoff of over-sizing a storage device and then limiting its operation to extend its lifetime.

Improvements could be made in the modeling of CAES. In this work, an effective efficiency was used to simplify the dynamics of a gas turbine operating at the discharge stage. However, this simplification ignores a unique advantage CAES offers when coupled with PV generation: The gas turbine can be operated as a small peaker generator during peak demand periods, thus allowing a reduction in size of the PV system required to meet a particular service requirement. This is because the system would no longer have to be oversized to meet the handful of peak-demand summer days. If the operation of a CAES plant were modeled in detail, analysis of this configuration would offer interesting insights for the baseload generation scenario. Future work should look at the use of a small peaker generator whether or not CAES is used as the storage technology, as this configuration potentially offers cost savings for the system as a whole. Expanding the model to include the lifetime financials of the PV and CSTP generator thus becomes an important area for future work to focus on, and would allow for the economic analysis of the entire solar-with-storage system.

The methodology described herein could readily be adapted to model other intermittent generators, such as wind or even tidal/ocean, coupled with storage. Furthermore, additional market scenarios (other rate schedules and/or market conditions) could be modeled to assess the potential of storage serving other energy arbitrage services.

Appendices

I. GAMS Optimization Code

The following appendices present the GAMS code used for (a) revenue maximization given storage size constraints, (b) PV-with-storage system size and cost minimization given a service requirement, (c) PV revenue maximization given system size and service requirement constraints, (d) CSTP-with-storage system size and cost minimization given a service requirement, and (e) CSTP revenue maximization given system size and service requirement constraints.

a. Temporal Rate Schedule – Revenue Maximization

```
* Choose appropriate GAMS solver
Option LP = CPLEX ;
Option  iterlim = 500000 ;

* Define the timeframe of optimization
Set
t           timeframe for optimization        / t1*t8760 /

* Define all input parameters (with place-holder values)
Parameters
eff                     storage efficiency                      / 1 /
disch                   storage self-discharge per hour         / 1 /
storagePower            power rating of storage                 / 1 /
storageCapacity         energy capacity of storage              / 1 /
g(t)                    generation in hour t
p(t)                    revenue (price of electricity) at hour t

* Define all variables
Variables
maxFlow(t)              maximum of discharged and stored energy in hour t
discharged(t)           energy discharged from storage in hour t
stored(t)               solar generation stored in hour t
used(t)                 solar energy not stored (used) in hour t
storageLevel(t)         the amount of energy in storage at hour t
storageCost             total cost of storage for optimization period
hourlyR(t)              revenue earned in hour t
totalR                  total revenue earned in whole timeperiod   ;

* Impose lower bound of zero on required variables
Positive Variables      discharged, stored, used, storageLevel, hourlyR   ;
```

```
* Define the objective function and constraint equations
Equations
maxFlowFnc1(t)          set max flow greater than discharged energy
maxFlowFnc2(t)          set max flow greater than stored energy
oneDirFnc(t)            set energy directional flow constraint
storageCostFnc          calculates total cost of storage for optimization period
usedFnc(t)              Energy-balance constraint function 1
storageCapacityFnc(t)   determines energy requirement of storage
storagePowerFnc1        first component of determining power requirement of storage
storagePowerFnc2        second component of determining power requirement of storage
storageLevelFnc(t)      Energy-balance constraint function 2
hourlyRFnc(t)           Hourly revenue function
RevenueFnc              Revenue (objective) function      ;

* This set of constraints finds the maximum of what is discharged and stored in hour t.
maxFlowFnc1(t) ..
maxFlow(t) =g= discharged(t) ;
maxFlowFnc2(t) ..
maxFlow(t) =g= stored(t) ;

* Imposes constraint that energy cannot be stored and discharged at the same time.
oneDirFnc(t) ..
discharged(t) + stored(t) =e= maxFlow(t) ;

* The energy generated must be either sent to storage or used directly.
usedFnc(t) ..
g(t) =e= used(t) + stored(t);

* The required storage size (capacity) is equal to the maximum state of charge of the storage device.
storageCapacityFnc(t) ..
storageLevel(t) =l= storageCapacity ;

* The required storage power rating is equal to the maximum discharged energy in a single hour.
storagePowerFnc1(t) ..
discharged(t) =l= storagePower ;
storagePowerFnc2(t) ..
stored(t) =l= storagePower ;

* The amount of energy in the storage device is equal to the storage level in
* the previous hour times the self-discharge rate, plus the amount of energy
* sent to storage for that hour times the efficiency, minus the amount of
* energy discharged from storage in that hour.
storageLevelFnc(t) ..
storageLevel(t) =e= storageLevel(t-1)*(1-disch) + stored(t)*eff - discharged(t);

* The hourly revenue is equal to the amount of energy being used directly
```

```
* plus the amount of energy being discharged from storage times the price
* of electricity for that hour.
hourlyRFnc(t) ..
hourlyR(t) =e= (discharged(t) + used(t))*p(t);

* The estimated total revenue is equal to the sum of the hourly revenue.
RevenueFnc ..
totalR =e= sum(t, hourlyR(t)) ;

* Define the model and variables to solve
Model   storage   / all /   ;

* Include the MATLAB-generated parameters
$if exist matdata.gms $include matdata.gms

* Set initial values and bounds
discharged.LO(t) = 0 ;
discharged.L(t) = 1 ;
discharged.UP(t) = 1.e10 ;

stored.LO(t) = 0 ;
stored.L(t) = 1 ;
stored.UP(t) = g(t) ;

used.LO(t) = 0 ;
used.L(t) = 1 ;
used.UP(t) = g(t);

storageLevel.LO(t) = 0 ;
storageLevel.L(t) = 1 ;
storageLevel.UP(t) = 1.e10 ;

* Solve statement
Solve    storage using lp maximizing totalR   ;

* Gather the desired variables for exporting to MATLAB
$libinclude matout storageCapacity.l
$libinclude matout storagePower.l
$libinclude matout totalR.l
$libinclude matout hourlyR.l t
$libinclude matout storageLevel.l t
$libinclude matout discharged.l t
$libinclude matout used.l t
$libinclude matout stored.l t

* Display results for trouble-shooting in GAMS
```

```
Display storageCapacity, storagePower, totalR.l, eff, disch, hourlyR.l, storageLevel.l, discharged.l, used.l,
        stored.l, g, p ;
```

b. Baseload Generation – PV System Size/Cost Minimization

```
* Choose appropriate GAMS solver and set iteration limit
Option  LP = Cplex;
Option  iterlim = 500000 ;

* Define the timeframe of optimization
Set
t timeframe for optimization      / t1*t8760 /

* Define all input parameters (with place-holder values)
Parameters
eff            storage efficiency                  / 1 /
disch          storage self-discharge per hour     / 1 /
powerCost      unit cost of storage power          / 1 /
energyCost     unit cost of storage energy         / 1 /
PVcost         unit cost of PV system              / 1 /
g(t)           generation in hour t
p(t)           price of electricity in hour t
d(t)           system demand at hour t  ;

* Define all variables
Variables
storageCapacity        energy capacity limit of storage
storagePower           power rating of storage
genMultiple            generation multiplier
gen(t)                 scaled generation profile
discharged(t)          energy discharged from storage in hour t
stored(t)              solar generation stored in hour t
used(t)                solar energy not stored (used) in hour t
storageLevel(t)        the amount of energy in storage at hour t
objective              cost variable to minimize
shunt(t)               shunted energy   ;

* Impose a zero lower bound on variables
Positive Variables  discharged, stored, used, storageLevel, shunt, genMultiple
           hourlyR, genMultiple ;

* Define the objective function and constraint equations
Equations
generationFnc(t)               set level of generation
storageCapacityFnc(t)          storage capacity constraint
storagePowerFnc1(t)            storage discharge power constraint
storagePowerFnc2(t)            storage charge power constraint
usedFnc(t)                     energy balance constraint
```

```
storageLevelFnc(t)          storage level energy balance constraint
demandFnc(t)                service requirement constraint
objectiveFnc                cost function to minimize  ;

* The cost objective function to minimize is equal to the system components
* times their respective unit costs.
objectiveFnc ..
objective =e=   storageCapacity*energyCost +
                storagePower*powerCost +
                genMultiple*10000*PVcost ;

* The usable generation is equal to the generation multiplier times the
* original generation amount in hour t.
generationFnc(t) ..
gen(t) =e= genMultiple*g(t) ;

* The energy generated must be either sent to storage or used directly.
usedFnc(t) ..
gen(t) =e= used(t) + stored(t) + shunt(t) ;

* The required storage size (capacity) is equal to the maximum state of charge
* of the storage device.
storageCapacityFnc(t) ..
storageLevel(t) =l= storageCapacity ;

* The required storage power rating is equal to the maximum discharged
* or stored energy in a single hour.
storagePowerFnc1(t) ..
discharged(t) =l= storagePower ;
storagePowerFnc2(t) ..
stored(t) =l= storagePower ;

* The amount of energy in the storage device is equal to the storage level in
* the previous hour times the self-discharge rate, plus the amount of energy
* sent to storage for that hour times the efficiency, minus the amount of
* energy discharged from storage in that hour.
storageLevelFnc(t) ..
storageLevel(t) =l= storageLevel(t-1)*(1-disch) + stored(t)*eff - discharged(t);

* The amount of energy discharged from storage plus the energy used directly
* must be greater than or equal to the deamnd profile.
demandFnc(t) ..
discharged(t) + used(t) =g= d(t) ;

* Define the Model and variables to be solved
Model  storage / all / ;
```

```
* Include MATLAB-generated parameters
$if exist matdata.gms $include matdata.gms

* Solve the specified model and objective function
Solve  storage using lp minimizing objective ;

* Send variables to MATLAB
$libinclude matout storageCapacity.l
$libinclude matout storagePower.l
$libinclude matout genMultiple.l

* Display results within GAMS for debugging/verification
Display  storageCapacity.l, storagePower.l, genMultiple.l, eff, disch
     storageLevel.l, discharged.l, used.l, stored.l, g, p, d, gen.l  ;
```

c. Baseload Generation – PV Revenue Maximization

```
* Choose appropriate GAMS solver and set iteration limit
Option  LP = Cplex;
Option  iterlim = 500000 ;

* Define the timeframe of optimization
Set
t timeframe for optimization       / t1*t8760 /

* Define all input parameters (with place-holder values)
Parameters
Eff                    storage efficiency                        / 1 /
Disch                  storage self-discharge per hour           / 1 /
storagePower           power rating of storage                   / 1 /
storageCapacity        energy capacity limit of storage          / 1 /
genMultiple            generation multiplier                     / 1 /
g(t)                   generation in hour t
p(t)                   price of electricity in hour t
d(t)                   system demand at hour t  ;

* Define all variables
Variables
gen(t)                 scaled generation profile
discharged(t)          energy discharged from storage in hour t
stored(t)              solar generation stored in hour t
used(t)                solar energy not stored (used) in hour t
storageLevel(t)        the amount of energy in storage at hour t
hourlyR(t)             revenue earned in hour t
totalR                 total revenue earned in whole timeperiod  ;

* Impose a zero lower bound on variables
Positive Variables  discharged, stored, used, storageLevel, hourlyR ;
```

```
* Define the objective function and constraint equations
Equations
generationFnc(t)         set level of generation
storageCapacityFnc(t)    storage capacity constraint
storagePowerFnc1         storage discharge power constraint
storagePowerFnc2         storage charge power constraint
usedFnc(t)               energy balance constraint
storageLevelFnc(t)       storage level energy balance constraint
demandFnc(t)             service requirement constraint
hourlyRFnc(t)            revenue earned in hour t
RevenueFnc               total revenue earned  ;

* The usable generation is equal to the generation multiplier times the
* original generation amount in hour t.
generationFnc(t) ..
gen(t) =e= genMultiple*g(t) ;

* The energy generated must be either sent to storage or used directly.
usedFnc(t) ..
gen(t) =e= used(t) + stored(t) ;

* The required storage size (capacity) is equal to the maximum state of charge
* of the storage device.
storageCapacityFnc(t) ..
storageLevel(t) =l= storageCapacity ;

* The required storage power rating is equal to the maximum discharged
* or stored energy in a single hour.
storagePowerFnc1(t) ..
discharged(t) =l= storagePower ;
storagePowerFnc2(t) ..
stored(t) =l= storagePower ;

* The hourly revenue is equal to the amount of energy being used directly
* plus the amount of energy being discharged from storage times the price
* of electricity for that hour.
hourlyRFnc(t) ..
hourlyR(t) =e= (discharged(t) + used(t))*p(t);

* The amount of energy in the storage device is equal to the storage level in
* the previous hour times the self-discharge rate, plus the amount of energy
* sent to storage for that hour times the efficiency, minus the amount of
* energy discharged from storage in that hour.
storageLevelFnc(t) ..
storageLevel(t) =l= storageLevel(t-1)*(1-disch) + stored(t)*eff - discharged(t);
```

```
* The amount of energy discharged from storage plus the energy used directly
* must be greater than or equal to the deamnd profile.
demandFnc(t) ..
discharged(t) + used(t) =g= d(t) ;

* The estimated total revenue is equal to the sum of the hourly revenue
RevenueFnc ..
totalR =e= sum(t,hourlyR(t));

* Define the Model and variables to be solved
Model  storage / all / ;

* Include Matlab-generated parameters
$if exist matdata.gms $include matdata.gms

* Solve the specified model and objective function
Solve  storage using lp maximizing totalR ;

* Send variables to MATLAB
$libinclude matout totalR.l
$libinclude matout hourlyR.l t
$libinclude matout storageLevel.l t
$libinclude matout discharged.l t
$libinclude matout used.l t
$libinclude matout stored.l t

* Display results within GAMS for debugging/verification
Display  storageCapacity, storagePower, totalR.l, eff, disch
      genMultiple, hourlyR.l, storageLevel.l, discharged.l
      used.l, stored.l, g, p, d, gen.l  ;
```

d. Baseload Generation – CSTP System Size/Cost Minimization

```
* Choose appropriate GAMS solver and set iteration limit
Option LP = Cplex ;
Option iterlim = 500000 ;

* Define the timeframe of optimization
Set
t timeframe for optimization       / t1*t8760 /

* Define all input parameters (with place-holder values)
Parameters
Eff                   storage efficiency                    / 1 /
Disch                 storage self-discharge per hour       / 1 /
turbineCost           unit cost of turbine                  / 1 /
fieldCost             unit cost of field                    / 1 /
storageEnergyCost     unit cost of storage energy           / 1 /
```

```
g(t)                    generation in hour t
p(t)                    revenue (price of electricity) at hour t
d(t)                    system demand at hour t  ;

* Define all variables
Variables
genMultiple             generation multiple
gen(t)                  scaled generation in hour t
storageCapacity         energy capacity limit of storage
turbineMaxOutput        maximum turbine operating power
discharged(t)           energy discharged from storage in hour t
stored(t)               solar generation stored in hour t
used(t)                 solar energy not stored (used) in hour t
storageLevel(t)         the amount of energy in storage at hour t
turbineOutput(t)        output of CSTP plant turbines at hour t
hourlyR(t)              revenue earned in hour t
totalR                  total revenue earned in whole timeperiod
savings                 total savings from storage during timeperiod
objective               cost variable to minimize
shunt(t)                shunted energy   ;

* Impose a zero lower bound on variables
Positive Variables discharged, stored, used, storageLevel, genMultiple, shunt
          hourlyR, turbineOutput ;

* Define the objective function and constraint equations
Equations
generationFnc(t)        set level of generation
storageCapacityFnc(t)   storage capacity constraint
turbineOutputFnc(t)     turbine output constraint
turbinePowerFnc(t)      turbine power constraint
usedFnc(t)              energy balance constraint
storageLevelFnc(t)      storage level energy balance constraint
demandFnc(t)            service requirement constraint
objectiveFnc            cost function to minimize  ;

* The cost objective function to minimize is equal to the system components
* times their respective unit costs.
objectiveFnc ..
objective =e=   storageCapacity*storageEnergyCost +
                turbineMaxOutput*turbineCost +
                genMultiple*10000*fieldCost ;

* The usable generation is equal to the generation multiplier times the
* original generation amount in hour t.
generationFnc(t) ..
gen(t) =e= genMultiple*g(t) ;
```

```
* The energy generated must be either sent to storage or used directly.
usedFnc(t) ..
used(t) + stored(t) + shunt(t) =e= gen(t) ;

* The required storage size (capacity) is equal to the maximum state of charge
* of the storage device.
storageCapacityFnc(t) ..
storageLevel(t) =l= storageCapacity ;

* The turbine output must be equal to what is discharged plus what is used
* directly in hour t.
turbineOutputFnc(t) ..
turbineOutput(t) =e= discharged(t) + used(t) ;

* The amount of energy discharged from storage plus the energy used directly
* must be greater than or equal to the deamnd profile.
demandFnc(t) ..
turbineOutput(t) =g= d(t) ;

* The turbine output in each hour must be less than or equal to the maximum
* turbine power rating.
turbinePowerFnc(t) ..
turbineOutput(t) =l= turbineMaxOutput ;

* The amount of energy in the storage device is equal to the storage level in
* the previous hour times the self-discharge rate, plus the amount of energy
* sent to storage for that hour times the efficiency, minus the amount of
* energy discharged from storage in that hour.
storageLevelFnc(t) ..
storageLevel(t) =e= storageLevel(t-1)*(1-disch) + stored(t)*eff - discharged(t);

* Define the Model and variables to be solved
Model storage / all /  ;

* Include MATLAB-generated parameters.
$if exist matdata.gms $include matdata.gms

* Solve the specified model and objective function
Solve storage using lp minimizing objective ;

* Gather variables to be sent back to MATLAB
$libinclude matout storageCapacity.l
$libinclude matout turbineMaxOutput.l
$libinclude matout genMultiple.l
$libinclude matout turbineOutput.l t
$libinclude matout discharged.l t
```

```
$libinclude matout stored.l t
$libinclude matout objective.l
$libinclude matout storageLevel.l t

* Display results within GAMS for debugging/verification
Display storageCapacity.l, turbineMaxOutput.l, objective.l
      genMultiple.l, turbineOutput.l, d ;
```

e. Baseload Generation – CSTP Revenue Maximization

```
* Choose appropriate GAMS solver and set iteration limit
Option LP = Cplex;
Option iterlim = 500000 ;

* Define the timeframe of optimization
Set
t timeframe for optimization      / t1*t8760 /

* Define all input parameters (with place-holder values)
Parameters
Eff                     storage efficiency                      / 1 /
Disch                   storage self-discharge per hour         / 1 /
turbineMaxOutput        maximum turbine operating power         / 1 /
storageCapacity         energy capacity limit of storage        / 1 /
genMultiple             generation multiple                     / 1 /
g(t)                    generation in hour t
p(t)                    revenue (price of electricity) at hour t
d(t)                    system demand at hour t  ;

* Define all variables
Variables
gen(t)                  scaled generation in hour t
discharged(t)           energy discharged from storage in hour t
stored(t)               solar generation stored in hour t
used(t)                 solar energy not stored (used) in hour t
storageLevel(t)         the amount of energy in storage at hour t
turbineOutput(t)        output of CSTP plant turbines at hour t
hourlyR(t)              revenue earned in hour t
totalR                  total revenue earned in whole timeperiod  ;

* Impose a zero lower bound on variables
Positive Variables discharged, stored, used, storageLevel
            hourlyR, turbineOutput ;

* Define the objective function and constraint equations
Equations
generationFnc(t)        set level of generation
storageCapacityFnc(t)   storage capacity constraint
```

```
turbineOutputFnc(t)     turbine output constraint
turbinePowerFnc(t)      turbine power constraint
usedFnc(t)              energy balance constraint
storageLevelFnc(t)      storage level energy balance constraint
demandFnc(t)            service requirement constraint
hourlyRFnc(t)           revenue earned in hour t
RevenueFnc              total revenue earned  ;

* The usable generation is equal to the generation multiplier times the
* original generation amount in hour t.
generationFnc(t) ..
gen(t) =e= genMultiple*g(t) ;

* The energy generated must be either sent to storage or used directly.
usedFnc(t) ..
gen(t) =e= used(t) + stored(t);

* The required storage size (capacity) is equal to the maximum state of charge
* of the storage device.
storageCapacityFnc(t) ..
storageLevel(t) =l= storageCapacity ;

* The turbine output must be equal to what is discharged plus what is used
* directly in hour t.
turbineOutputFnc(t) ..
turbineOutput(t) =e= discharged(t) + used(t) ;

* The amount of energy discharged from storage plus the energy used directly
* must be greater than or equal to the deamnd profile.
demandFnc(t) ..
turbineOutput(t) =g= d(t) ;

* The turbine output in each hour must be less than or equal to the maximum
* turbine power rating.
turbinePowerFnc(t) ..
turbineOutput(t) =l= turbineMaxOutput ;

* The hourly revenue is equal to the amount of energy output by the turbine
* times the price of electricity for that hour.
hourlyRFnc(t) ..
hourlyR(t) =e= turbineOutput(t)*p(t);

* The amount of energy in the storage device is equal to the storage level in
* the previous hour times the self-discharge rate, plus the amount of energy
* sent to storage for that hour times the efficiency, minus the amount of
* energy discharged from storage in that hour.
storageLevelFnc(t) ..
```

```
storageLevel(t) =e= storageLevel(t-1)*(1-disch) + stored(t)*eff - discharged(t);

* The estimated total revenue is equal to the sum of the hourly revenue.
RevenueFnc ..
totalR =e= sum(t,hourlyR(t))  ;

* Define the Model and variables to be solved
Model storage / all /  ;

* Include MATLAB-generated parameters.
$if exist matdata.gms $include matdata.gms

* Solve the specified model and objective function
Solve storage using lp maximizing totalR ;

* Gather variables to be sent back to MATLAB.
$libinclude matout totalR.l
$libinclude matout hourlyR.l t
$libinclude matout storageLevel.l t
$libinclude matout discharged.l t
$libinclude matout used.l t
$libinclude matout stored.l t
$libinclude matout turbineOutput.l t

* Display results within GAMS for debugging/verification
Display storageCapacity, turbineMaxOutput, genMultiple, totalR.l
      eff, disch, turbineOutput.l, hourlyR.l, storageLevel.l
      discharged.l, used.l, stored.l, g, p ;
```

II. Example Excel Cashflow Model

Inputs From MATLAB

First Year Discharged Energy (kWh)	730
First Year Savings from Storage ($)	$500
Average Depth-of-Discharge (%)	30%
Cycles per Year (Cycles)	183
Power Control System Base Price ($/kW)	230
Req. Capacity (kWh)	4.0
Req. Power (kW)	2.0
System Lifetime (years)	30
Discount Rate (%)	10%
Power Control System Lifetime (years)	7
Total Cycles Required (Cycles)	5,490

Storage Characteristics	Lead-Acid
System Architecture	FIXED
Require DC-AC Conversion at Discharge?	YES
Roundtrip Efficiency (%)	87.50%
Self-Discharge ($/month)	2.00%
Self-Discharge ($/day)	
Self-Discharge ($/hour)	0.0028%
Cost ($/kWh Capacity)	$150
Cost ($/kW Power)	$250
Balance of Plant ($/kWh)	$50
Balance of Plant ($/kW)	$0
Fixed O&M ($/kW-yr)	$1.55
Variable O&M ($/kWh)	$0.0100
Lifetime (Years)	10
Lifetime at 100% DoD (Cycles)	1,500
Effective Lifetime (Cycles)	3,600
Total # of Capital Purchases	3
Storage Capital Cost per unit ($/unit)	$800
Total Power Control Expense ($)	$1,594

Number of Times PCS is Replaced	1	2	3	4
Years in Which PCS is Replaced	8	15	22	29

Lead-Acid

Number of Times Storage is Replaced	1	2
Years in Which Storage is Replaced	11	21

Year	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Replacement Cost ($)								
PCS Replacement Cost ($)								
Fixed O&M Cost ($)		$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10
Variable O&M Cost ($)		$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30
Total Cost-Flow ($)	$2,394	$10.40	$10.40	$10.40	$10.40	$10.40	$10.40	$10.40
Year	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Replacement Cost ($)				$800.00				
PCS Replacement Cost ($)	$1,594.23							$1,594.23
Fixed O&M Cost ($)	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10
Variable O&M Cost ($)	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30
Total Cost-Flow ($)	$1,605	$10.40	$10.40	$810.40	$10.40	$10.40	$10.40	$1,604.63
Year	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Replacement Cost ($)						$800.00		
PCS Replacement Cost ($)							$1,594.23	
Fixed O&M Cost ($)	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10
Variable O&M Cost ($)	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30
Total Cost-Flow ($)	$10	$10.40	$10.40	$10.40	$10.40	$810.40	$1,604.63	$10.40
Year	**24**	**25**	**26**	**27**	**28**	**29**	**30**	
Replacement Cost ($)								
PCS Replacement Cost ($)						$1,594.23		
Fixed O&M Cost ($)	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	$3.10	
Variable O&M Cost ($)	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	$7.30	
Total Cost-Flow ($)	$10	$10.40	$10.40	$10.40	$10.40	$1,604.63	$10.40	

III. MATLAB Code for Integration and Visualization – Temporal Rate Schedules

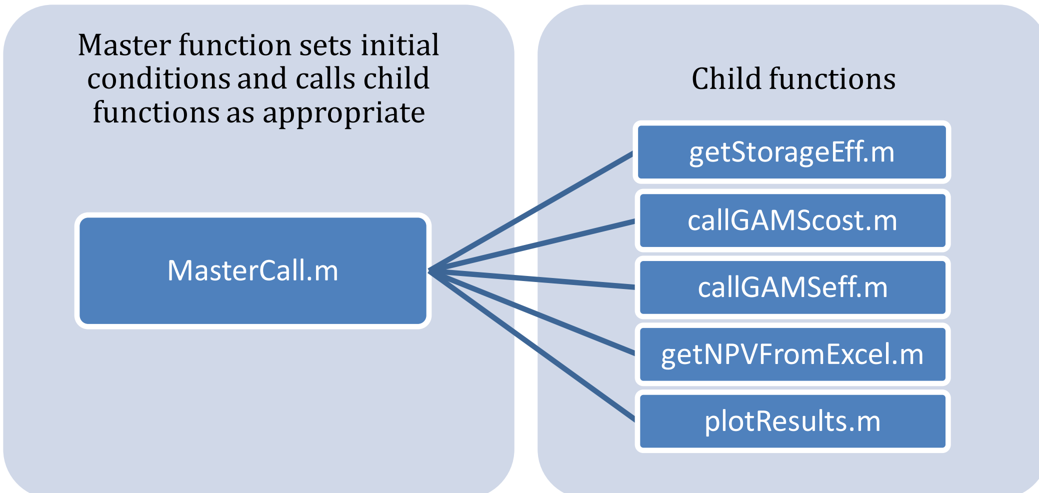

Figure III-1: Schematic of MATLAB Code – Temporal Rate Schedules

a. MasterCall.m

```
% THIS IS THE MASTER CALL FUNCTION FOR THE TEMPORAL RATE SCHEDULE SCENARIOS:
% INTEGRATING THE GAMS OPTIMIZATION MODEL AND THE EXCEL FINANCIAL MODEL;
% AND FOR VISUALIZING THE RESULTS.

% Clears the workspace and checks for a preexisting 'outputData.mat'
% structure.  If preexisting data is used, only the financial runs and/or
% plot generation programs will be run:
clc
clear input
try keep outputData MASTER FINAL_NPV
catch
  try keep MASTER FINAL_NPV, catch end
end
if(exist('outputData','var'))
  currentOutputData = input...
    ('USE CURRENT outputData STRUCTURE (''y'' or ''n'')? ','s');
  switch currentOutputData
    case 'n'
      clear all
  end
end
close all
clc

% Generate the inputs structure:
```

```
inputs.generationType = 'CSTP';     % Either 'PV' or 'CSTP'
inputs.turbineMin = 0;              % Minimum turbine operation (kW)
inputs.turbineMax = 10000;          % Maximum turbine rating (kW)
inputs.genMultiple = 0:0.2:4;
inputs.storageTechnology = 'custom';    % 'custom', 'Lead-Acid', 'LiIon'
                                        % 'NiCd', 'CAES', 'H2'
                                        % 'VRB', 'ZnBr', 'PHES', 'NaS', 'Tech1'
inputs.PVsystemLifetime = 30;     % PV system lifetime in years
inputs.discountRate = 0.1;        % Discount rate (%)
inputs.PCScost = 230;             % Cost of power control system ($/kW)
inputs.PCSlifetime = 7;           % Lifetime of PCS (years)
inputs.numberDaysToOptimize = 365; % Optimization timeframe (days)
inputs.plots = 'yes';             % Whether or not to generate plots
inputs.startHour = 1;             % First hour to generate plots for
inputs.duration = 8759;           % Duration of plot preview (hours)

% Which GAMS model to use for optimization:
switch inputs.generationType
   case 'CSTP'
      inputs.GAMSmodel = 'CSTPwStorage';
   case 'PV'
      inputs.GAMSmodel = 'EPlimited';
end

% Name of file containing production, consumption, and price vectors:
% inputs.fileName = '10MW_BlytheCA_PV.xls';     % Central real-time Global
inputs.fileName = '10MW_BlytheCA_CSTP.xls';     % Central real-time Direct
% inputs.fileName = 'Residential_TOU_92223.xlsx'; % Residential TOU

% Select appropriate input/output directories:
inputs.dir = ['xxxxxxxxx\',inputs.fileName];
inputs.outputDir = 'xxxxxxxxx\';
inputs.File = 'xxxxxxxxx\storageEconomics_FINAL.xlsx';

% Energy capacity limit of storage (kWh):
inputs.energyLimit = 0:5000:400000;
% Power rating of storage (kW):
inputs.powerLimit =  0:0.4:20;
if(strcmp(inputs.generationType,'CSTP')...
      || strcmp(inputs.generationType,'CSTP_dispatch'))
      inputs.powerLimit = 9e99;
end

% Option to define efficiencies manually:
if(strcmp(inputs.storageTechnology,'custom'))
   inputs.efficiency = sqrt(0.95);     % Storage Efficiency
   inputs.selfDis = 0;                 % Self discharge rate
```

```
else
  % Retreive efficiencies and unit costs from excel file
  [inputs] = getStorageEff(inputs);
end


%% Extract Production and Prices from Excel File
[inputs.values,inputs.strings] = xlsread(inputs.dir);

%% Load Optimization Profile Parameters
inputs.startHourOriginal = 1;  % First hour of first segment

% Identify if there is only one simulation to perform:
inputs.lastRunFlag = 0;
if(strcmp(inputs.generationType,'PV') || ...
    strcmp(inputs.generationType,'PV_dispatch'))
  if((length(inputs.energyLimit)*length(inputs.powerLimit)) == 1)
    inputs.lastRunFlag = 1;
  end
else
  if((length(inputs.genMultiple)*length(inputs.energyLimit)) == 1)
    inputs.lastRunFlag = 1;
  end
end

% Call the GAMS optimization programs and organize outputs:
if(~exist('outputData','var') && ~exist('FINAL_NPV','var'))
  h = 24*inputs.numberDaysToOptimize(1);
  if(length(inputs.efficiency)>1 || length(inputs.selfDis)>1)
    [MATRIX, aggResults, excelInputs] = callGAMSeff(inputs);
    outputData.excelInputs = excelInputs;
    outputData.technology = {inputs.storageTechnology};
    outputData.energy = inputs.energyLimit;
    outputData.power = inputs.powerLimit;
    outputData.Z_revenue = MATRIX;
    outputData.X_selfDis = inputs.selfDis;
    outputData.Y_eff = inputs.efficiency;
  else
    [MATRIX, aggResults, excelInputs] = callGAMScost(inputs);
    outputData.excelInputs = excelInputs;
    outputData.technology = {inputs.storageTechnology};
    outputData.roundtripEff = inputs.efficiency;
    outputData.selfDis = inputs.selfDis;
    try outputData.Z_genMultiple = excelInputs.MULTIPLE; catch end
    outputData.Z_revenue = MATRIX;
    outputData.X_Cenergy = inputs.energyLimit;
    outputData.Y_Cpower = inputs.powerLimit;
```

```
    end

    %% Remove Infeasible Solutions:
    outputDataBackup = outputData;
    if(strcmp(inputs.generationType,'PV_dispatch'))
      outputData.Z_genMultiple(excelInputs.feasible == 0) = 0;
    end
    outputData.Z_revenue(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.energyCapacity(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.powerCapacity(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.annualDischarged(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.avgDOD(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.annualCycles(excelInputs.feasible == 0) = 0;
    outputData.excelInputs.annualSavings(excelInputs.feasible == 0) = 0;
    outputDataFeasible = outputData;
    outputData = outputDataBackup;
    clear outputDataBackup
  elseif(~exist('FINAL_NPV','var'))
    disp('NOTICE: Not refreshing "outputData" structure')
    disp('       only running NPV simulations...')
  else
    disp('FINAL_NPV exists, plotting results...')
  end

  if(~exist('FINAL_NPV','var'))
    % Get NPV of each profile:
    runNPV = 1;
    try
      if(length(outputData.X_Cenergy)==1)
        disp('Skipping NPV Analysis')
        disp('Generating Efficiency Plots...')
      else
        runNPV = 1;
      end
    catch
      runNPV = 1;
    end

    if(runNPV == 1)
      try NPV_MATRIX = zeros(size(outputData.Z_revenue));
      catch NPV_MATRIX = zeros(size(outputData.Z_genMultiple)); end

      Excel = actxserver ('Excel.Application');
      if ~exist(inputs.File,'file')
        ExcelWorkbook = Excel.workbooks.Add;
        ExcelWorkbook.SaveAs(inputs.File,1);
        ExcelWorkbook.Close(false);
```

```
end
invoke(Excel.Workbooks,'Open',inputs.File);

analyze = 1;
for t = 1:length(outputData.Y_Cpower)
   for u = 1:length(outputData.X_Cenergy)
      [NPV] = getNPVFromExcel(inputs, outputData, Excel, t, u);
      clc
      disp(['NPV Analysis: ',num2str(analyze),'/',...
         num2str(length(outputData.Y_Cpower)*...
         length(outputData.X_Cenergy))])
      analyze = analyze + 1;
      NPV_MATRIX(t,u) = NPV;

   end
end
Excel.ActiveWorkbook.Save;
Excel.Quit
Excel.delete
clear Excel

npvOriginal = NPV_MATRIX;
if(abs(mean(mean(NPV_MATRIX(NPV_MATRIX>0)))/...
      median(median(NPV_MATRIX(NPV_MATRIX>0)))-1) > 0.2)
   NPV_MATRIX_NEW = zeros(size(NPV_MATRIX));

   for xcount = 1:length(NPV_MATRIX(:,1))
      for ycount = 1:length(NPV_MATRIX(1,:))
         if(NPV_MATRIX(xcount,ycount)>=median(median(NPV_MATRIX)))
            NPV_MATRIX_NEW(xcount,ycount) = ...
               NPV_MATRIX(xcount,ycount);
         else
            NPV_MATRIX_NEW(xcount,ycount) = NaN;
         end
      end
   end
   NPV_MATRIX = NPV_MATRIX_NEW;
end

outputData.Z_NPV = NPV_MATRIX;
outputData.NPVoriginal = npvOriginal;
[maxX, maxY] = find(NPV_MATRIX == max(max(NPV_MATRIX)));
maxX = maxX(1); maxY = maxY(1);
outputData.maxCenergy = outputData.X_Cenergy(maxY);
outputData.maxCpower = outputData.Y_Cpower(maxX);

%% Rerun Optimization for Maximum NPV Scenario
```

```
    if(length(outputData.X_Cenergy)*length(outputData.Y_Cpower) > 1)
      disp(' ')
      disp('Running Maximum NPV Scenario...')
      inputs.lastRunFlag = 1;
      tempEnergy = inputs.energyLimit;
      inputs.energyLimit = outputData.maxCenergy;
      tempPower = inputs.powerLimit;
      inputs.powerLimit = outputData.maxCpower;
      [MATRIX, aggResults, excelInputs] = callGAMScost(inputs);
      inputs.energyLimit = tempEnergy;
      inputs.powerLimit = tempPower;
      outputData.maxStorageProfile = excelInputs;
    else
      outputData.maxStorageProfile = excelInputs;
    end

    %% Display Results:
    disp(['Total Annual Savings = $',num2str(round(sum...
      (aggResults.aggSavings)))])
    electronFlowTest = aggResults.aggDischargedFromStorage.*...
      aggResults.aggSentToStorage;
    if(max(electronFlowTest)>0)
      disp('ERROR - CHARGING AND DISCHARGING AT THE SAME TIME!!!')
      disp(['Number of occurances = ',num2str(length(find...
        (electronFlowTest>0)))])
      disp(['With a maximum product of ',num2str(max...
        (electronFlowTest(electronFlowTest>0)))])
    end

    maxTime = max(diff(find...
      (outputData.maxStorageProfile.storageLevel==0)));
    disp(['Maximum Time Energy is Stored = ',num2str(maxTime),...
      ' Hours (',num2str(maxTime/24),' Days)'])
    maxTime2 = max(diff(find...
      (outputData.maxStorageProfile.dischargedEnergy > 0)));
    disp(['Maximum Time Between Discharges = ',num2str(maxTime2),...
      ' Hours (',num2str(maxTime2/24),' Days)'])
  end

  %% Plot Results
  if(strcmp(inputs.plots,'yes'))
    plotResults(outputData,inputs.startHour,inputs.duration);
  end

else

  try storageVector = unique(cell2mat(FINAL_NPV(2:end,24))); catch end
```

```
    try fieldVector = unique(cell2mat(MASTER(2:end,22))); catch end

    try outputData.X_Cenergy = storageVector; catch end
    try outputData.X_CenergyVector=cell2mat(FINAL_NPV(2:end,24)); catch end
    try outputData.Y_genMultiple = fieldVector; catch end
    try outputData.Y_genMultipleVector=cell2mat(MASTER(2:end,22)); catch end
    try outputData.Z_NPV_vector = cell2mat(FINAL_NPV(2:end,5)); catch end
    try outputData.turbineSize = inputs.turbineMax; catch end
    try outputData.realLCOE = cell2mat(FINAL_NPV(2:end,6)); catch end

    plotResults(outputData,inputs.startHour,inputs.duration);
end
```

b. getStorageEff.m

```
% This function retrieves the appropriate storage efficiencies and unit
% costs

function [inputs] = getStorageEff(inputs)

Excel = actxserver ('Excel.Application');
if ~exist(inputs.File,'file')
    ExcelWorkbook = Excel.workbooks.Add;
    ExcelWorkbook.SaveAs(inputs.File,1);
    ExcelWorkbook.Close(false);
end
invoke(Excel.Workbooks,'Open',inputs.File);

xlswrite1(inputs.File,inputs.PCScost,1,'B6');
xlswrite1(inputs.File,inputs.PVsystemLifetime,1,'B9');
xlswrite1(inputs.File,inputs.discountRate,1,'B10');
xlswrite1(inputs.File,inputs.PCSlifetime,1,'B11');

switch inputs.storageTechnology
    case 'Lead-Acid'
        efficiency = xlsread1(inputs.File,1,'F3');
        selfDis = xlsread1(inputs.File,1,'G3');
        energyCost = xlsread1(inputs.File,1,'B23');
        powerCost = xlsread1(inputs.File,1,'B24');

    case 'LiIon'
        efficiency = xlsread1(inputs.File,1,'F4');
        selfDis = xlsread1(inputs.File,1,'G4');
        energyCost = xlsread1(inputs.File,1,'C23');
        powerCost = xlsread1(inputs.File,1,'C24');

    case 'NiCd'
        efficiency = xlsread1(inputs.File,1,'F5');
```

```
    selfDis = xlsread1(inputs.File,1,'G5');
    energyCost = xlsread1(inputs.File,1,'D23');
    powerCost = xlsread1(inputs.File,1,'D24');

  case 'CAES'
    efficiency = xlsread1(inputs.File,1,'F7');
    selfDis = xlsread1(inputs.File,1,'G7');
    energyCost = xlsread1(inputs.File,1,'F23');
    powerCost = xlsread1(inputs.File,1,'F24');

  case 'H2'
    efficiency = xlsread1(inputs.File,1,'F8');
    selfDis = xlsread1(inputs.File,1,'G8');
    energyCost = xlsread1(inputs.File,1,'G23');
    powerCost = xlsread1(inputs.File,1,'G24');

  case 'VRB'
    efficiency = xlsread1(inputs.File,1,'F9');
    selfDis = xlsread1(inputs.File,1,'G9');
    energyCost = xlsread1(inputs.File,1,'H23');
    powerCost = xlsread1(inputs.File,1,'H24');

  case 'ZnBr'
    efficiency = xlsread1(inputs.File,1,'F10');
    selfDis = xlsread1(inputs.File,1,'G10');
    energyCost = xlsread1(inputs.File,1,'I23');
    powerCost = xlsread1(inputs.File,1,'I24');

  case 'PHES'
    efficiency = xlsread1(inputs.File,1,'F11');
    selfDis = xlsread1(inputs.File,1,'G11');
    energyCost = xlsread1(inputs.File,1,'J23');
    powerCost = xlsread1(inputs.File,1,'J24');

  case 'NaS'
    efficiency = xlsread1(inputs.File,1,'F12');
    selfDis = xlsread1(inputs.File,1,'G12');
    energyCost = xlsread1(inputs.File,1,'K23');
    powerCost = xlsread1(inputs.File,1,'K24');

  case 'Tech1'
    efficiency = xlsread1(inputs.File,1,'F13');
    selfDis = xlsread1(inputs.File,1,'G13');
    energyCost = xlsread1(inputs.File,1,'L23');
    powerCost = xlsread1(inputs.File,1,'L24');

  case 'Thermal'
```

```
    efficiency = xlsread1(inputs.File,1,'F14');
    selfDis = xlsread1(inputs.File,1,'G14');
    energyCost = xlsread1(inputs.File,1,'M23');
    powerCost = xlsread1(inputs.File,1,'M24');
end

Excel.ActiveWorkbook.Save;
Excel.Quit
Excel.delete
clear Excel

inputs.efficiency = efficiency;
inputs.selfDis = selfDis;
inputs.powerCost = powerCost;
inputs.energyCost = energyCost;

end
```

c. callGAMScost.m

```
% This function compiles the inputs and calls the appropriate GAMS
% optimization model.  The results are then compiled to be sent back to
% MATLAB for processing

function [MATRIX, aggResults, excelInputs] = callGAMScost(inputs)

MATRIX = zeros(length(inputs.powerLimit),length(inputs.energyLimit));

for t = 1:length(inputs.powerLimit)
  for u = 1:length(inputs.energyLimit)
    disp(['Analyzing System #',num2str(u + ...
      length(inputs.energyLimit)*(t-1)),'/',num2str(length...
      (inputs.powerLimit)*length(inputs.energyLimit))])
    for z = 1:length(inputs.numberDaysToOptimize);
      clear opt_segments h g s eff disch Cpower Cenergy PVlife...
        replace gen price aggRevenue aggSaings startHour...
        production aggStorageLevel aggDischargedFromStorage...
        aggUsedDirectly aggSentToStorage aggHourlyRevenue...
        aggPrice aggTurbineOutput turbineMax

      % Number of segments to optimize for:
      opt_segments = floor(365/inputs.numberDaysToOptimize(z));
      % Number of hours within each segment (note: must match values
      % in GAMS file - update if necessary):
      h = 24*inputs.numberDaysToOptimize(z);


      %% Compile GAMS Variables
```

```
            % Define set labels:
set = cell(1,h);
for n = 1:h
   set{n} = ['t',num2str(n)];
end

% Efficiency of Storage Device
eff.name = 'eff';
eff.val = inputs.efficiency;

% Self-Discharge of Storage Device
disch.name = 'disch';
disch.val = inputs.selfDis;

% Power Rating of Storage
Cpower.name = 'storagePower';
Cpower.val = inputs.powerLimit(t);

% Energy Capacity of Storage
Cenergy.name = 'storageCapacity';
Cenergy.val = inputs.energyLimit(u);

if(strcmp(inputs.generationType,'PV_dispatch'))
   % Demand
   d.name = 'd';
   d.labels = set;
   d.val = inputs.demand;
end

% Generation
gen.name = 'g';
gen.labels = set;

% Price of electricity
price.name = 'p';
price.labels = set;

%% Start Segment Loop
aggRevenue = zeros(1,opt_segments);
aggSavings = zeros(1,opt_segments);
for x = 1:opt_segments
   clear startHour production pricevector gen.val...
      price.val revenue
   if(inputs.lastRunFlag == 0)
      clc
      try disp(['NPV from last analysis = ',num2str(NPV)]),...
      catch end
```

```
        disp(['Analyzing System #',num2str(u + length...
            (inputs.energyLimit)*(t-1)),'/',num2str(length...
            (inputs.powerLimit)*length(inputs.energyLimit))])
        disp(['Analyzing Segment # ',num2str(x),'/',...
            num2str(opt_segments)])
    else
        disp(['Analyzing Segment # ',num2str(x),'/',...
            num2str(opt_segments)])
    end
    startHour = inputs.startHourOriginal + h*(x-1);
    production = inputs.values(startHour:startHour-1+h,3);
    pricevector = inputs.values(startHour:startHour-1+h,5);

    %% Finish Compiling GAMS Variables
    % Generation
    gen.val = production';
    % Prices
    price.val = pricevector';

    %% Call GAMS Solver
    if(strcmp(inputs.generationType,'PV_dispatch'))
        [storageCapacity,storagePower,totalRevenue,...
            hourlyRevenue,storageLevel,dischargedFromStorage,...
            usedDirectly,sentToStorage,genMultiple]...
        = gams(inputs.GAMSmodel,eff,disch,Cpower,Cenergy,...
        gen,price,d);
    else
    [storageCapacity,storagePower,totalRevenue,hourlyRevenue,...
        storageLevel,dischargedFromStorage,usedDirectly,...
        sentToStorage] = gams(inputs.GAMSmodel,eff,disch,...
        Cpower,Cenergy,gen,price);
    end
    aggStorageLevel(h*(x-1)+1:h*x) = storageLevel.val;
    aggDischargedFromStorage(h*(x-1)+1:h*x) = ...
        dischargedFromStorage.val;
    aggUsedDirectly(h*(x-1)+1:h*x) = usedDirectly.val;
    aggSentToStorage(h*(x-1)+1:h*x) = sentToStorage.val;
    aggHourlyRevenue(h*(x-1)+1:h*x) = hourlyRevenue.val;
    aggPrice(h*(x-1)+1:h*x) = price.val;
    aggGen(h*(x-1)+1:h*x) = gen.val;

    aggRevenue(x) = sum(hourlyRevenue.val);
    aggSavings(x) = sum(hourlyRevenue.val)-...
        sum(price.val.*gen.val);

end
```

```
if(aggSavings < 0), aggSavings = 0; end
MATRIX(t,u) = sum(aggSavings);
try excelInputs.MULTIPLE(t,u) = genMultiple.val; catch end

%% Calculate Storage Characteristics
excelInputs.annualDischarged(t,u) =...
  sum(aggDischargedFromStorage);
if(max(aggStorageLevel)>0)
  excelInputs.avgDOD(t,u) = mean(aggDischargedFromStorage...
    (aggDischargedFromStorage>0)./max(aggStorageLevel));
else
  excelInputs.avgDOD(t,u) = 0;
end
excelInputs.annualCycles(t,u) = length...
  (aggDischargedFromStorage(aggDischargedFromStorage>0));
excelInputs.energyCapacity(t,u) = max(aggStorageLevel);
excelInputs.powerCapacity(t,u) = max(max(aggSentToStorage),...
  max(aggDischargedFromStorage));
excelInputs.annualSavings(t,u) = sum(aggSavings);

excelInputs.feasible(t,u) = 1; % Default, solution is feasible.
try
  if(max(aggStorageLevel) > Cenergy.val ||...
        min(aggStorageLevel) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(max(max(aggDischargedFromStorage),...
        max(aggSentToStorage)) > Cpower.val)
    excelInputs.feasible(t,u) = 0;
  elseif(min(min(aggDischargedFromStorage),...
        min(aggSentToStorage)) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(max(aggTurbineOutput) > turbineMax.val ||...
        min(aggTurbineOutput) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end

try
```

```
            if(min(aggRevenue) < -1e5)
                excelInputs.feasible(t,u) = 0;
            end
        catch
        end

        if(inputs.lastRunFlag == 1)
            excelInputs.storageLevel = aggStorageLevel;
            excelInputs.dischargedEnergy = aggDischargedFromStorage;
            excelInputs.usedDirectly = aggUsedDirectly;
            excelInputs.storedEnergy = aggSentToStorage;
            excelInputs.price = aggPrice;
            excelInputs.gen = aggGen;
        end
    end
  end
end

aggResults.aggStorageLevel = aggStorageLevel;
aggResults.aggDischargedFromStorage = aggDischargedFromStorage;
aggResults.aggUsedDirectly = aggUsedDirectly;
aggResults.aggSentToStorage = aggSentToStorage;
aggResults.aggHourlyRevenue = aggHourlyRevenue;
aggResults.aggPrice = aggPrice;
aggResults.aggGen = aggGen;
aggResults.aggRevenue = aggRevenue;
aggResults.aggSavings = aggSavings;
aggResults.aggStorageCapacity = max(aggStorageLevel);
aggResults.aggStoragePower = max(max(aggSentToStorage),...
  max(aggDischargedFromStorage));

end
```

d. callGAMSeff.m

This function is almost identical to the *callGAMScost.m* function, so it will not be repeated here. The main difference is that the roundtrip and self-discharge efficiencies are the parametric inputs instead of the energy capacity and power rating.

e. getNPVFromExcel.m

```
% This function retrieves the NPV from the Excel financial model

function [NPV] = getNPVFromExcel(inputs, outputData, Excel, t, u)

xlswrite1(inputs.File,outputData.excelInputs.annualDischarged(t,u),1,'B2');
xlswrite1(inputs.File,outputData.excelInputs.annualSavings(t,u),1,'B3');
```

```
xlswrite1(inputs.File,outputData.excelInputs.avgDOD(t,u),1,'B4');
xlswrite1(inputs.File,outputData.excelInputs.annualCycles(t,u),1,'B5');

try xlswrite1(inputs.File,outputData.X_Cenergy(u),1,'B7');
catch xlswrite1(inputs.File,...
    outputData.excelInputs.energyCapacity(t,u),1,'B7');
end

try xlswrite1(inputs.File,outputData.Y_Cpower(t),1,'B8');
catch xlswrite1(inputs.File,...
    outputData.excelInputs.powerCapacity(t,u),1,'B8');
end

switch outputData.technology{1}
  case 'Lead-Acid'
    NPV = xlsread1(inputs.File,1,'H3');
  case 'LiIon'
    NPV = xlsread1(inputs.File,1,'H4');
  case 'NiCd'
    NPV = xlsread1(inputs.File,1,'H5');
  case 'CAES'
    NPV = xlsread1(inputs.File,1,'H7');
  case 'H2'
    NPV = xlsread1(inputs.File,1,'H8');
  case 'VRB'
    NPV = xlsread1(inputs.File,1,'H9');
  case 'ZnBr'
    NPV = xlsread1(inputs.File,1,'H10');
  case 'PHES'
    NPV = xlsread1(inputs.File,1,'H11');
  case 'NaS'
    NPV = xlsread1(inputs.File,1,'H12');
  case 'Tech1'
    NPV = xlsread1(inputs.File,1,'H13');
  case 'Thermal'
    NPV = xlsread1(inputs.File,1,'H14');
end

end
```

f. plotResults.m

The *plotResults.m* script is quite lengthy and includes code for plotting all of the relevant figures in this thesis. In the interest of space, and avoiding redundancy, a sample is given here for generating the contour plot of NPV vs. storage energy capacity and power rating.

```
% Select appropriate energy units:
try
  if(max(outputData.X_Cenergy)>1000)
    X_Cenergy = outputData.X_Cenergy./1000;
    try maxCenergy = outputData.maxCenergy./1000; catch end
    Eunit = '(MWh)';
  else
    X_Cenergy = outputData.X_Cenergy;
    try maxCenergy = outputData.maxCenergy; catch end
    Eunit = '(kWh)';
  end
catch
end
% Select appropriate power units:
try
  if(max(outputData.Y_Cpower)>1000)
    Y_Cpower = outputData.Y_Cpower./1000;
    try maxCpower = outputData.maxCpower./1000; catch end
    Punit = '(MW)';
  else
    Y_Cpower = outputData.Y_Cpower;
    try maxCpower = outputData.maxCpower; catch end
    Punit = '(kW)';
  end
catch
end
% Select appropriate monetary units:
try
  if(max(max(abs(outputData.Z_NPV)))>1000000)
    Z_NPV = outputData.Z_NPV./1000000;
    try NPVoriginal = outputData.NPVoriginal./1000000; catch end
    Munit = '(Million $)';
  elseif(max(max(abs(outputData.Z_NPV)))>1000)
    Z_NPV = outputData.Z_NPV./1000;
    try NPVoriginal = outputData.NPVoriginal./1000; catch end
    Munit = '(Thousand $)';
  else
    Z_NPV = outputData.Z_NPV;
    try NPVoriginal = outputData.NPVoriginal; catch end
    Munit = '($)';
  end
catch
end
% Generate the figure:
try
  figure
  [Colors,handle] = contour(X_Cenergy,Y_Cpower,Z_NPV,'LineWidth',1.5);
```

```
   clabel(Colors,handle,'labelspacing',200,'rotation',0)
   xlabel(['Energy Capacity ',Eunit],'fontsize',12,'fontname','arial')
   ylabel(['Power Rating ',Punit],'fontsize',12,'fontname','arial')
   zlabel(['NPV ',Munit])
   title({['Energy and Power Effects on Net Present Value ',Munit],...
      ['Technology = ',outputData.technology{1}]},...
      'fontsize',12,'fontweight','bold','fontname','arial')
   text(maxCenergy,maxCpower,'O','BackgroundColor',[.7 .9 .7])
   text(maxCenergy,maxCpower,'+')
   text((max(X_Cenergy)-min(X_Cenergy))/2 + min(X_Cenergy),...
      (max(Y_Cpower)-min(Y_Cpower))/2 + min(Y_Cpower),...
      {['Energy = ',num2str(maxCenergy)],...
      ['Power = ',num2str(maxCpower)],...
      ['NPV = $',num2str((Z_NPV((Y_Cpower==maxCpower)>0,...
      (X_Cenergy==maxCenergy)>0)))]},'BackgroundColor',[.7 .9 .7])
catch
   close
end
```

IV. MATLAB Code for Integration and Visualization – Baseload Generation

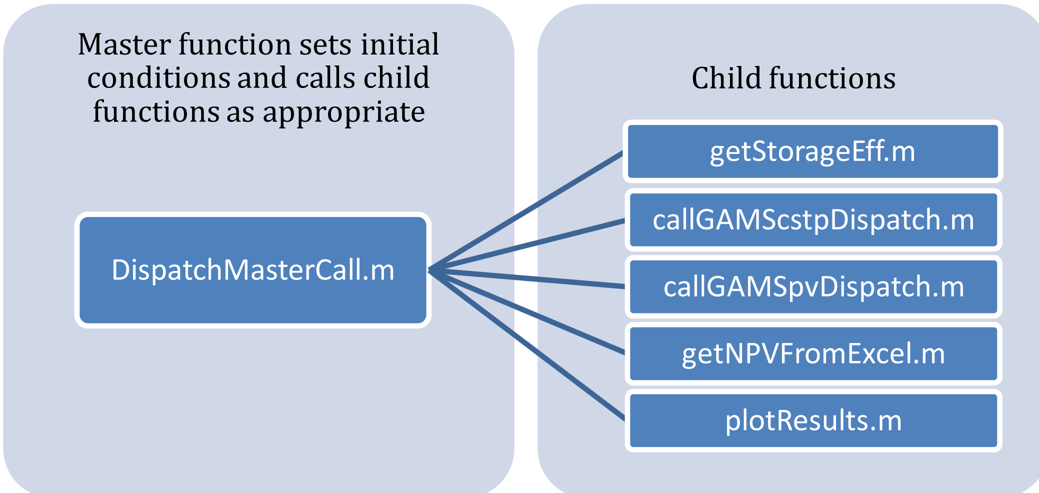

Figure IV-1: Schematic of MATLAB Code – Baseload Generation

a. DispatchMasterCall.m

```
% THIS IS THE MASTER CALL FUNCTION FOR THE BASELOAD SERVICE REQUIREMENT
% SCENARIOS: INTEGRATING THE GAMS OPTIMIZATION MODEL AND THE EXCEL FINANCIAL
% MODEL; AND FOR VISUALIZING THE RESULTS.

%% Service Requirement Model
% Clear the workspace:
clear
close all
clc

% Declare global variables:
global inputs excelInputs

% Generate the inputs structure:
inputs.systemSize = 10000;  % Must match insolation data file below (kW)
inputs.peakDemand = 10;     % peak demand requirement in MW
% hour in which to start the demand requirement:
inputs.demandStartHour = 1:24;
% duration of demand requirement for each day (hours):
inputs.demandDuration = 1:24;
inputs.generationType = 'PV_dispatch';  % 'PV_dispatch', or 'CSTP_dispatch'
inputs.storageTechnology = 'CAES';  % 'Thermal', 'Lead-Acid', 'LiIon'
                                    % 'NiCd', 'CAES', 'H2'
                                    % 'VRB', 'ZnBr', 'PHES', 'NaS', 'Tech1'
inputs.PVsystemLifetime = 30;   % PV system lifetime in years
inputs.discountRate = 0.1;      % Discount rate (%)
```

```
inputs.PCScost = 230;        % Cost of power control system ($/kW)
inputs.PCSlifetime = 7;      % Lifetime of power control system (years)
inputs.plots = 'yes';        % Whether or not to generate plots
inputs.startHour = 1;        % First hour to generate plots for
inputs.duration = 8759;      % Duration to generate plot preview (hours)
inputs.writeResults = 'no';  % Whether or not to write results to excel

%% Costs
switch inputs.generationType
  case 'CSTP_dispatch'
    % CSTP Costs
    powerDensity = 160; % W/m^2 - Power density of the solar field
    colectionSystem = 234;  % $/m^2
    supportStruct = 61;     % $/m^2
    heatElements = 43;      % $/m^2
    mirrors = 43;           % $/m^2
    powerBlock = 0.367;     % $/W-turbine
    BOS = 0.193;            % $/W-turbine
    storageCost = 27.1;     % $/kWh
    solarFieldCost = (colectionSystem + supportStruct +...
      heatElements + mirrors)/powerDensity;  % $/W-field

    inputs.turbineCost = (powerBlock + BOS)*1000;  % $/kW-turbine
    inputs.fieldCost = solarFieldCost*1000;        % $/kW-field
    inputs.storageCost = storageCost;              % $/kWh

  case 'PV_dispatch'
    if(strcmp(inputs.storageTechnology,'Thermal'))
      disp('Error - PV Cannot Use Thermal Storage!')
      disp('Exiting Simulation...')
      return
    end
    % PV Cost:
    inputs.PVcost = 3500;   % $/kW
end

% Name of file containing production, consumption, and price vectors:
switch inputs.generationType
  case 'PV_dispatch'
    % Central real-time Global:
    inputs.fileName = '10MW_BlytheCA_PV.xls';
  case 'CSTP_dispatch'
    % Central real-time Direct:
    inputs.fileName = '10MW_BlytheCA_CSTP.xls';
end

% Select appropriate input/output directories:
```

```
inputs.dir = ['xxxxxxx\',inputs.fileName];
inputs.outputDir = 'xxxxxxx\';
inputs.File = 'xxxxxxx\storageEconomics_FINAL.xlsx';
inputs.loadFile = 'xxxxxxx\CAISOsystemLoad.xlsx';
inputs.sensitivityFile = 'xxxxxxx\storageEconomics_Sensitivity.xlsx';

% Option to define efficiencies manually:
if(strcmp(inputs.storageTechnology,'custom'))
    inputs.efficiency = sqrt(0.95); % Storage Efficiency
    inputs.selfDis = 0;             % Self discharge rate
else
    % Retrieve efficiencies and unit costs from excel file
    disp('Retrieving Storage Efficiencies and Costs...')
    [inputs] = getStorageEff(inputs);
end

%% Extract Production and Prices from Excel File
disp('Loading Production and Pricing Data...')
[inputs.values,inputs.strings] = xlsread(inputs.dir);

%% Extract System Load Profile from Excel File
disp('Loading System Service Requirement (Demand Profile)...')
[inputs.loadValues,stringPlaceholder] = xlsread(inputs.loadFile);
% Convert to kW from MW and scale to peak demand:
inputs.loadValues = inputs.peakDemand*(inputs.loadValues(:,2)/10)*1000;

% Compile inputs for Excel financial model:
excelInputs.MULTIPLE = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.annualDischarged = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.totalGen = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.avgDOD = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.annualCycles = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.energyCapacity = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.powerCapacity = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.turbinePower = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.annualSavings = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
excelInputs.capFactor = zeros(length(inputs.demandStartHour),...
    length(inputs.demandDuration));
```

```
excelInputs.feasible = zeros(length(inputs.demandStartHour),...
  length(inputs.demandDuration));

% Define the service requirement (demand profile)
durationOriginal = inputs.demandDuration;
for t = 1:length(inputs.demandStartHour)
  for u = 1:length(inputs.demandDuration)
    if(inputs.demandDuration(u)+inputs.demandStartHour(t)>24)
      disp('Demand Profile Too Long. Skipping to Next Simulation...')
    else
      clear inputs.demand aggResults

      disp(['System #',num2str(length(inputs.demandStartHour)*...
        (t-1)+u),'/',num2str(length(inputs.demandStartHour)*...
        length(inputs.demandDuration))])
      inputs.demand = zeros(1,8760);
      for n = 2:365
        inputs.demand((n-1)*24+(inputs.demandStartHour(t)+1):...
          (n-1)*24+(inputs.demandStartHour(t)+...
          inputs.demandDuration(u))) =...
          inputs.loadValues((n-1)*24+(inputs.demandStartHour...
          (t)+1):(n-1)*24+(inputs.demandStartHour(t)+...
          inputs.demandDuration(u)));
      end
      if(strcmp(inputs.generationType,'CSTP_dispatch'))
        [aggResults] = callGAMScstpDispatch(t,u);
      else
        [aggResults] = callGAMSpvDispatch(t,u);
      end
    end
  end
end
outputData.excelInputs = excelInputs;
outputData.technology = {inputs.storageTechnology};
outputData.inputs = inputs;

%% Get NPV from Excel
disp('Calculating Storage NPV...')
Excel = actxserver ('Excel.Application');
if ~exist(inputs.File,'file')
  ExcelWorkbook = Excel.workbooks.Add;
  ExcelWorkbook.SaveAs(inputs.File,1);
  ExcelWorkbook.Close(false);
end
invoke(Excel.Workbooks,'Open',inputs.File);

for t = 1:length(outputData.inputs.demandStartHour)
```

```
  for u = 1:length(outputData.inputs.demandDuration)
    disp(['System #',num2str(length...
      (outputData.inputs.demandStartHour)*(t-1)+u),'/',num2str...
      (length(outputData.inputs.demandStartHour)...
      *length(outputData.inputs.demandDuration))])
    if(outputData.inputs.demandDuration(u)+...
        outputData.inputs.demandStartHour(t)>24)
      outputData.storageNPV(t,u) = NaN;
    else
      outputData.storageNPV(t,u) =...
        getNPVFromExcel(inputs,outputData,Excel,t,u);
    end

    disp(['NPV = $',num2str(outputData.storageNPV(t,u))])
  end
end

Excel.ActiveWorkbook.Save;
Excel.Quit
Excel.delete
clear Excel

%% Retrieve sensitivity data
if(strcmp(inputs.generationType,'PV_dispatch'))
  disp('Generating NPV Sensitivity Plot')
  [outputData.sensitivity] = getSensitivityFromExcel(outputData);
end

%% Plot Results
plotResults(outputData)
```

b. getStorageEff.m

See section III-b.

c. callGAMScstpDispatch.m

```
% This function compiles the inputs and calls the appropriate GAMS
% optimization model.  The results are then compiled to be sent back to
% MATLAB for processing

function [aggResults] = callGAMScstpDispatch(t,u)

% Declare global variables
global inputs excelInputs

%% Compile GAMS Variables
% Generate label set:
```

```
h1 = 8760;
labelSet = cell(1,h1);
for n = 1:h1
   labelSet{n} = ['t',num2str(n)];
end

% Efficiency of Storage Device
eff.name = 'eff';
eff.val = inputs.efficiency;

% Self-Discharge of Storage Device
disch.name = 'disch';
disch.val = inputs.selfDis;

% Demand
d.name = 'd';
d.labels = labelSet;
d.val = inputs.demand;

% Generation
gen.name = 'g';
gen.labels = labelSet;
gen.val = inputs.values(1:h1,3)';

% Price of electricity
price.name = 'p';
price.labels = labelSet;
price.val = inputs.values(1:h1,5)';

% Unit price of turbine
turbineCost.name = 'turbineCost';
turbineCost.val = inputs.turbineCost;

% Unit price of field
fieldCost.name = 'fieldCost';
fieldCost.val = inputs.fieldCost;

% Unit price of storage capacity
storageEnergyCost.name = 'storageEnergyCost';
storageEnergyCost.val = inputs.energyCost;

%% Call GAMS Solver
% Step 1 - find minimum system size to satisfy demand:
disp('Calculating Minimum System Size...')
[storageCapacity,maxTurbineOutput,genMultiple,turbineOutput,...
   discharged,stored,cost] = gams('CSTPloadFollow_Step1',eff,disch,...
   turbineCost,fieldCost,storageEnergyCost,gen,price,d);
```

```
disp(['Storage Size = ',num2str(storageCapacity.val),' kWh'])
disp(['Turbine Size = ',num2str(maxTurbineOutput.val),' kW'])
disp(['Field Multiple = ',num2str(genMultiple.val)])
disp(' ')
disp(['Charge/Discharge Product = ',...
   num2str(max(discharged.val.*stored.val))])
disp(['Total System Cost = ',num2str(cost.val)])
if(sum((turbineOutput.val' - d.val) > 1e-5)>0)
   disp(['ERROR - DEMAND PROFILE NOT MET FOR ',...
      num2str(sum((turbineOutput.val' - d.val) > 1e-5)),' HOURS'])
end
clear turbineOutput discharged stored cost storageLevel

% Energy Capacity of Storage
Cenergy.name = 'storageCapacity';
Cenergy.val = storageCapacity.val;

% Turbine maximum output
turbineMax.name = 'turbineMaxOutput';
turbineMax.val = maxTurbineOutput.val;

% Field Multiple
genMultipleVar.name = 'genMultiple';
genMultipleVar.val = genMultiple.val;

% Step 2 - find maximum revenue attainable with
%       this system (still satisfying demand):
disp('Calculating Maximum Revenue...')
[totalRevenue,hourlyRevenue,storageLevel,dischargedFromStorage,...
   usedDirectly,sentToStorage,turbineOutput] = ...
   gams('CSTPloadFollow_Step2',eff,disch,turbineMax,Cenergy,...
   genMultipleVar,gen,price,d);
aggSavings = sum(hourlyRevenue.val)-sum(price.val.*gen.val*genMultiple.val);
disp(['Total Revenue = $',num2str(totalRevenue.val)])
disp(['First Year Savings with Storage = $',num2str(aggSavings)])

% Form results structure:
aggStorageLevel = storageLevel.val;
aggDischargedFromStorage = dischargedFromStorage.val;
aggUsedDirectly = usedDirectly.val;
aggSentToStorage = sentToStorage.val;
aggTurbineOutput = turbineOutput.val;
aggHourlyRevenue = hourlyRevenue.val;
aggPrice = price.val;
aggGen = gen.val;
aggRevenue = sum(hourlyRevenue.val);
```

```
%% Compile Excel Inputs File
excelInputs.serviceReqRevenue(t,u) = sum(d.val.*aggPrice);
excelInputs.optimizedRevenue(t,u) = sum(aggTurbineOutput'.*aggPrice);
excelInputs.MULTIPLE(t,u) = genMultiple.val;
excelInputs.annualDischarged(t,u) = sum(aggDischargedFromStorage);
excelInputs.totalGen(t,u) = sum(aggTurbineOutput);
if(max(aggStorageLevel)>0)
  excelInputs.avgDOD(t,u) = mean(aggDischargedFromStorage...
    (aggDischargedFromStorage>0)./max(aggStorageLevel));
else
  excelInputs.avgDOD(t,u) = 0;
end
excelInputs.annualCycles(t,u) = length(aggDischargedFromStorage...
  (aggDischargedFromStorage>0));
excelInputs.energyCapacity(t,u) = storageCapacity.val;
excelInputs.turbinePower(t,u) = turbineMax.val;
excelInputs.annualSavings(t,u) = aggSavings;
excelInputs.capFactor(t,u) = sum(aggTurbineOutput)/(turbineMax.val*8760);

% Default, solution is feasible:
excelInputs.feasible(t,u) = 1;
try
  if(min(aggDischargedFromStorage+aggUsedDirectly-inputs.demand)<-1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(max(aggStorageLevel) > Cenergy.val || min(aggStorageLevel) < 0)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(min(min(aggDischargedFromStorage),min(aggSentToStorage)) < 0)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(max(aggTurbineOutput) > turbineMax.val || min(aggTurbineOutput) < 0)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(min(aggRevenue) < 0)
```

```
      excelInputs.feasible(t,u) = 0;
    end
catch
end

if(length(inputs.demandStartHour)*length(inputs.demandDuration) == 1)
    excelInputs.storageLevel = aggStorageLevel;
    excelInputs.dischargedEnergy = aggDischargedFromStorage;
    excelInputs.usedDirectly = aggUsedDirectly;
    excelInputs.turbineOutput = aggTurbineOutput;
    excelInputs.storedEnergy = aggSentToStorage;
    excelInputs.price = aggPrice;
    excelInputs.gen = aggGen;
end

aggResults.aggStorageLevel = aggStorageLevel;
aggResults.aggDischargedFromStorage = aggDischargedFromStorage;
aggResults.aggUsedDirectly = aggUsedDirectly;
aggResults.aggSentToStorage = aggSentToStorage;
aggResults.aggTurbineOutput = aggTurbineOutput;
aggResults.aggHourlyRevenue = aggHourlyRevenue;
aggResults.aggPrice = aggPrice;
aggResults.aggGen = aggGen;
aggResults.aggRevenue = aggRevenue;
aggResults.aggSavings = aggSavings;
aggResults.aggStorageCapacity = max(aggStorageLevel);
aggResults.aggStoragePower = max(max(aggSentToStorage),...
    max(aggDischargedFromStorage));

end
```

d. callGAMSpvDispatch.m

```
% This function compiles the inputs and calls the appropriate GAMS
% optimization model.  The results are then compiled to be sent back to
% MATLAB for processing

function [aggResults] = callGAMSpvDispatch(t,u)

% Declare global variables
global inputs excelInputs

%% Compile GAMS Variables
% Generate label set:
h = 8760;
set = cell(1,h);
for n = 1:h
    set{n} = ['t',num2str(n)];
```

```
end

% Efficiency of Storage Device
eff.name = 'eff';
eff.val = inputs.efficiency;

% Self-Discharge of Storage Device
disch.name = 'disch';
disch.val = inputs.selfDis;

% Demand
d.name = 'd';
d.labels = set;
d.val = inputs.demand;

% Generation
gen.name = 'g';
gen.labels = set;
gen.val = inputs.values(1:h,3)';

% Price of electricity
price.name = 'p';
price.labels = set;
price.val = inputs.values(1:h,5)';

% Unit price of power
powerCost.name = 'powerCost';
powerCost.val = inputs.powerCost;

% Unit price of field
energyCost.name = 'energyCost';
energyCost.val = inputs.energyCost;

% Unit price of capacity
PVcost.name = 'PVcost';
PVcost.val = inputs.PVcost;

%% Call GAMS Solver
% Step 1 - find minimum system size to satisfy demand:
disp('Calculating Minimum System Size...')
[storageCapacity,storagePower,genMultiple]...
   = gams('PVloadFollow_Step1',eff,disch,powerCost,energyCost,...
   PVcost,gen,price,d);
disp(['Storage Size = ',num2str(storageCapacity.val),' kWh'])
disp(['Power Rating = ',num2str(storagePower.val),' kW'])
disp(['PV Multiple = ',num2str(genMultiple.val)])
totalCost = inputs.PVcost*genMultiple.val*inputs.systemSize + ...
```

```matlab
    inputs.energyCost*storageCapacity.val + ...
    inputs.powerCost*storagePower.val;
disp(['Total Upfront Capital Cost = $',num2str(totalCost)])
disp(' ')

% Energy Capacity of Storage
Cenergy.name = 'storageCapacity';
Cenergy.val = storageCapacity.val;

% Storage Power Rating
Cpower.name = 'storagePower';
Cpower.val = storagePower.val;

% Field Multiple
genMultipleVar.name = 'genMultiple';
genMultipleVar.val = genMultiple.val;

% Step 2 - find maximum revenue attainable with
%       this system (still satisfying demand):
disp('Calculating Maximum Revenue...')
[totalRevenue,hourlyRevenue,storageLevel,dischargedFromStorage,...
    usedDirectly,sentToStorage] = gams('PVloadFollow_Step2',eff,disch,...
    Cpower,Cenergy,genMultipleVar,gen,price,d);
aggSavings = sum(hourlyRevenue.val)-sum(price.val.*gen.val*genMultiple.val);
disp(['Total Revenue = $',num2str(totalRevenue.val)])
disp(['First Year Savings with Storage = $',num2str(aggSavings)])

% Form results structure:
aggStorageLevel = storageLevel.val;
aggDischargedFromStorage = dischargedFromStorage.val;
aggUsedDirectly = usedDirectly.val;
aggSentToStorage = sentToStorage.val;
aggHourlyRevenue = hourlyRevenue.val;
aggPrice = price.val;
aggGen = gen.val;
aggRevenue = sum(hourlyRevenue.val);

%% Compile Excel Inputs File
excelInputs.serviceReqRevenue(t,u) = sum(d.val.*aggPrice);
excelInputs.optimizedRevenue(t,u) = sum((aggUsedDirectly+...
    aggDischargedFromStorage)'.*aggPrice);
excelInputs.MULTIPLE(t,u) = genMultiple.val;
excelInputs.annualDischarged(t,u) = sum(aggDischargedFromStorage);
excelInputs.totalGen(t,u) = sum(aggDischargedFromStorage + aggUsedDirectly);
if(max(aggStorageLevel)>0)
    excelInputs.avgDOD(t,u) = mean(aggDischargedFromStorage...
        (aggDischargedFromStorage>0)./max(aggStorageLevel));
```

```
else
  excelInputs.avgDOD(t,u) = 0;
end
excelInputs.annualCycles(t,u) = length(aggDischargedFromStorage...
  (aggDischargedFromStorage>0));
excelInputs.energyCapacity(t,u) = storageCapacity.val;
excelInputs.powerCapacity(t,u) = storagePower.val;
excelInputs.annualSavings(t,u) = aggSavings;
excelInputs.capFactor(t,u) = sum(aggDischargedFromStorage + ...
  aggUsedDirectly)/(inputs.systemSize*8760);

% Default, solution is feasible:
excelInputs.feasible(t,u) = 1;
try
  if(min(aggDischargedFromStorage + aggUsedDirectly - ...
      inputs.demand) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if((max(aggStorageLevel) - Cenergy.val) > 1e5 || ...
      min(aggStorageLevel) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end
try
  if(min(min(aggDischargedFromStorage),min(aggSentToStorage)) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end

try
  if(min(aggRevenue) < -1e5)
    excelInputs.feasible(t,u) = 0;
  end
catch
end

if(length(inputs.demandStartHour)*length(inputs.demandDuration) == 1)
  excelInputs.storageLevel = aggStorageLevel;
  excelInputs.dischargedEnergy = aggDischargedFromStorage;
  excelInputs.usedDirectly = aggUsedDirectly;
  excelInputs.storedEnergy = aggSentToStorage;
  excelInputs.price = aggPrice;
```

```
    excelInputs.gen = aggGen;
end

aggResults.aggStorageLevel = aggStorageLevel;
aggResults.aggDischargedFromStorage = aggDischargedFromStorage;
aggResults.aggUsedDirectly = aggUsedDirectly;
aggResults.aggSentToStorage = aggSentToStorage;
aggResults.aggHourlyRevenue = aggHourlyRevenue;
aggResults.aggPrice = aggPrice;
aggResults.aggGen = aggGen;
aggResults.aggRevenue = aggRevenue;
aggResults.aggSavings = aggSavings;
aggResults.aggStorageCapacity = max(aggStorageLevel);
aggResults.aggStoragePower = max(max(aggSentToStorage),...
    max(aggDischargedFromStorage));

end
```

e. getNPVFromExcel.m

See section III-e.

f. plotResults.m

See section III-f.

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