ENERGY STORAGE SYSTEMS AND UTILITY COST SAVINGS FOR DOD INSTALLATIONS

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ENERGY STORAGE SYSTEMS AND UTILITY COST SAVINGS FOR DOD INSTALLATIONS

by

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The benefits of energy storage systems (ESSs) include reduced utility costs, back-up power, and the integration of renewable energy. This research developed energy storage heuristics that determine how much energy should be sent to and from storage in a given time period. The researchers evaluated the economic impact of each heuristic given various energy demand profiles and utility rate structures. The researchers utilized several ESS configurations, two different rate structures, and two historic annual energy demand profiles to test each heuristic and estimate potential cost savings of energy storage.

ESSs reduced overall energy costs in both volatile and stable demand environments. Annual cost savings achieved by employing an ESS was a function of the energy storage heuristic and characteristics of the ESS. The research offers several key takeaways. First, utility rate structures can be used to determine the required efficiency rate to generate cost savings, and maximum capacity of the ESS can be a limitation. Second, capacity limitations can be mitigated with the application of a safety stock. Finally, volatile demand profiles with large demand spikes require a maximum discharge power equal to that spike to maximize savings, whereas stable demand profiles are not constrained by this characteristic.

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ENERGY STORAGE SYSTEMS AND UTILITY COST SAVINGS FOR DOD INSTALLATIONS

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ABSTRACT

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	alternate current
BESS	battery energy storage system
BTM	behind-the-meter
CAES	compressed air energy storage
CBA	cost-benefit analysis
CES	cryogenic energy storage
CIO	Chief Information Officer
DC	direct current
DISA	Defense Information Systems Agency
DoD	Department of Defense
DoN	Department of the Navy
ESD	energy storage device
ESS	energy storage system
FES	flywheel energy storage
FBES	flywheel battery energy storage
FC-HES	fuel cell-hydrogen energy storage
HECO	Hawaiian Electric Company
HOMER	hybrid optimization of multiple energy resources
KCP&L	Kansas City Power and Lighting
LA	lithium acid
LAES	liquid air energy storage
LI	lithium ion
MCEITS	Marine Corps Enterprise Information Technology Services
NEM	net-metering
NGS	natural gas storage
NREL	National Renewable Energy Laboratory
NSA	naval support activity
PG&E	Pacific Gas and Electric
RTP	real-time pricing
SECNAV	Secretary of the Navy

SMES	superconducting magnetic energy storage
SOFC	solid oxide fuel cells
SSCAES	small scale compressed air energy storage
TOU	time of use
UC	ultra-capacitors
UET	UniEnergy Technologies
UPS	uninterrupted power supply
USMC	United States Marine Corps

EXECUTIVE SUMMARY

There are many benefits of energy storage systems (ESSs). They include back-up power to increase resilience, the integration of renewable resources, and the ability to time shift demand to reduce costs. Renewable generation assets paired with storage systems could to eliminate the reliance and vulnerability of the commercial grid. However, such a large investment may not be possible in fiscally constrained environments. Investing in only the renewable generation assets or the ESS is a potential solution. ESSs can still provide back-up power and reduce costs as stand-alone systems. However, there is a trade-off between having back-up power when needed to increase energy assurance and reducing costs. Energy or installation managers can choose whether to employ ESSs to achieve cost savings or resiliency as they desire. This research analyzes how ESSs can be used to reduce utility costs.

This research develops heuristics that determine how much energy should be sent to and from storage in a given time period. Furthermore, the research evaluates the economic impact of each heuristic given various energy demand profiles and utility rate structures. The primary research question is, "how can ESSs reduce energy costs in Department of Defense (DoD) installations?" The results of this study will be valuable to the DoD in developing heuristics to apply to different energy and storage technology variables to assist in future cost estimation, selection, and sizing of storage systems.

Researchers formulated three heuristics capable of using historical electricity demand data to determine how to use an ESS to reduce total energy costs. The energy storage heuristics were termed Load-Shifting, Averaging, and Load-Shifting and Averaging. To accomplish this, the research team mathematically formulated common commercial electricity rate structures to calculate energy costs. The team utilized rate structures from Pacific Gas and Electric (PG&E) and Kansas City Power and Light (KCP&L). The PG&E rate structure is a good sample of a time-of-use and demand charge rate structure. KCP&L is an interesting rate structure because it uses a combination of tiered, demand, and ratchet adjustment charges for billing their commercial customers.

Additionally, 2017 historical energy demand data was obtained from a Defense Information System Agency (DISA) data center in Columbus, Ohio and Naval Support Activity (NSA) Monterey in Monterey, California to demonstrate and test the impact of the heuristics. The stable demand profile from DISA and the volatile demand profile from NSA Monterey allowed to the researchers to analyze the impact on different energy demand profiles. Different configurations of ESSs produced by Tesla's Powerpack and Uni.Energy Technologies (UET) Uni.System were the last variable in the analysis.

This research focused on the cost reduction benefit of ESSs and found that they can reduce overall energy costs in volatile demand environments, and can to a lesser extent in stable demand environments. Annual cost savings achieved by employing an ESS was a function of the characteristics of the ESS and the implementation of different heuristics. The annual cost summary for the volatile demand profile is summarized in Figures 1 and 2.

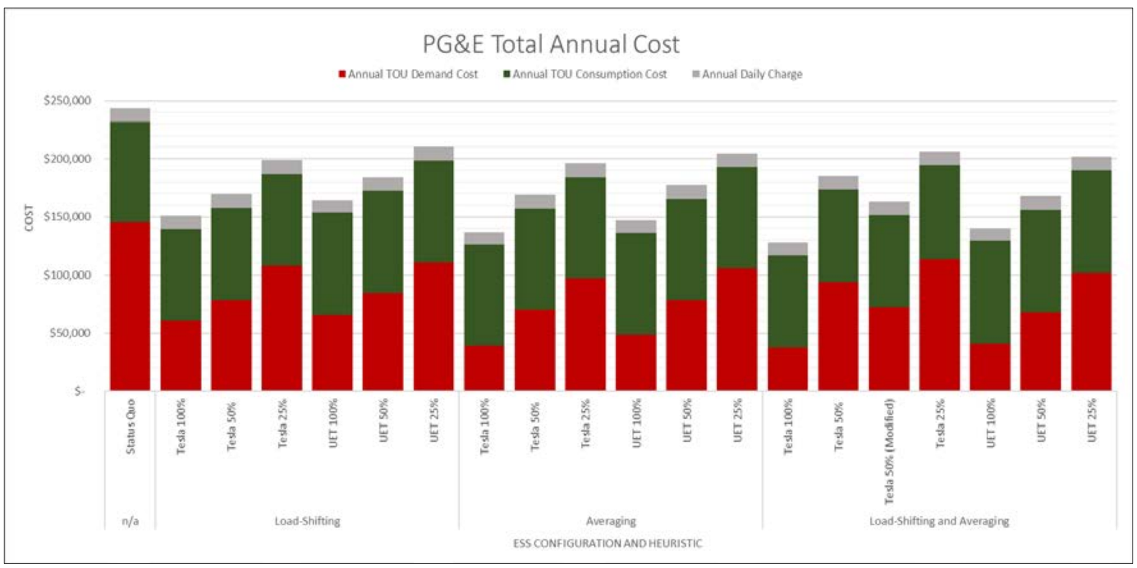

Figure 1. Volatile Profile Annual Total PG&E Cost

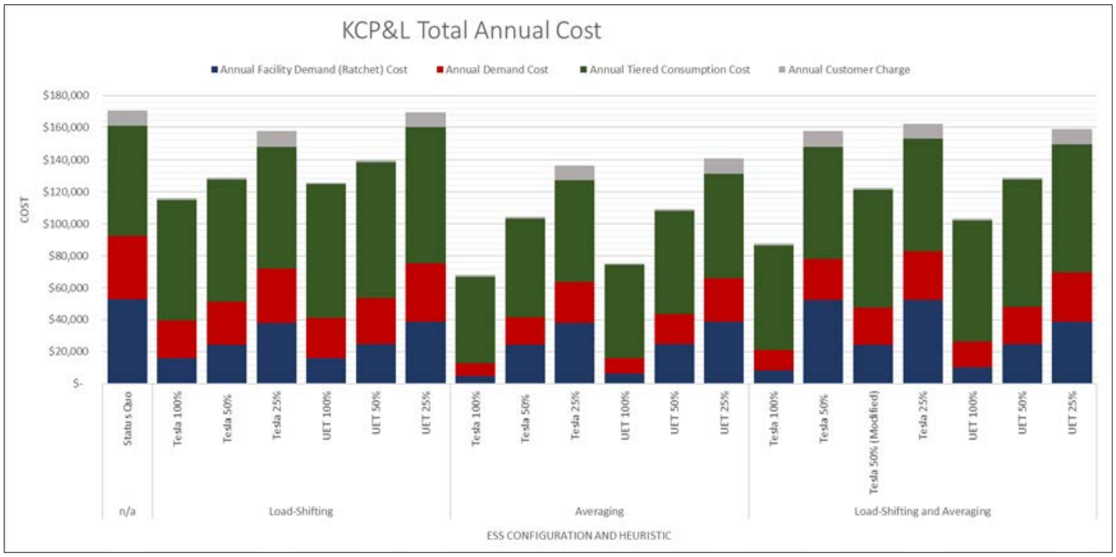

Figure 2. Volatile Profile Annual Total KCP&L Cost

The annual cost summary for the stable demand profile is summarized in Figures 3 and 4.

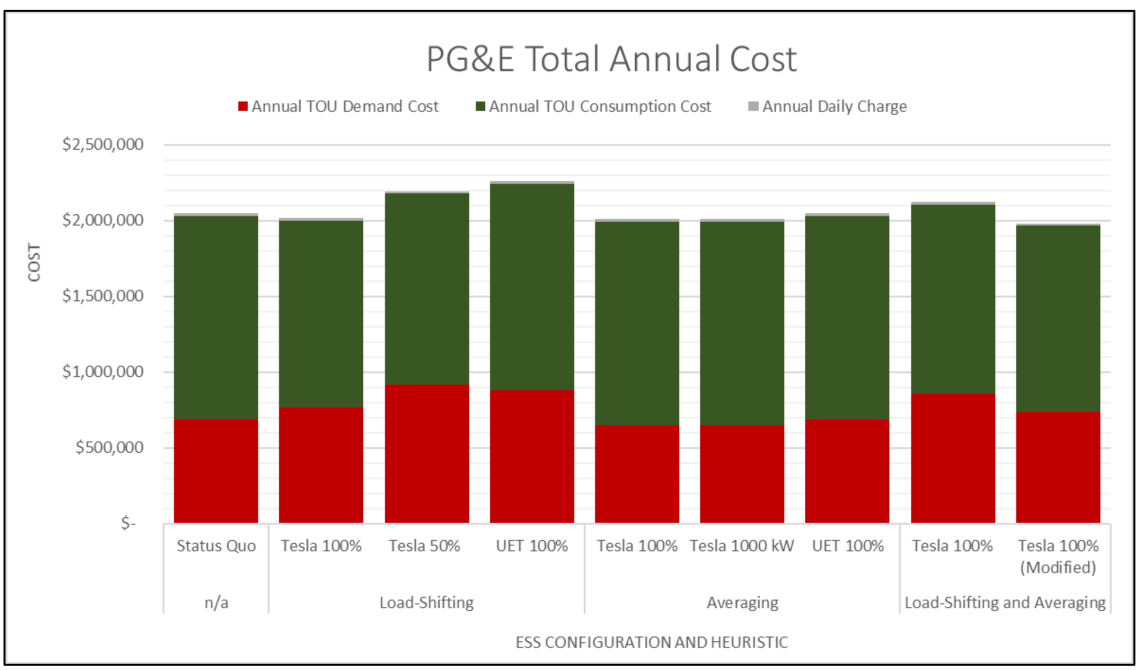

Figure 3. Stable Profile Annual Total PG&E Cost

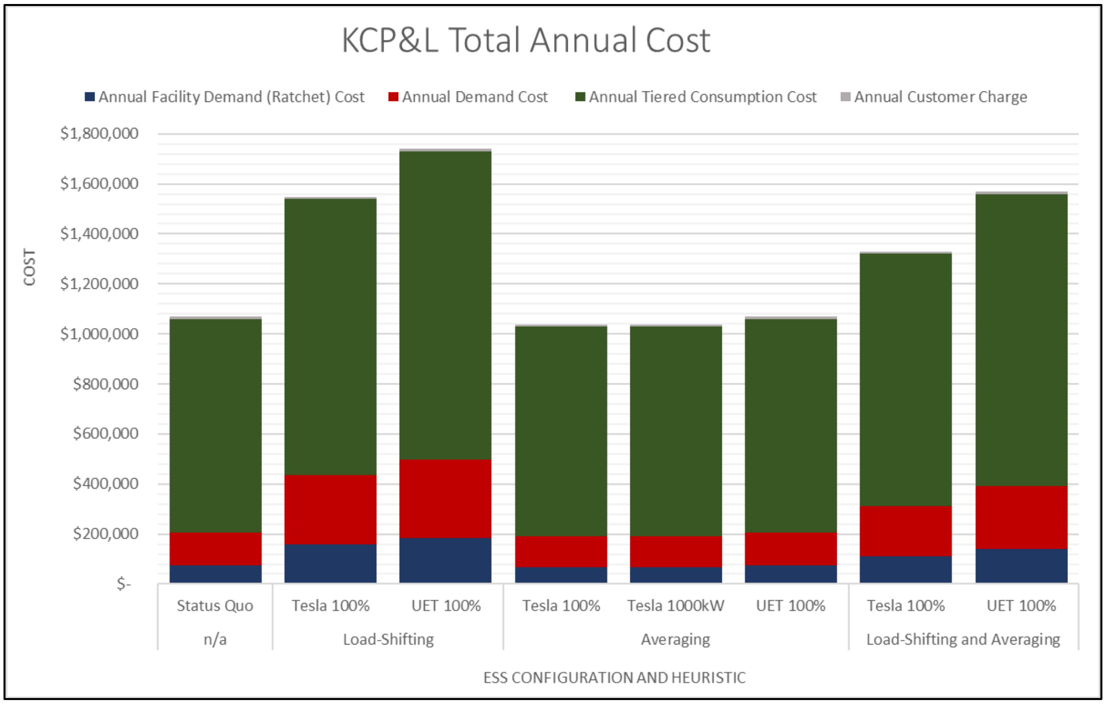

Figure 4. Stable Profile Annual Total KCP&L Cost

The researchers developed a two-step decision criterion, heuristic determination and ESS selection, to determine what combination of ESS and heuristic is best for a given energy demand profile and rate structure. The first step is heuristic determination, which is largely impacted by a user's utility rate structure. The Load-Shifting and Averaging heuristic should be used when users are subject to time-of-use (TOU) energy charges. Shifting demand from more expensive billing periods to cheaper periods is the primary goal of this heuristic. The Load-Shifting heuristic follows a similar logic but does not average the shifted energy over all off-peak time periods in the month. This heuristic is beneficial when users desire to completely restore the ESS to full charge each day, and may be appropriate when reliable back-up power is necessary and/or when the operational cost of not having available stored energy is high. The Averaging heuristic should be used when users are not subject to TOU energy charges like the KCP&L rate structure.

The second step in the determination criteria is the ESS selection. Efficiency rate, maximum discharge power, and capacity are characteristics of ESSs that impacted cost savings. The Tesla Powerpack configurations achieved greater cost savings than the UET

Uni.System because of the higher efficiency rate of the Tesla Powerpack. Higher efficiency rates require less energy to be purchased to account for efficiency loss.

The demand profile will also influence the decision of which ESS to employ. For example, the volatile demand profile required an ESS with a maximum discharge power large enough to service the largest spike in energy demand. On the other hand, with the stable demand profile, heuristics' performance was not limited by the maximum discharge power of the ESSs.

The maximum capacity of the ESS can also be a limitation. However, the researchers also found that capacity limitations can be mitigated with the application of a safety stock. Demand profiles will also require different capacities. The stable demand profile was influenced more by the capacity of the ESS. Rate structure is also an important factor into how much capacity is required.

In conclusion, the research team found that ESSs can reduce utility costs by peak shaving and time-shifting consumption to purchase energy when it is cheapest. Future research recommendations include:

- A study to apply ESSs in a tactical environment. For example, a study analyzing the deployment of batteries with generators to capture excess energy and reduce the number of hours the generator runs and the amount of fuel consumed.

- A study to analyze the impact of renewable energy on utility bills with each heuristic. The research could determine what size energy storage system and how much renewable energy generation would be necessary to eliminate reliance on the energy grid for a given demand profile and renewable generation profile.

- A complete cost benefit analysis of various ESSs given the cost savings demonstrated in this study.

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I. INTRODUCTION

A. BACKGROUND

The centralized energy industry today will soon be replaced by renewable energy and distributed energy storage systems (ESSs) (Seba, 2014). This disruption is the result of a convergence of two major technologies: photovoltaics, or solar panels, and energy storage. Solar panel production has seen exponential growth over the last 10 years (Seba, 2014). This exponential growth allows companies to invest more money in research and development, improve the technology, and achieve economies of scale. Photovoltaic cost has improved by a factor of 154 times since 1970 while the technology has drastically improved (Seba, 2014).

The other technology that is complementing renewable energy generation technologies is energy storage. There are many types of ESSs. Compressed air and liquid air energy storage, solid state batteries, such as lithium-ion batteries, are a few of the storage technologies most relevant. Similar to the improvements in photovoltaics, lithium-ion has and will continue to show exponential cost reductions in the coming decade (Seba, 2014).

Seba (2014) stated that the convergence of these two technologies will replace the large, centralized energy grid with modular, distributed energy. The convergence supports one of the objectives of the most recently published defense strategy. The 2018 National Defense Strategy calls for a transition away from large, centralized infrastructure to establish a more resilient force (Mattis, 2018). The strategy highlights the modern-day threats that include both state and non-state actors with the ability to conduct cyber attacks against large centralized infrastructures such as the energy grid. The combination of renewable energy and energy storage enables the ability to remove all reliance on the energy grid, reducing the vulnerability and improving resilience.

The best approach may be to invest in a complete system that incorporates both renewable energy and energy storage. However, a fiscally constrained environment may prevent this solution. One approach in a fiscally constrained environment is to only invest in either photovoltaics or an ESS. Although photovoltaics appears to be invested in at a higher rate than ESSs, the researchers find it important to highlight the benefits of ESSs. This research analyzes the benefits of ESSs.

Energy storage systems offer many benefits that include providing back-up power, integrating renewable energy sources, and enabling time-shifting consumption to reduce utility costs. However, there is a trade-off with these benefits. For example, you cannot achieve the maximum benefits of reducing utility cost with time-shifting consumption while also getting the maximum benefits of back-up power. This research analyzes how energy storage systems can be employed to reduce utility costs.

Leaders emphasize the importance of energy efficiency in the Department of Defense (DoD) and United States Marine Corps (USMC). Energy policies and strategies focusing on cost reduction and energy efficiency were published directing installations, operational units, and acquisition professionals to drastically reduce energy consumption and to consider energy requirements in future construction and procurement (Mabus, Neller, & Richardson, 2016). At the same time, the DoD is working to meet the renewable energy goal of 10 U.S.C §2911(e) and, as always, working to manage its facilities costs, including utility bills. Concurrently, the DoD and Marine Corps published strategic directives to consolidate their data centers in an effort to reduce information technology (IT) costs (Department of the Navy Chief Information Officer, 2012). The energy and data center consolidation policies intersect at a critical time where the energy efficiency policy affects the implementation of the data center consolidation strategy, which presents an opportunity to reconfigure data center utility consumption to increase energy efficiency and reduce costs. One way to make data centers more cost efficient and enable the integration of intermittent renewable energy generation is to invest in energy storage technologies. The researchers' objective is to develop simple heuristics for the operational use of energy storage to support decision making regarding ESS investments.

B. PROBLEM STATEMENT

There are no simple heuristics for the operational use of energy storage to determine how energy should be sent to and from storage in a given time period that may be used in advance to estimate potential energy cost savings generated by the investment in ESSs. Cost savings is achieved using storage to time-shift power consumption and reduce utility charges for peak loads and consumption during high-cost periods. This is a problem because DoD is pursuing investments to reduce overall energy costs, but there are no published decision criteria to determine a combination of ESSs and operational use policies to reduce cost given an installations utility rate structure.

This quantitative study tests heuristics for operational use of energy storage combined with ESS configurations to estimate potential energy cost savings of energy storage. Energy demand profiles were collected from two installations to test the heuristics. A possible outcome of this research will be tool that is applicable to a range of stakeholders from energy program managers to facility managers across the DoD to better estimate cost savings of energy storage.

C. PURPOSE STATEMENT

The purpose of this research is to develop energy storage heuristics that determine how much energy should be sent to and from storage in a given time period. Furthermore, the research evaluates the economic impact of each heuristic given various energy demand profiles and utility rate structures.

First, the study will review DoD energy policies to highlight the need for reducing energy use across the institution. Next, the research will introduce different energy storage technologies and examine how they relate to the mission of energy reduction. Then, the researchers will build heuristics that allocate energy to storage and to demand. Next, the research will use data provided by DoD installations and two commercial ESSs to instantiate and demonstrate the impact of the heuristics. The conclusion of this research will demonstrate how to select the appropriate energy storage heuristic and ESS given a demand profile and utility rate structure for future energy storage technology investments.

The results of this study will be valuable to the DoD in developing heuristics to apply to different energy and storage technology variables to assist in future cost estimation and selection and sizing of storage technologies. Graduate students in the Information

Technology Management and Information Systems Management programs at the Naval Postgraduate School led this research.

D. RESEARCH QUESTIONS

This research will be guided by the following question:

1. How can ESSs reduce energy costs in DoD installations?

To answer this, the research will incorporate the following additional questions to enrich understanding:

2. How are other industries incorporating alternative energy storage technologies to reduce overall energy costs? How can the DoD adopt such practices?

3. How do characteristics of ESSs impact cost savings?

4. How does volatility in energy demand profiles influence the ESS required?

5. How do rate structures influence how ESSs are employed?

6. What energy storage heuristics can be applied to the energy demand data to determine how and when to move energy to and from storage to estimate cost savings?

E. POTENTIAL BENEFITS AND LIMITATIONS

1. Benefits

The potential benefit of this research is a demonstration of the economic impact of energy storage solutions. Moreover, the research may reveal that certain storage technologies are more cost effective than others, which can focus investors to certain energy storage technologies.

2. Limitations

This research has several limitations. The research does not consider the cost of energy storage systems. The focus of this research is to provide the potential cost savings benefits of employing ESS and to determine how and when to move energy to and from storage. Obtaining ESS cost information from commercial suppliers would be beneficial for conducting a cost benefit analysis.

Additionally, the research does not consider renewable generation. This research is designed to isolate the benefits of using an ESS. However, incorporating renewable energy into the models may reduce overall energy costs even further and potentially eliminate all energy costs.

Furthermore, the research is limited to only two rate structures. Although the researchers believe the two rate structures provide a good representation of the various types of energy charges throughout the industry, it is still only two combinations of rate charges. Most types of energy charges are covered, but they could be combined in various ways from other utility companies that may impact total cost differently.

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II. LITERATURE REVIEW

The Department of Defense (DoD) has an opportunity to synchronize efforts of energy and data center consolidation strategies by adopting and investing in energy storage systems (ESSs) to minimize energy demand costs for installations and data centers. Researchers summarize literature regarding energy rate schedules, behind the meter energy (BTM) storage, energy storage concepts, and types of ESSs that are relevant to developing viable heuristics to reduce energy demand costs. The following section reviews each strategy, policy, journal article, and market data to create a complete picture of the problem space and current status of the energy environment.

A. DEPARTMENT OF DEFENSE ENERGY INITIATIVES

Several policies and orders signed in 2016 outlined energy initiatives as a key priority in the DoD (Office of the Assistant Secretary of Defense for Energy Installations and Environment, 2016). Secretary of the Navy (SECNAV), The Honorable Ray Mabus, the Chief of Naval Operations, Admiral J.M. Richardson, and the Commandant of the Marine Corps, General Robert Neller, released a message in February 2016, stating that the maintenance of the presence around the globe was dependent upon the access to secure, reliable energy. They challenged the Navy and Marine Corps team to find ways to get more out of every gallon and kilowatt-hour (kWh). Additionally, they created the Marine Corps' Energy Ethos campaign and the Navy Energy Warrior initiative to maximize the combat capability of the force (Mabus et al., 2016). The challenge ranged from the expeditionary battlefield all the way back to installations and support establishments that train and support forces. Marine Corps leadership nested its own energy strategy in the directives published by top defense leadership.

1. Marine Corps Installation Energy Initiatives

Major General J.A. Kessler, Commander of Marine Corps Installations, summarized his commitment "to the efficient use of energy and the overall energy security of all Marine Corps installations" in the Marine Corps Installations Energy Policy statement (Kessler, n.d.). He stated, “Bases and stations must become increasingly energy efficient and energy independent to cost effectively perform their critical missions and support Marine Corps readiness” (Kessler, n.d.). Furthermore, he emphasized that conserving energy and reducing costs on installations make constrained funds available for operational needs and future warfighting requirements (Kessler, n.d.). His policy statement was expanded in more detail in the United States Marine Corps Installations Energy Strategy (Kessler, n.d.).

The United States Marine Corps Installations Energy Strategy set three measurable goals to achieve by 2020. Two of the three directly relate to energy demand and consumption. The first was to reduce energy intensity by 37.5% compared to the 2003 baselines. The second was to produce at least 50% of energy requirements from alternative sources (Kessler, 2013). Energy intensity measures how much a bit of energy benefits the economy and is calculated by taking the ratio of energy use to GDP (Hanania et al., n.d.). In the context of an organization, energy intensity is a way to measure the efficiency of energy consumption. Moreover, two of the lines of operation of the strategy were to implement efficient technologies and best management practices to both achieve cost savings and utilize renewable energy and alternative fuels to produce cost savings (Kessler, 2013). In total, the strategy highlighted that the Marine Corps values energy efficiency and cost savings and seeks solutions to achieve these goals.

2. Marine Corps Data Center Consolidation

The Marine Corps is in the midst of consolidating its data centers in order to reduce costs at the same time it is implementing energy efficiency strategies. The Department of Navy (DoN) Chief Information Officer (CIO) published the Department of the Navy Performance Plan for Reduction of Resources Required for Data Servers and Centers in Support of the National Defense Authorization Act for Fiscal Year 2012. This strategy detailed the Navy and Marine Corps’ plan to consolidate data centers “to deliver cost and environmental efficiencies and increase overall information technology (IT) security” (DoN CIO, 2012). DoN CIO policy explicitly stated that the Marine Corps would reduce its data center energy usage by 50% after the strategy is fully implemented (DoN CIO, 2012).

Energy storage to manage energy costs may be a valuable investment for data centers. Therefore, developing heuristics for different energy demand profiles is useful to assist the Marine Corps in determining the best ESS to install in its installations, and specifically its data centers, to reduce costs across the organization. The development of energy storage heuristics requires a thorough understanding of utility charges and rate structures, energy storage concepts, and the current state of ESSs.

B. UTILITY RATE STRUCTURES

The first step in developing heuristics to minimize energy demand costs in installations and data centers is to understand utility rate structures. Standard rate structures may be comprised of a combination of rate charges: Standard Residential Charges, Residential Time-of-Use (TOU) Charges, Demand Charges, Demand Charges with a Ratchet Adjustment, Load Factor, and Real-Time Pricing (RTP) (Masters, 2004). Utility company rate structures include these six charge categories that can be implemented alone or in conjunction with multiple types of charges to create a more complex rate structure. In any case, energy demand in all rate structures is measured in kilowatts (kW), consumption is measured in kilowatt per hour (kWh), and cost is measured in dollars (Masters, 2004).

1. Standard Residential Charges

The first type of charge is a standard residential electric rate charge. In this model, rates increase with an increase in demand. This model is also known as an inverted block rate structure and discourages excessive demand. Furthermore, a distinction may exist between seasons to incentivize customers to limit consumption during peak periods in high-demand seasons. In contrast, another type of charge is a declining block rate charge, where price decreases as demand increases, similar to a bulk discount. The declining block rate charge is not as commonly used today (Masters, 2004).

2. Residential Time-of-Use Charges

The second type of charge is a residential TOU charge, and is a tool for utility companies to discourage excessive consumption during peak hours. In this model, customers are encouraged to shift their energy demand away from peak hours and toward non-peak hours. Utility companies categorize peak demand times by seasons and time of day. For example, in the middle of a hot summer afternoon when air conditioning units are at maximum capacity, the cost of electricity is at its highest. This defines a peak time period. Similarly, charges are categorized as non-peak in the winter time and at night when total consumption, and therefore price, is at its relative lowest (Masters, 2004). TOU charges incentivize customers to allocate their energy demand, based on time and periods, which creates an opportunity for customers to apply technologies to achieve a lower energy bill.

3. Demand Charges

The third type of charge is a demand charge and is typically applied to industrial and commercial customers. It is based on the highest peak power demand drawn by a customer over a 15-minute interval during a given billing period. The peak demand charge may be recorded at any time of day (Masters, 2004). For example, if a consumer has consistent demand of 100 kW for a sustained period, but then has a power spike of 150 kW during a 15-minute interval, then the customer's demand charge is based on the 150 kWs rather than the 100 kW demand series. Therefore, this charge creates incentive for customers to reach their peak demands during off-peak or non-peak hours.

4. Demand Charges with a Ratchet Adjustment

The fourth type of charge is a demand charge with a ratchet adjustment. The purpose of this charge is to adjust the revenue flow to the utility company to account for months of the year that a customer may not achieve the same peak demand. In short, this is a way for utility companies to spread the revenue from peak demand charges across the entire year and not concentrate higher revenues in certain months (Masters, 2004). For example, if a customer has a peak demand of 100 kW during one period, then that peak demand may be ratcheted to 70% of the annual peak demand and applied against all months. Utility companies determine the actual percentage of the peak demand charged. This charge provides considerable incentive to reduce peak demand consumption, but can also penalize customers who add additional loads to their annual peak demand 15-minute intervals (Masters, 2004).

Demand charges with a ratchet adjustment are common for DoD installations. For example, Priester, Grusich, and Tortura (2015) encountered the Hawaiian Electric Company (HECO) ratchet adjustment rate structure in their thesis on renewable energy and storage implementation in Joint Base Pearl Harbor (Priester, Grusich, & Tortora, 2015). This research will continue to explore ratchet rate structures in more depth because of its applicability to DoD installations.

5. Load Factor

The fifth charge is load factor. Masters (2004) defines load factor as the ratio of a customer's average power demand to its peak demand. Utility companies use this factor to characterize the cost of providing power to a given customer (Masters, 2004). Load factor is annotated in the equation below:

$$Load\ factor\ (\%) = \frac{AveragePower}{PeakPower}\ X\ 100\%$$

6. Real-Time Pricing

The final charge is RTP. RTP is a more sophisticated method of computing TOU charges because it captures rate changes throughout the day every day of the year. In contrast, TOU charges are divided into peak, partial-peak, and off peak and by seasons. RTP charges do not include any demand charges, and utility companies will often publish next day rates to allow customers to adjust their consumption accordingly. Furthermore, the RTP rate structure is constructed with the assumption that the real-time market will drive customers to efficiently manage their demand (Masters, 2004).

7. Summary

Utility companies combine charges to create a rate structures for residential, commercial, and industrial customers. In all structures, consumers are encouraged to reduce or optimize their energy demand to reduce the load on the network and the cost to the overall system. The specific rate structures for the utility companies, Pacific Gas & Electric (PG&E) and Kansas City Power and Light Company (KCP&L), are defined in Chapter III. PG&E is an example of a TOU and demand rate structure, while KCP&L is an example of a ratchet demand structure. The following section describes methods by which customers can reduce their energy demand profile and achieve cost savings.

C. BEHIND-THE-METER ENERGY STORAGE

Behind-the-meter (BTM) energy storage is the bulk storage of energy in installations and facilities for on-site use. BTM energy storage is being adapted by the commercial and industrial sector to reduce energy demand profiles and costs. The energy storage market in the United States is expanding. From 2014–2020, over 700 megawatts of energy storage will be deployed across the country (Wu, Kintner-Meyer, Yang, & Balducci, 2016). BTM ESSs may be used to achieve utility cost savings by shifting the time at which electricity is purchased from the utility company.

Nguyen and Byrne (2017) expand the concept of cost-savings for TOU customers using BTM energy storage systems (ESSs). ESSs are technologies that provide a way to store and recover energy for future applications (Quanta Technology, n.d.). ESSs are utilized by both suppliers and customers to reduce their respective costs. This research will focus specifically on the customer benefits of ESSs and does not analyze the costs associated with ESSs.

ESSs provide on-site back-up power, storage for on-site renewable systems, and a means for load-shifting and peak shaving for commercial and industrial customers. The purpose of the Nguyen and Byrne (2017) research was to minimize the electricity for TOU and net-metering (NEM) customers. They concluded that “energy storage can significantly reduce electricity cost by peak shaving and load shifting for the commercial customer and by storing excess renewable energy for the residential customer” (Nguyen & Byrne, 2017).

Wu et al. (2016) research developed an optimization model "using typical load profiles, energy demand charge rates, and a set of battery parameters to estimate the potential benefits of battery storage." Furthermore, they analyzed the optimal energy and power capacity of BTM energy storage. Their research was limited to evaluating battery storage solutions and did not assess other means of storing energy, such as pumped hydro, flywheel, compressed air, superconducting energy storage, and advanced capacitors. Wu et al. (2016) revealed that "there is benefit trade-off between energy and demand charge reduction." Further, they determined that "the optimal battery size varies with many factors such as load profile, rate tariff, and battery cost" (Wu et al., 2016). This research focuses on implementing different battery types on two different demand profiles and two unique rate structures.

Many different types of BTM ESSs are available in the market and can be applied to energy storage optimization models, to demonstrate the utility of BTM applications. Additional research refers to BTM ESSs as Energy Storage Devices (ESDs) (Wang, Ren, Sivasubramaniam, Urgaonkar, & Fathy, 2012). The balance of this thesis, however, will use the term ESS for clarity. The following section explores the types, characteristics and applications of ESSs.

D. ENERGY STORAGE SYSTEMS

Electricity is a common consumer good expected to total 34% of the total energy processed by humans in 2025 (Ibrahim, Ilinca, & Perron, 2008). The emergence of renewable energy, which fluctuates independent of consumer demand, revealed the importance and requirement for energy storage technologies. Wu et al. (2012) and Nguyen and Byrne (2017) demonstrated the potential application of energy storage technologies through their BTM ESS research. In conclusion, there are many benefits of ESSs that the public and private sector can apply to their respective domains. Additionally, many characteristics distinguish one ESS from another and determine the utility of ESSs in different contexts.

1. Benefits of Energy Storage

Teleke (n.d) argued that there are many applications and benefits of energy storage technologies for utility companies and end users. They include but are not limited to:

- Integration of renewable energy sources: Storage systems can harvest and store energy generated from renewable resources such as solar, wind, hydro, etc.

- Arbitrage: Large storage systems may purchase energy when demand is low and sell or discharge the energy when demand is high.

- Spinning reserve: Utilities have a spinning reserve requirement and ESS can satisfy those requirements by reacting quickly to generation or transmission outages.

- Enables more efficient use of existing generation assets: Storage systems can create efficiencies along the grid because they reduce the need to employ large coal-fired plants.

- Reduces greenhouse gas emission (Teleke, n.d.).

Additional benefits to energy storage include peak reduction and load flattening, voidance of congestion charges, deferral of capital additions to utility systems, rate reduction, and reliability augmentation (Quanta Technology, n.d.). Nonetheless, the scope of this research focuses on the peak reduction and load flattening capability of ESSs because it is most applicable to cost savings for installations and data centers.

2. Peak Shaving, Load-Shifting, and Load Reduction

Peak reduction and load flattening is also referred to as peak shaving, load-shifting, and load reduction. It is the process of storing energy when costs are low and applying the stored energy to periods in which costs and demand are high for a given user (Teleke, n.d.). Peak reduction and load shaving is most applicable to the customer side of the energy industry and specifically residential, commercial, and industrial users (Teleke, n.d.). Figure 1 illustrates the concept of peak reduction and load flattening. The blue line represents the daily demand profile of a utility customer, and the yellow area represents times that the customer buys and stores cheap energy. Then, the consumer applies the stored energy to reduce the peak demand charge by 10% (green area) during peak demand hours between noon and six (Teleke, n.d.). The ultimate goal of peak shaving and load reduction is to reduce demand costs by creating low variance in average demand over a given period.

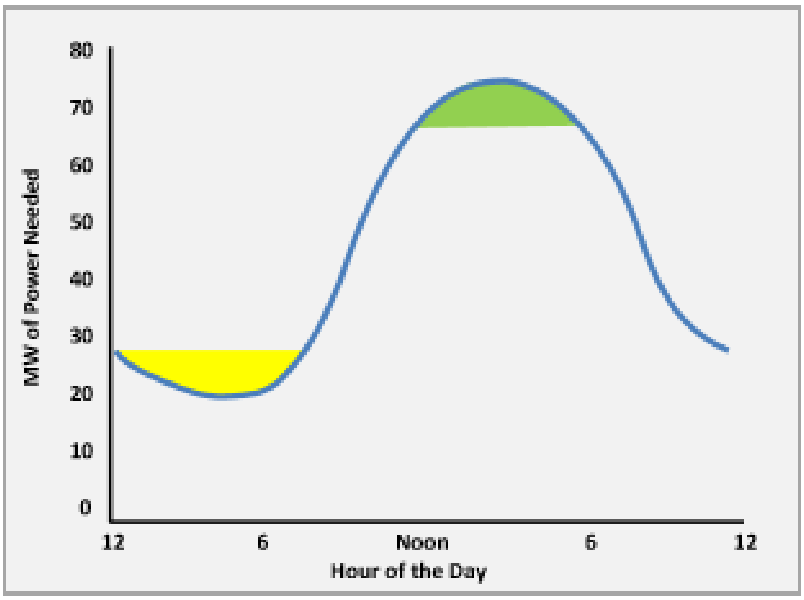

Figure 1. Peak Reduction and Load Shaving. Source: Quanta Technology (n.d.).

3. Components of an ESS

There are four main components of an ESS: the storage mechanism, the charging system, the discharging system, and the monitoring and control system. Figure 2 illustrates the parts of an ESS.

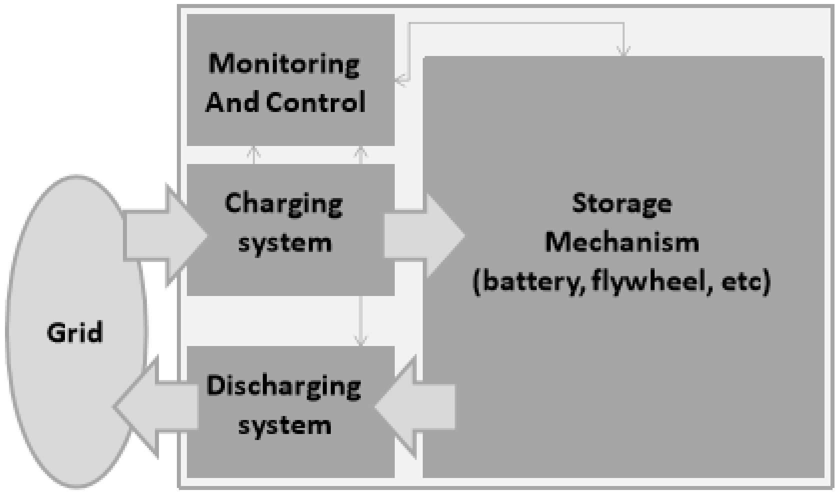

Figure 2. Components of an ESS. Source: Quanta Technology (n.d.)

The storage mechanism is the most important factor in determining the capacity of a given ESS. The second part of the system is the charging mechanism. Charging mechanisms harvest power from the grid or utility provider and convert it into a form that is compliant with the storage mechanism. The discharging system extracts stored energy from the storage mechanism and converts it back to electricity to satisfy the customer's demand from the grid. Moreover, it dictates the quality and quantity of power output, voltage regulation, etc. The charging and discharging systems combine to make the converter, which are either included with the storage mechanism or a complete separate component (Quanta Technology, n.d.). The fourth and final component of the system is the control system.

The control system is comprised of two sub-systems (Quanta Technology, n.d.). The first control sub-system is the device that monitors and controls the ESS. Two important functions of this sub-system are to notify the charge system when the storage mechanism is full as well as notify the discharge system when the energy in the storage mechanism is depleted. Furthermore, the first control sub-system functions as a diagnostics and protection system that detects any anomalies and activates protective equipment to address any problems (Quanta Technology, n.d.).

The second control sub-system is the electrical energy storage system control, functioning as the ‘brains’ of the entire ESS. The electrical energy storage system control may be as simple as a standard Uninterrupted Power Supply (UPS) control system that performs backup operations for a piece of equipment or it can be as complex as a computer algorithm that determines when, where, how, and the charge and discharge of energy (Quanta Technology, n.d.). In addition to its four components, ESSs have various characteristics that contribute to the overall system specifications.

4. Characteristics of Energy Storage Systems

Ibrahim et al. (2008) summarizes the several characteristics of ESSs. A complete understanding of the major ESS characteristics is important to thoroughly compare different technologies.

Storage Capacity

Storage capacity is the total quantity of energy available in the storage system after charging. Capacity is measured in watt hours (Wh) (Ibrahim et al., 2008).

Efficiency

Efficiency is the ratio between released energy and stored energy (Ibrahim et al., 2008). The converter of the ESS creates loss when converting from grid alternate current (AC) to direct current (DC) and back to AC when energy is released from the storage system (Quanta Technology, n.d.). Commercial vendors market this characteristic as round-trip AC-AC efficiency and is defined as a percentage. Current efficiency rates range from 60–90% depending on the type of storage system (Ralon, Taylor, Ilas, Diaz-Bone, & Kairies, 2017).

Maximum Discharge Power

Maximum discharge power is the maximum amount of power that the storage mechanism can discharge in any given 15-minute time series (HOMER Energy, n.d.-b)

Other Characteristics

Ibrahim et al. (2008) includes other characteristics, including durability or cycling capacity, autonomy, costs, reliability, self-discharge, mass and volume of densities of energy, monitoring and control equipment, operational constraints, ease of maintenance, etc. A thorough cost-benefit analysis (CBA) would consider all ESS characteristics to determine the cheapest solution to satisfy a historical demand profile. Nonetheless, the purpose of this research is to evaluate the cost reduction benefits of ESSs. Thus, the researchers exclusively consider capacity, efficiency, and maximum discharge power to develop energy storage heuristics to achieve cost savings in two unique energy demand profiles and two different rate schedules.

5. Types of Energy Storage Systems

There are six main types of storage systems: solid state batteries, flow batteries, flywheels, compressed air energy storage (CAES)/liquid air energy storage (LAES), thermal, and pumped hydro-power (Energy Storage Association, n.d.). Other technologies include superconducting magnetic energy storage (SMES) and super-capacitors (Teleke, n.d.), natural gas storage (NGS) and fuel cell-hydrogen energy storage (FC-HES) (Ibrahim et al., 2008).

Each one of these storage systems can be applied to a spectrum of applications, from local residential use to large-scale utility company transmission sites. A Ragone plot depicts ESSs and how they relate to their specific energy (Wh/kg) and specific power (W/kg) (Wang et al., 2012). Specific energy is the nominal battery energy per unit mass, and specific power is the maximum available power per unit mass (Ralon et al., 2017).

The Ragone plot in Figure 3 shows that capacitors have a high specific power but low specific energy, which means they can sustain large power demand over a short period of time. In contrast, CAES can sustain a slow power draw over a longer period of time (Wang et al., 2012). All of the ESS technologies are defined by the same set of characteristics and could be applied to the researchers' energy storage heuristics outlined in Chapter III. However, the research team elected to concentrate on battery energy storage systems, CAES/LAES, flywheels, flow batteries, fuel cells, and capacitors because they are examples that cover the spectrum of the Ragone plot. Moreover, lithium ion battery and flow battery are manufactured by private companies, Tesla and UniEnergy Technologies, respectively, and are used for bulk energy storage by large companies ("Tesla Powerpack," n.d.; UniEnergy Technologies, n.d.-b).

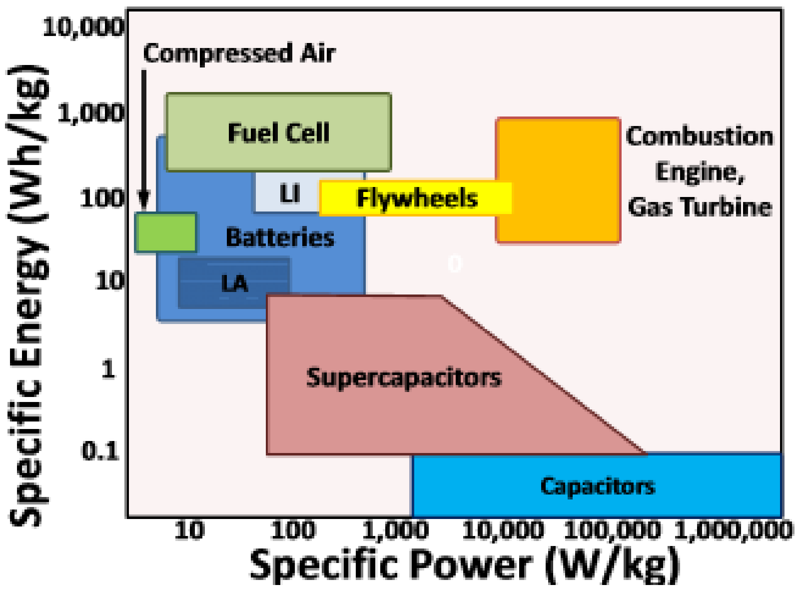

Figure 3. Ragone Plot. Source: Wang et al. (2012)

Solid State Batteries

Battery Energy Storage Systems (BESS) store energy electrochemically. The different kinds of BESS are lead-acid (LA), lead-carbon, lithium-ion (LI), vanadium flow, sodium-sulphur. LA and LI batteries are the most prevalent BESS used for data center energy storage (Wang et al., 2012). The key factors of a BESS include its high energy density, round trip efficiency, cycling capability, life span, and cost (Teleke, n.d.). Tesla is an example of a commercial manufacturer of a LI BESS that is being applied to installations and data centers ("Tesla Powerpack," n.d.).

Figure 4. Example of a BESS. Source: Teleke (n.d.)

Compressed Air Energy Storage

The second type of ESS is CAES. CAES compresses air into large confined places that are later converted back into electricity as required. This technology requires significant space to store the compressed air and convert it back into electricity (Wu et al., 2016). Thus, this technology is usually reserved for large utility companies and energy suppliers that have access to large, natural storage mechanisms. Another form of CAES is Small Scale Compressed Air Energy Storage (SSCAES). This form of CAES is good for small to medium-scale applications for both suppliers and consumers of energy (Ibrahim et al., 2008). In any case, CAES technologies are not applicable to data center energy storage because of their requirements for large spaces to store compressed air in natural caverns or man-made tanks. Instead, they highlight the left-extreme of the Ragone plot and are used for central power distributors.

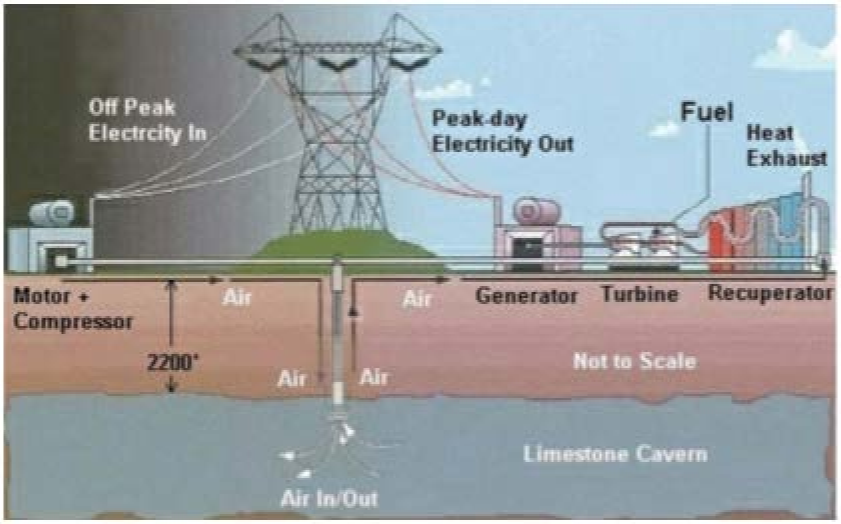

Figure 5. Example of CAES System Requiring a Cavern for Energy Storage. Source: Ibrahim et al. (2008)

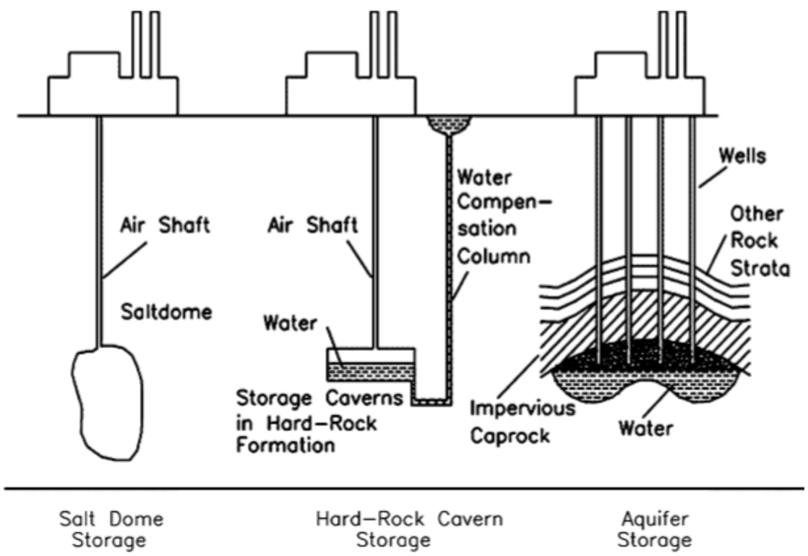

Figure 6. Types of CAES Storage Mechanisms. Source: Ibrahim et al. (2008)

Liquid Air Energy Storage

Priester et al. (2015) explored the viability of applying LAES as a micro-grid solution for Naval Air Station Pearl Harbor. LAES, also known as Cryogenic Energy Storage (CES), uses liquefied air to store energy for long duration, large scale applications.

LAES systems can range from 5 MWs to 100s MWs, and are scalable to a host of applications (Energy Storage Association, n.d.).

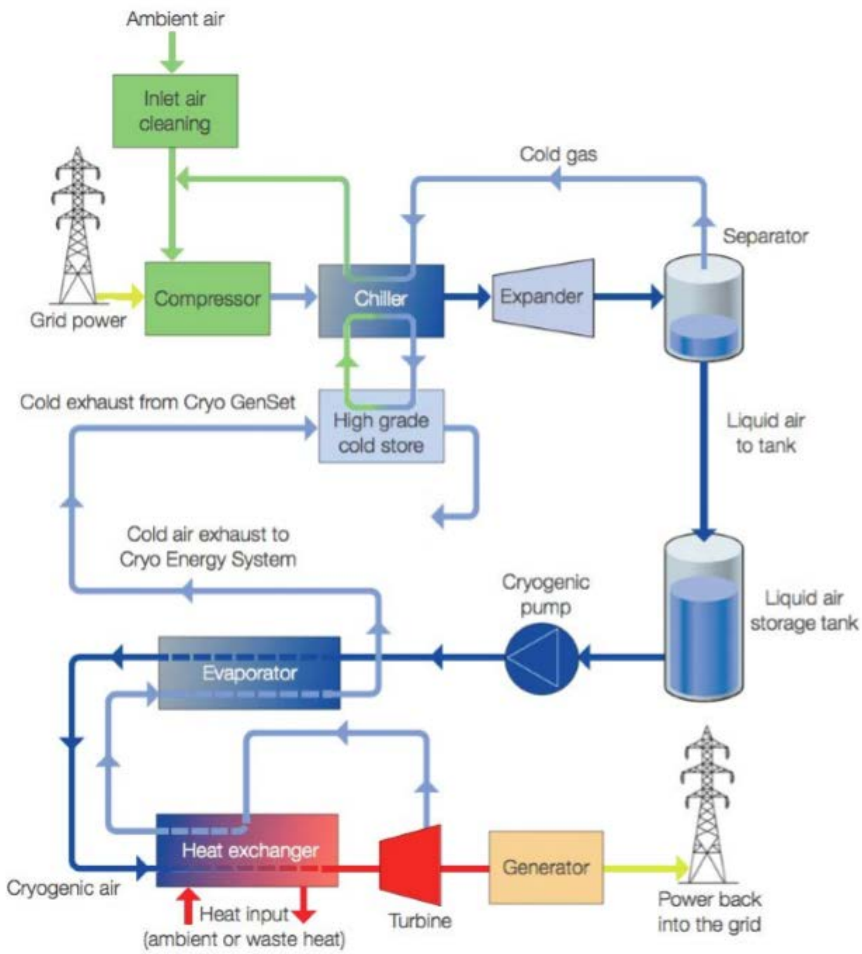

Figure 7. Schematic of a Liquid Air Energy Storage System. Source: Strahan (2013)

Flywheel Energy Storage

The third type of ESS is Flywheel Energy Storage (FES). The system is charged when the flywheel accelerates, and the system is discharged when the flywheel decelerates (Teleke, n.d.). FESs bridge short-term energy outages and are often used as Uninterrupted Power Supply (UPS) devices for data centers to protect the infrastructure against power outages. FES technology has not been implemented for bulk energy storage for installations or data centers to achieve peak reduction or load flattening (Wu et al., 2016).

Figure 8. FES Illustration. Source: Teleke (n.d.)

Fuel cells-hydrogen energy storage

The fourth ESS is Fuel cells-hydrogen energy storage (FC-HES). First, a FC-HES restores spent energy into hydrogen through water electrolysis that uses off-peak electricity. Then, the fuel cell uses the hydrogen and oxygen to produce peak-hour electricity. Fuel cells come in many different forms and are differentiated by the type of electrolyte they use. Private sector installations and data centers implemented Solid Oxide Fuel Cell (SOFC) technologies to reduce energy costs (Ibrahim et al., 2008). Bloom Energy is an example of a SOFC manufacturer that is using its technologies to data centers and installations (“Bloom Energy,” n.d.).

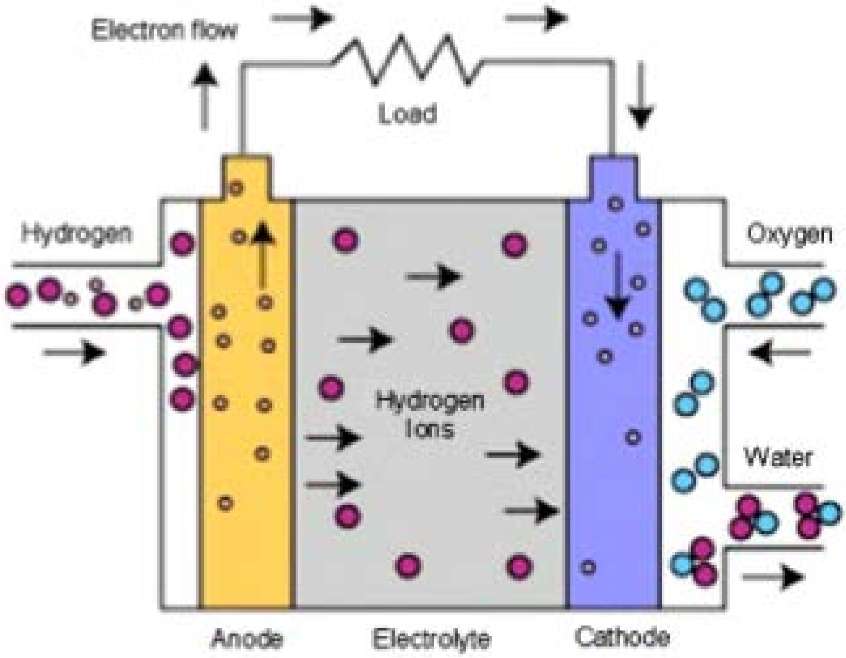

Figure 9. Fuel Cell Technology. Source: Ibrahim et al. (2008)

Flow Battery

The fifth type of ESS is flow battery energy storage (FBES). FBES is a two electrolyte system that feeds a regenerative fuel cell (Ibrahim et al., 2008). FBES can be nearly instantaneously recharged, and the fundamental difference between flow batteries is that energy is stored as electrolytes in flow cells rather than the electrode material in traditional batteries (Energy Storage Association, n.d.). UET is an example of a private firm that manufactures flow battery technology for installation application (UniEnergy Technologies, n.d.-b).

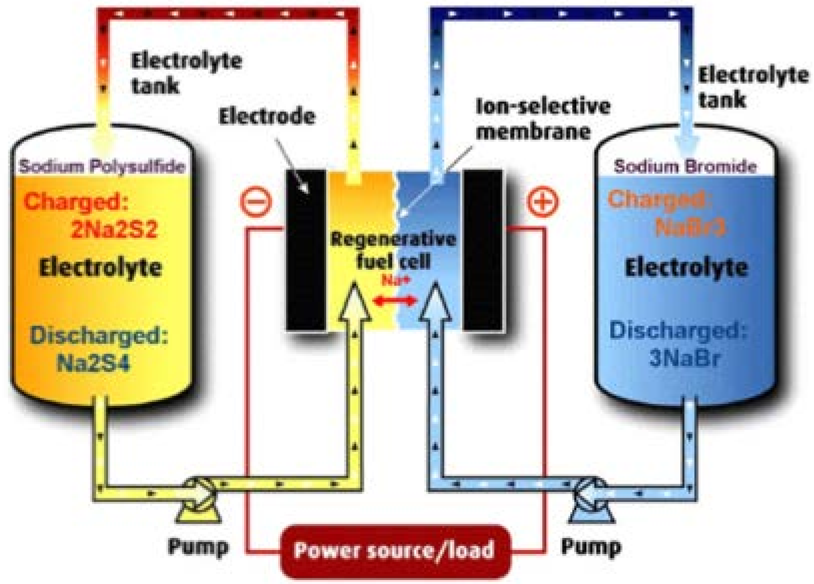

Figure 10. Flow battery system. Source: Ibrahim et al. (2008)

Ultra/Super-capacitors

Ultra-capacitors (UCs) store energy in an electric field between two electrodes, and the stored energy must be used quickly because they have a 5% per day self-discharge (Ibrahim et al., 2008). Moreover, UCs have a faster charge and discharge time compared to BESS and can be cycled tens of thousands of times (Teleke, n.d.). These characteristics make UCs suitable when energy needs to be accessed quickly and repeatedly. UCs and super-capacitors are on the lower right area of the Ragone plot, and are being used as UPS devices in data centers (Wang et al., 2012). UCs are typically not implemented for demand storage in installations or data centers, but provide an example of the right extreme of the Ragone plot.

Figure 11. Series of super-capacitors. Source: Ibrahim et al. (2008)

6. Comparison and Evaluation of ESSs

Energy consumers must decide what type of ESS they want to invest to reduce their demand profile and costs. ESS evaluation is complex because of the multitude of characteristics and features of each type of system. Ibrahim et al. (2008) developed a performance index to determine the highest performing ESS across a range of applications. They divided ESSs into four categories that are associated with their unique application and they scale from small to large.

1. Low-power application in isolated areas, essentially to feed transducers and emergency terminals.

2. Medium-power application in isolated areas (individual electrical systems, town supply).

3. Network connection application with peak leveling.

4. Power-quality control applications. (Ibrahim et al., 2008)

The first two categories have small-scale application and are most appropriate for Marine Corps installations and data centers. The second two categories are large-scale applications associated with energy suppliers (Ibrahim et al., 2008). Therefore, the research team elected to focus its analysis on available and proven category 1 and 2 ESS technologies. Figure 12 summarizes Ibrahim et al.'s (2008) ESS performance index for four categories.

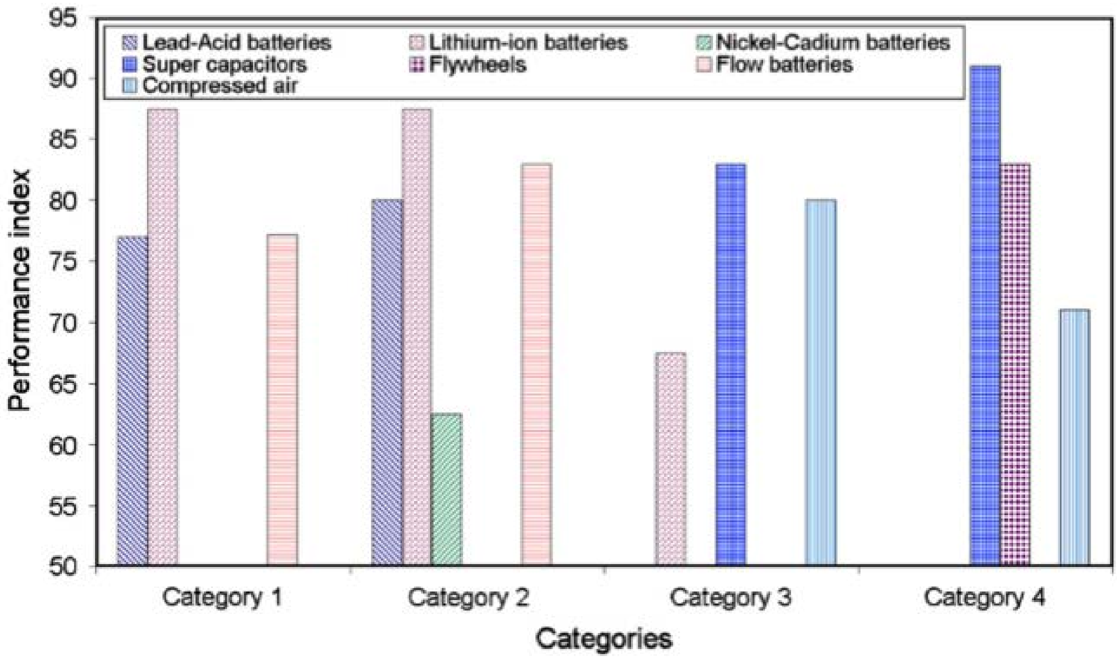

Figure 12. Performance index for storage technologies for four categories of application. Source: Ibrahim et al. (2008)

The top two category 1 and 2 technologies are LI batteries and flow batteries (Ibrahim et al., 2008). Therefore, the research team researched companies that produce BESS and flow battery technology for use in buildings and potentially data centers. Tesla's Powerpack is an example of LI BESS and UET's Uni.System is an example of flow battery energy storage that installations and consumers can purchase today for energy storage ("Tesla Powerpack," n.d.; UniEnergy Technologies, n.d.-b).

E. COMMERCIAL ENERGY STORAGE SYSTEMS

1. Tesla

Tesla's Powerpack is an example of a LI BESS. Tesla advertises that the Powerpack is a state of the art battery system that is scalable and is a fully integrated, AC-connected solution. Furthermore, Tesla markets that the Powerpack is applicable to commercial consumers that seek a peak shaving, load-shifting, emergency backup, and demand response solution ("Tesla Powerpack," n.d.).

Figure 13. Tesla Powerpack. Source: Tesla (n.d.)

Figure 14. Inside Tesla's Powerpack. Source: Tesla (n.d.).

The Powerpack was successfully implemented in many different industries on varying scales. Firms that adopted and implemented the Powerpack were Advanced Microgrid Solutions, Target, Jackson Family Wines, Vector, and PowerSmart solar ("Tesla Powerpack," n.d.). Additionally, Tesla supplied a 52 megawatt-hour (MWh) BESS to SolarCity in their project to meet the peak demand on the Hawaiian island Kauai (Kelley, 2016). These examples prove the scalability and availability of a LI BESS that could be adopted by installations and data centers today. Table 1 summarizes the characteristics of Tesla's Powerpack.

Table 1. Tesla Powerpack Overall System Specs. Source: Tesla (n.d.)

Overall System Specs

AC Voltage	380 to 480V, 3 phases	Energy Capacity	210 kWh (AC) per Powerpack
Communications	Modbus TCP/IP; DNP3	Operating Temperature	-22°F to 122°F / -30°C to 50°C
Power	50kW (AC) per Powerpack	Enclosures	Pods: IP67 Powerpack: IP35/NEMA 3R Inverter: IP66/NEMA 4
Scalable Inverter Power	from 50kVA to 625kVA (at 480V)		
Depth of Discharge	100%	System Efficiency (AC) *	88% round-trip (2 hour system) 89% round-trip (4 hour system)
Dimensions	**Powerpack** Length: 1,308 mm (51.5") Width: 822 mm (32.4") Height: 2,185 mm (86") Weight: 1622 kg (3575 lbs) **Industrial Inverter** Length: 1,014 mm (39.9") Width: 1254 mm (49.4") Height: 2192 mm (86.3") Weight: 1200 kg (2650 lbs)	Certifications	Nationally accredited certifications to international safety, EMC, utility and environmental legislation.

* Net Energy delivered at 25°C (77°F) ambient temperature including thermal control

2. UniEnergy Technologies

UET's Uni.System is an example of a FBES. The Uni.System is a modular, "lug and play," system that is comprised of five twenty-foot containers that provide 500 kW of power for four hours with a maximum energy of 2.2 MWh. The Uni.System's low cost of energy over the 20-year system life is a market leader and its overall value is unmatched in the ESS market (UniEnergy Technologies, n.d.-b). The Uni.System was implemented at a Bronx hospital in October 2017 to help reduce costs and improve resiliency (UniEnergy Technologies, n.d.-a).

Figure 15. Uni.System installed at Schweltzer Engineering Laboratories in Pullman, Washington. Source: UniEnergy Technologies (n.d.-b).

Table 2. Uni.System Performance Data. Source: UniEnergy Technologies (n.d.-b).

UNI.SYSTEM™ (AC) PERFORMANCE DATA			
Peak Power	600 kW_{AC}		
Maximum Energy	2.2 MWh_{AC}		
Discharge time	2h	4h	8h
Power	600 kW_{AC}	500 kW_{AC}	275 kW_{AC}
AC (Roundtrip) Efficiency	≈70%		
Voltage	12.47kV +/- 10%		
Current THD (IEEE 519)	<5%THD		
Response Time	<100ms		
Reactive Power	+/- 450kVAR		
Humidity	95%RH noncondensing		
Footprint	820 ft^2 ($76m^2$)		
Envelope	41'[W] x 20'[D] x 9.5'[H] (12.5m[W]x6.1m[D]x2.9m[H])		
Total Weight	375,000 lbs (170,000 kg)		
Cycle and Design Life	Unlimited cycles over the 20 year life		
Ambient Temp.	-40ºF to 122ºF (-40ºC to 50ºC)		
Self Discharge	Max 2% of stored enegy		

F. THE FUTURE OF BATTERY ENERGY STORAGE SYSTEMS

BESSs are available for residential, commercial, and industrial use today, and the cost of these technologies is expected to decrease in the future. For example, the cost of LI batteries is expected to decrease by an additional 54%-61% by 2030 in stationary applications such as BTM energy storage. Moreover, flow battery total cost is forecast to decline by 66% by 2030 (Ralon et al., 2017). Figure 16 summaries the projected cost reduction of BESSs.

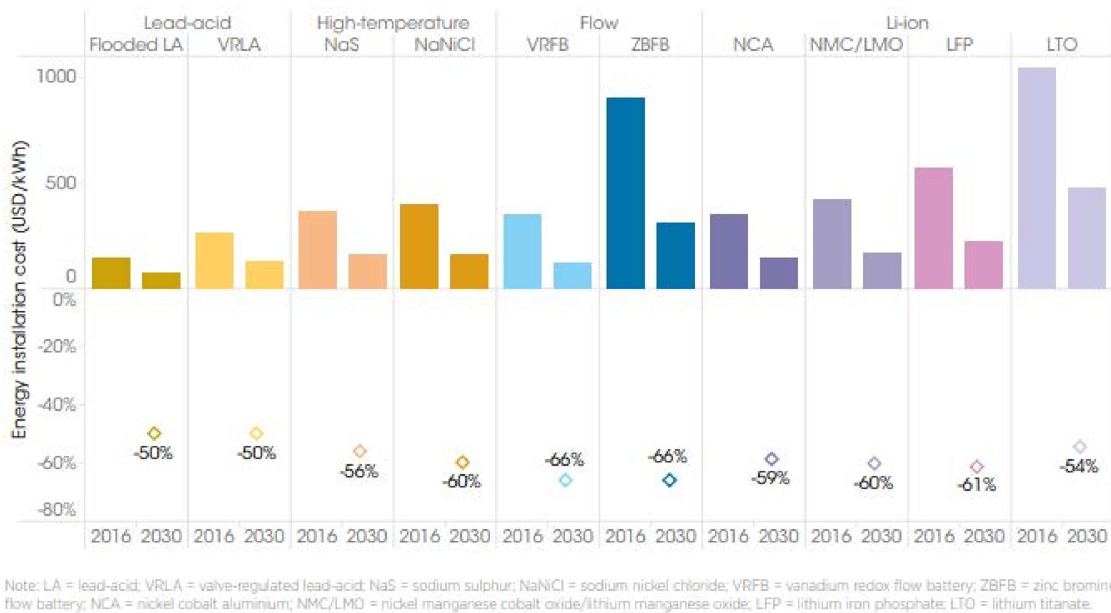

Figure 16. Battery ESS Installed Energy Cost Reduction Potential, 2016–2030. Source: Ralon et al. (2017)

Round trip efficiencies of BESSs are expected to increase through 2030. LI batteries currently have round trip efficiencies of around 90% and is expected to increase to up to 98% by 2030 (Ralon et al., 2017). Furthermore, flow batteries currently have between 60%-85% efficiency, and are forecasted to increase to 67%-95% by 2030 because of improved electrode, flow, and membrane design (Ralon et al., 2017).

The combination of decreased installed energy costs and increased efficiencies make BESS a compelling market for DoD installations and data centers to explore to satisfy the DoD energy and data center consolidation strategies. However, the efficient use of Tesla’s Powerpack and UET’s Uni.System is contingent upon employing effective heuristics to reduce total energy costs. The research team summarized literature regarding utility rate structures, BTM energy storage technologies. Chapter III outlines the methodology the research team developed to test three separate heuristics on two unique demand profiles and multiple configurations of Tesla’s Powerpack and UET’s Uni.System.

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III. METHODOLOGY

A. OVERVIEW OF DESIGN

Researchers formulated three heuristics capable of using historical electricity demand data to determine how to employ and use an energy storage system (ESS) to reduce total energy costs. To accomplish this, the research team mathematically formulated common commercial electricity rate structures to calculate energy costs. The team utilized rate structures from Pacific Gas and Electric (PG&E) and Kansas City Power and Light (KCP&L). Additionally, the team used data from a Defense Information System Agency (DISA) data center in Columbus, Ohio and Naval Support Activity (NSA) Monterey in Monterey, California to demonstrate and test the impact of the heuristics.

The heuristics were designed to support various ESS configurations using current industry examples such as Tesla's Powerpack and UniEnergy's Uni.System. Each storage system has a defined capacity, maximum discharge power, and an efficiency that accounts for energy loss during the conversion process. The researchers determined these ESS characteristics to be the most relevant in determining the limitations on employing ESSs. The heuristics were built to allow users to modify these parameters to estimate the impact on utility charges of different ESSs. The demand data utilized is assumed to be the net demand for electricity after any renewable energy has been applied. For example, if photovoltaics were used to generate energy on site, that energy is applied to gross demand. The remaining demand is considered to be demand, net of any locally generated energy.

The heuristics were designed to reduce monthly energy costs by determining the amount of energy added or removed from storage during each 15-minute period. For each 15-minute time period, the heuristics determine how to satisfy the historical net demand using a combination of stored energy and/or purchased energy. The demand for electricity to be purchased from the grid is a function of the net demand in the time period, minus any energy used from storage, and plus any energy purchased to add to storage. For example, energy may be purchased in excess of the net demand and stored during times in which the cost of electricity is lowest to provide energy from storage when electricity costs from the grid are highest.

B. SAMPLE DATA

Historical electricity demand data was obtained from two different sources: DISA data center in Columbus, Ohio, and NSA Monterey, CA. These data sets offer very different profiles to test the heuristics and ESS configurations. The DISA data center represents a relatively stable demand profile and NSA Monterey represents a volatile demand profile. The different demand profiles will provide valuable insights to what profiles benefit most from different combinations of heuristics and ESS configurations.

1. Stable Demand

DISA "provides, operates and assures command and control, information sharing capabilities, and a globally accessible enterprise information infrastructure in direct support to joint warfighters, national level leaders, and other mission and coalition partners across the full spectrum of operations" ("About DISA," n.d.). DISA operates nine independently managed data centers; seven in the United States and two overseas in Germany and Bahrain (Purvis, 2017). Researchers obtained the 2017 energy demand profile from the Columbus, Ohio DISA data center. The Columbus, Ohio DISA data center is a one floor, 91,569 square foot building that was built in 1992 (Caves, 2018). Eighty five percent of the building is dedicated to data center operations with only 15% of the building used for administrative activities (Caves, 2018). Therefore, the DISA demand profile represents data center operations with minimal overhead demanding energy. The DISA demand profile will be referred to as the stable demand profile for the remainder of the thesis.

Figure 17 represents the monthly maximum and average demand data for the DISA data center in Columbus, Ohio. It indicates that that there is slightly more variation in the maximum monthly demand than the average monthly demand.

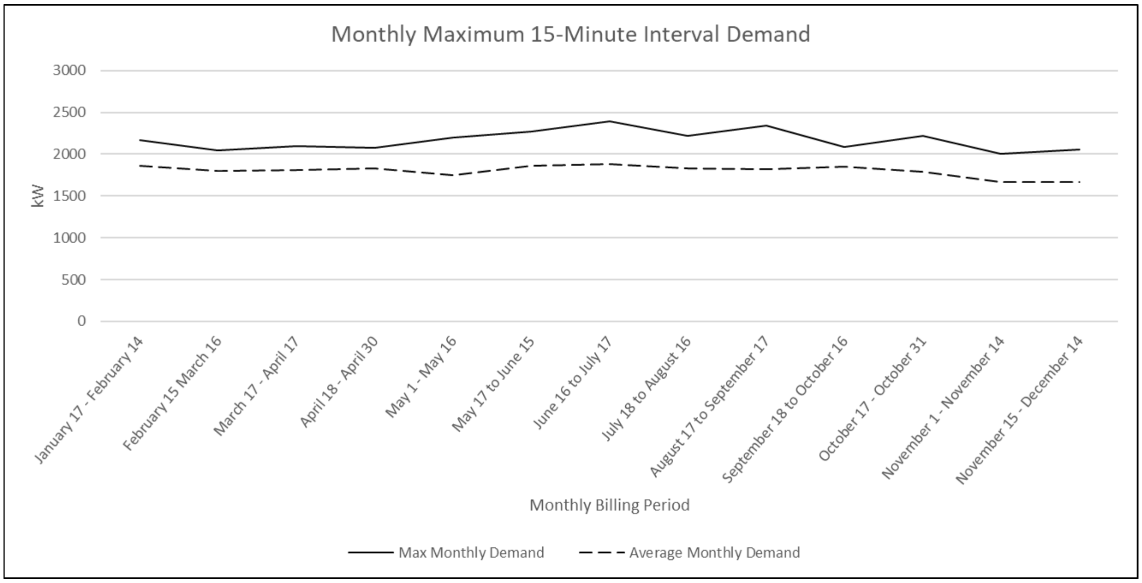

Figure 17. 2017 Stable Profile Maximum and Average Monthly Demand

Figure 18 illustrates the typical daily consumption for the stable demand profile. Although there some minor peaks, there is little variation in demand throughout the day.

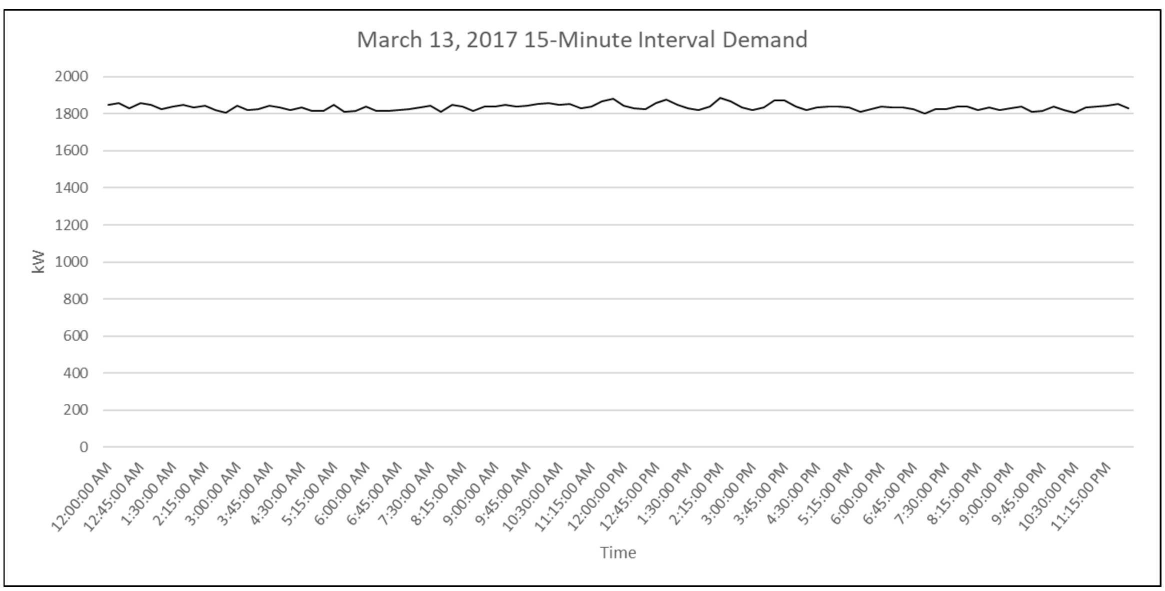

Figure 18. March 13, 2017, Sample Daily Stable Demand

2. Volatile Demand

The second profile displays extreme volatility in the maximum electricity demand. This demand profile was obtained from NSA Monterey and represents the demand for the LabRec area. The LabRec area consists of several laboratories that support research for Naval Postgraduate School. For example, the propulsion laboratory within the LabRec area utilizes a large air compressor to create a supersonic wind tunnel. The sporadic use of the air compressor creates a significant draw of power and results in the large demand spike. The volatility within this demand profile represents an extreme case to test the heuristics and configurations. The LabRec demand profile will be referred to as the volatile demand profile for the remainder of the thesis.

Figure 19 represents the monthly maximum and average 15-minute interval demand for the LabRec area for NSA Monterey. It indicates that there is significantly more variation in the maximum monthly demand than the average monthly demand.

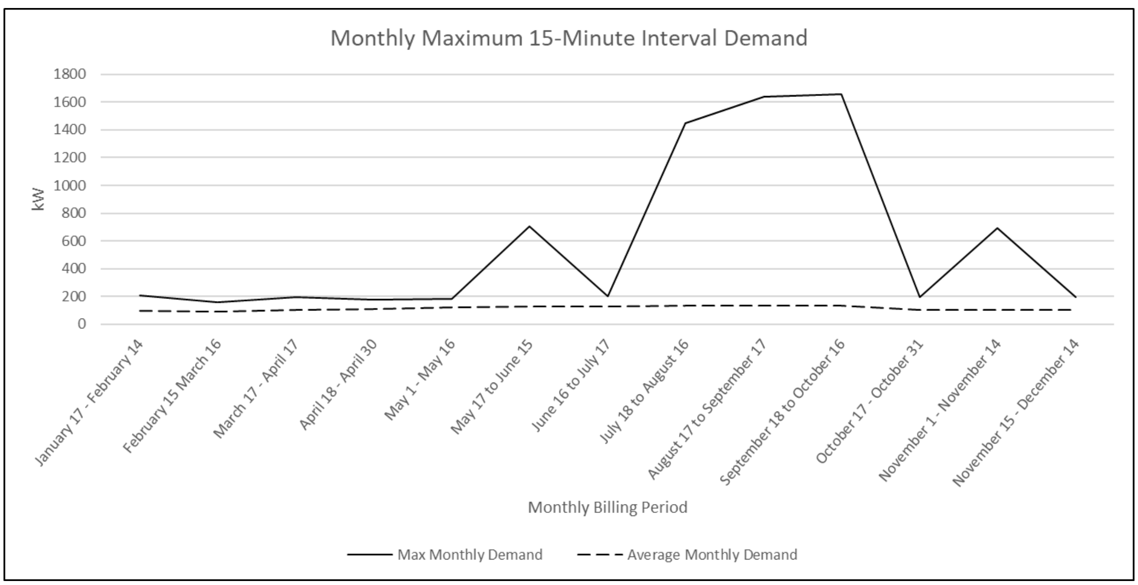

Figure 19. 2017 Volatile Profile Maximum and Average Monthly Demand

Figure 20 illustrates the typical daily 15-minute interval demand for the volatile demand profile. Although the typical daily consumption is relatively smooth, daytime consumption is slightly higher than consumption and night.

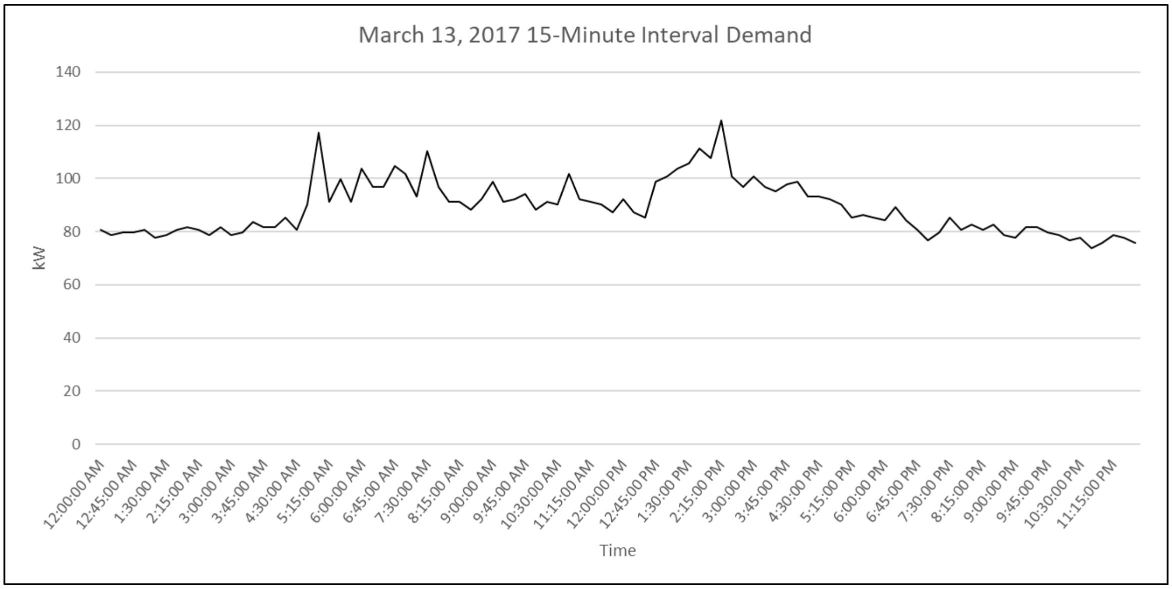

Figure 20. March 13, 2017, Sample Daily Volatile Demand

Tables 3 and 4 summarize the demand profiles using relevant periods of time in 2017. The team chose the monthly period between July 18 to August 16 because that was the month that the LabRec profile had the most variance. Moreover, the team focused analysis on the week of July 30th to August 5th and specifically August 4th when the LabRec area experienced its most drastic demand spike during the month. A professor in the LabRec area conducted an experiment that required the use of the aforementioned generators on August 4th. This resulted in a significant demand spike that significantly impacted the monthly utility bill. The week of the spike, July 30th to August 5th, and the day of the spike, August 4th, are defined as ‘spike week’ and ‘spike day’ respectively. Table 3 highlights the differences in volatility between LabRec and DISA.

Table 3. Demand Profile 2017 Summary Statistics

	Volatile (LabRec)				Stable (DISA)			
Summary Statistics	Annual (2017)	Spike Month* (July 18 to August 16)	Spike Week* (July 30 to August 5)	Spike Day* (August 4)	Annual (2017)	Spike Month* (July 18 to August 16)	Spike Week* (July 30 to August 5)	Spike Day* (August 4)
Mean	115.51	135.46	142.78	209.98	1811.32	1830.04	1855.39	1852.808
Standard Deviation	52.51	81.33	104.70	261.80	199.43	243.73	54.84	22.15
Coefficient of Variation	45.46%	60.04%	73.33%	124.68%	11.01%	13.23%	2.96%	1.20%
Maximum	1655.04	1447.68	1366.08	1366.08	2392.5	2217	2051	1893
Minimum	0	91.2	91.2	103.68	0	0	1758.5	1795
Range	1655.04	1356.48	1274.88	1262.4	2394.5	2219	292.5	98
Normalized Range**	1.00	0.94	0.93	0.92	1.00	1.00	0.14	0.05

*Spike Month, Spike Week, and Spike Day were the month, week, and day with the highest variance for the volatile demand profile.

**Normalized range is defined as the ratio of the Range to the Maximum of a set of numbers.

All values are in kW of demand, and are recorded for each 15-minute period.

C. SAMPLE RATE STRUCTURES

Time-of-use (TOU), demand, tiered, and ratchet adjustment are types of electricity charges utility companies use to develop their rate structures. Each electric company combines these charges differently. Each unique rate structure requires a different formulation to estimate the utility cost. Cost savings are likely to be significantly different depending on the rate structure applied. Therefore, it is important that different rate structures are analyzed to understand the impact of employing ESSs.

TOU and demand are the most commonly used electricity charges utility companies apply to commercial customers. TOU charges determine the dollar per kWh charge based on time of day (Masters, 2004). Demand charges are based on the peak demand within a billing period, or the “highest amount of power drawn by the facility” (Masters, 2004). Although TOU and demand charges are most common, tiered and ratchet adjustment charges are still utilized by some utility companies. Tiered, or inverted block, charges apply different rates at defined levels based on total consumption (Masters, 2004). Ratchet adjustment charges are applied monthly based on the annual peak demand (Masters, 2004).

Utility companies use a combination of these types of charges to construct rate structures that apply to commercial customers.

The rate structures utilized in this research to validate the energy storage heuristics are PG&E and KCP&L.

1. Pacific Gas and Electric

PG&E provides residential and commercial gas and electric energy to northern and central California (PG&E, n.d.). PG&E uses a combination of TOU and demand charges to build rate structures for billing their commercial customers. The rate structures in Table 4 and Table 5 were the rate structures that PG&E applied to the LabRec area on NSA Monterey in 2017. Table 4 represents electric schedule E-19P and applies to "customers with medium general-demand" (PG&E, 2017). The E-19P rate structure applied to the Lab Rec area from January 17, 2017, to October 17, 2017.

Table 4. PG&E E-19P Rate Structure. Source: PG&E (2017).

Equation Mapping	Total Customer/Meter Charge Rates		
DailyCharge	Daily Charge Mandatory E-19 ($ per meter per day)	$	32.85421
Demand Charge ($ per kW)			
PeakDemandCharge	Maximum Peak Demand Summer	$	16.60
PartPeakDemandCharge	Maximum Part-Peak Demand Winter	$	0.15
	Maximum Part-Peak Demand Summer	$	4.53
MaxDemandCharge	Maximum Demand Summer	$	14.40
	Maximum Demand Winter	$	14.40
Energy Charge ($ per kWh)			
EnergyCharge	Peak Summer	$	0.14165
	Part-Peak Summer	$	0.10327
	Off-Peak Summer	$	0.07860
	Part-Peak Winter	$	0.09809
	Off-Peak Winter	$	0.08469
Time of Day Definitions			
Summer	May 1 through October 31		
Winter	November 1 through April 30		
Peak-Summer	12:00 noon to 6:00 PM (Monday through Friday)		
Part-Peak Summer	8:30 AM to 12:00 noon AND 6:00 PM to 9:30 PM (Monday through Friday)		
Off-Peak Summer	9:30 PM to 8:30 AM (Monday through Friday) All Day (Saturday and Sunday)		
Part-Peak Winter	8:30 AM to 9:30 PM (Monday through Friday)		
Off-Peak Winter	9:30 PM to 8:30 AM (Monday through Friday) All Day (Saturday and Sunday)		

Table 5 represents electric schedule E-20 and applies to "customers with maximum demands of 1000 kilowatts or more" (PG&E, 2017). The E-20 rate structured applied to the Lab Rec area from October 17, 2017, to December 15, 2017. The utility bill calculation for PG&E is given in the objective function in Section III.F.4.

Table 5. PG&E E-20 Rate Structure. Source: PG&E (2017).

Equation Mapping	Total Customer/Meter Charge Rates		
DailyCharge	Daily Charge Mandatory E-19 ($ per meter per day)	$	49.28131
Demand Charge ($ per kW)			
PeakDemandCharge	Maximum Peak Demand Summer	$	19.26
PartPeakDemandCharge	Maximum Part-Peak Demand Winter	$	0.12
	Maximum Part-Peak Demand Summer	$	5.13
MaxDemandCharge	Maximum Demand Summer	$	15.09
	Maximum Demand Winter	$	15.09
Energy Charge ($ per kWh)			
EnergyCharge	Peak Summer	$	0.14165
	Part-Peak Summer	$	0.10327
	Off-Peak Summer	$	0.07860
	Part-Peak Winter	$	0.09809
	Off-Peak Winter	$	0.08469
Time of Day Definitions			
Summer	May 1 through October 31		
Winter	November 1 through April 30		
Peak-Summer	12:00 noon to 6:00 PM (Monday through Friday)		
Part-Peak Summer	8:30 AM to 12:00 noon AND 6:00 PM to 9:30 PM (Monday through Friday)		
Off-Peak Summer	9:30 PM to 8:30 AM (Monday through Friday) All Day (Saturday and Sunday)		
Part-Peak Winter	8:30 AM to 9:30 PM (Monday through Friday)		
Off-Peak Winter	9:30 PM to 8:30 AM (Monday through Friday) All Day (Saturday and Sunday)		

2. Kansas City Power and Light

KCP&L provides residential and commercial gas and electric energy to northwest Missouri and eastern Kansas (KCP&L, n.d.-b). KCP&L is an interesting rate structure to examine because it uses a combination of tiered, demand, and ratchet adjustment charges for billing their commercial customers. In particular, the ratchet adjustment charge can have a big impact on the best use of an ESS. This rate structure was chosen to examine the impact on DoD facilities in the Kansas City, MO area such as the Marine Corps Enterprise Information Technology Services (MCEITS) data center. The research team determined KCP&L's rate structure represents both tiered and ratchet adjustment charges, and replicated their schedule to demonstrate ratchet charge costs. Table 6 summarizes the large general service rate structure that is relevant to commercial and industrial customers. This utility bill calculation is given in the objective function in Section III.F.4.

Table 6. KCP&L Commercial and Industrial Rate Structure. Source: (KCP&L, n.d.-a)

Equation Mapping	Common Missouri Commercial & Industrial Pricing					
			Small General Service	Medium General Service	Large General Service	Large Power Service
	Customer Charge ($ per month)					
MonthlyCharge	0-24 kW (of Facilities Demand)		$ 16.45	$ 47.67	$ 101.15	$ 961.50
	25-199 kW (of Facilities Demand)		$ 45.60	$ 47.67	$ 101.15	$ 961.50
	200-999 kW (of Facilities Demand)		$ 96.64	$ 96.82	$ 101.15	$ 961.50
	1000 kW or more (of Facilities Demand)		$ 790.99	$ 826.71	$ 863.59	$ 961.50
	Facility Demand Charge ($ per kW)					
FacilityDemandCharge			$ 2.650	$ 2.770	$ 2.894	$ 2.669
	Demand Charge ($ per kW)					
MaxDemandCharge	**Summer Demand Charge ($ per kW)**					
	General Service			$ 3.624	$ 5.778	
	Large Power Service:	First 2500 kW				$ 12.206
		Next 2500 kW				$ 9.765
		First 2500 kW				$ 8.179
		Over 7500 kW				$ 5.972
	Winter Demand Charge ($ per kW)					
	General Service			$ 1.844	$ 3.109	
	Large Power Service:	First 2500 kW				$ 8.296
		Next 2500 kW				$ 6.476
		First 2500 kW				$ 5.712
		Over 7500 kW				$ 4.399
	Energy Charge ($ per kWh)					
	Summer Energy Charge ($ per kWh)					
Tier1Charge	First 180 Hours of Use		$0.14682	$0.09473	$0.08486	$0.07643
Tier2Charge	Next 180 Hours of Use		$0.06966	$0.06479	$0.06075	$0.04800
Tier3Charge	Over 360 Hours of Use		$0.06207	$0.05464	$0.04260	$0.02507
	Winter Energy Charge ($ per kWh)					
Tier1Charge	First 180 Hours of Use		$0.11408	$0.08185	$0.07798	$0.06480
Tier2Charge	Next 180 Hours of Use		$0.05570	$0.04889	$0.04670	$0.04365
Tier3Charge	Over 360 Hours of Use		$0.05027	$0.04109	$0.03580	$0.02484

D. ENERGY STORAGE SYSTEM DESIGN

1. Background

Hybrid Optimization of Multiple Energy Resources (HOMER) is a commercial micro-grid optimization software that was originally developed for the U.S. Department of Energy's National Renewable Energy Laboratory (NREL). In 2009, Dr. Peter Lilienthal founded HOMER Energy and officially commercialized the software product (HOMER Energy, n.d.-a). The research team purchased a HOMER license and utilized the software to design specific ESSs that were large enough to service the demand of the volatile and stable demand profiles. The researchers extracted maximum discharge power and capacity characteristics for each configuration from HOMER.

2. Building and Validating the ESS in HOMER

The first step of building an ESS to satisfy each demand profile was to upload the historical demand data into HOMER. Figure 21 displays the HOMER interface with the volatile demand profile uploaded.

Figure 21. HOMER Electric Load Interface

Next, the research team built two ESSs, the UET Uni.System and Tesla PowerPack. Finally, the HOMER output was used to validate the total capacity and maximum discharge power for each system. Each system was first designed to be able to service part-peak and peak periods from storage only, without having to purchase anything from the grid during these time periods. Enough capacity was required to account for the maximum daily consumption in peak and part-peak periods.

Furthermore, each system required enough maximum discharge power to meet the maximum demand for any 15-minute interval during peak or part-peak periods. The maximum discharge power of the ESS increases as capacity increases. Both of these requirements must be met to achieve complete coverage. For example, the volatile demand profile configurations exceed the required capacity because a larger system was necessary to meet the maximum discharge power requirement. The systems that provide complete coverage are referred to as the 100% coverage systems for the duration of this research. Next, 50% and 25% coverage systems were designed based off the 100% coverage system. The systems are summarized in Table 7.

3. Summary of Tesla and UET Specifications

The researchers selected specific characteristics from each unique ESS produced by Tesla and UET. The roundtrip efficiencies were extracted from the company's technical data and the maximum discharge rate and capacity were extracted from the HOMER model outputs.

Table 7. Energy Storage System Configurations

Demand Profile	Manufacturer	Coverage	Number of Batteries	Total Capacity (kWh)	Round Trip Efficiency Factor	Maximum Discharge Power (kW)
Volatile	Tesla	100%	37	7,770	0.88	1,727
		50%	19	3,990	0.88	887
		25%	10	2,100	0.88	467
	UET	100%	16	14,278	0.70	1,751
		50%	8	7,139	0.70	876
		25%	4	3,570	0.70	438
Stable	Tesla	100%	156	32,758	0.88	7,285
		50%	78	3,990	0.88	3,642
		25%	37	7,770	0.88	1,727
	UET	100%	48	42,835	0.70	5,254
		50%	24	21,418	0.70	2,627
		25%	16	14,278	0.70	1,751

E. PROCEDURES

The following steps were followed to design and test the heuristics and ESS configurations for each rate structure and for each demand profile:

1. Model rate structures by formulating equations for each type of rate structure. These formulas were validated by evaluating the output against known electricity bills.

2. Design and validate ESSs in HOMER.

3. Develop heuristics to reduce energy costs.

4. Test sensitivity of heuristics to various ESS configurations with various capacity, efficiency, and maximum discharge power characteristics.

5. Repeat for each demand profile.

F. FORMULATION

1. List of Parameters

t	Index of 15-minute time steps
S_t	Energy stored in battery at the end of time step, measured in units of kWh
$e_{RoundTrip}$	Round-trip efficiency rate which can be calculated by multiplying the charge efficiency factor by discharge efficiency factor, a function of ESS configuration.
$demand_t$	Electricity demand at time step t. This is the demand required from the facility at time step t, net of any on-site generation, e.g., from renewable energy. Measured in units of kW
$EnergyCharge_t$	Energy charge for purchasing power from the commercial grid at time step t. These values can be found in Tables 4 through 6 and are titled "Energy Charge." The energy charge is applied to each kWh during each time step at a rate that may depend on the time of use. Measured in units of \$/kWh.
$MaxDemandCharge_t$	Charge applied to the highest power draw from the commercial grid in a given billing period. This value can be found in Tables 4 through 6 and represents the "Demand Charge" that corresponds to the maximum demand for the entire billing period. Tables 4 and 5 refer this charge as "maximum demand summer" or "maximum demand winter" depending on season. Table 6 refers to this charge as "summer demand charge" or "winter demand charge" depending on the season. Measured in units of \$/kW.
$PeakDemandCharge_t$	Charge applied to the highest power draw from the commercial grid during "peak times" of given billing period. This value can be found in Tables 4 and 5 and represents the "Demand Charge" that corresponds to the maximum demand within the time periods defined at "Peak." Measured in units of \$/kW.
$PartPeakDemandCharge_t$	Charge applied to the highest power draw from the commercial grid during "partial-peak times" of given billing period. This value can be found in Tables 4 and 5 and represents the "Demand Charge" that corresponds to the

maximum demand within the time periods defined at "Part-Peak." Measured in units of $/kW.

$FacilityDemandCharge$	Monthly charge applied to the highest power draw from the commercial grid in the past 12 months. This value can be found in Table 6 and represents the "Facilities Charge" that corresponds to the maximum demand in the past 12 months including the current month. Measured in units of $/kW.
$DailyCharge$	Meter charge applied per day. This charge applies to PG&E and the values can be found in Tables 4 and 5 and represent the "Daily Charge" per meter. Measured in units of $/day.
$MonthlyCharge$	Meter charge applied per billing month. This charge applies to KCP&L and the values can be found in Table 6 and represents the "Customer Charge" which is a monthly charge. Measured in units of $/month.
$MaxCapacity_{storage}$	Maximum storage capacity of battery, measured in units of kWh.
$MaxDischarge_{storage}$	Maximum rate of discharging battery, measured in units of kW.
T	Number of time steps in a given billing period. For example, if a billing period has 30 days T is calculated by multiplying the 30 by 96 (the number of 15-minute periods per day).
$T_{Off-peak}$	Number of off-peak time steps in a given billing period.
$HoursOfUse$	Determined by dividing the total monthly kWh by the maximum demand in the current month.
$TargetPurchase$	Target amount of energy to be purchased for each time step, measured in units of kW
$SafetyStockRate$	Energy to be purchased as safety stock, measured as percentage of target daily energy purchased, used in Averaging heuristics.

2. List of Decision Variables

$p_{charge,t}$	Energy sent to storage at time step t prior to the application of round-trip efficiency loss, measured in units of kW

$p_{discharge,t}$ Energy pulled from storage at time step t net of round-trip efficiency loss, measured in units of kW

$P_{buy,t}$ Power purchased from grid at time step t, depends on $p_{charge,t}$ and $p_{discharge,t}$ as in equation 1.1. Measured in units of kW

3. Equations

$$P_{buy,t} = demand_t + p_{charge,t} - p_{discharge,t} \tag{1.1}$$

Equation 1.1 determines the amount of energy to be purchased at time step t. The net demand of energy, $demand_t$, can be calculated by subtracting any renewable energy generated during time step t from the gross demand at time step t. This net demand can be fulfilled by choosing to use stored energy which would reduce the amount of energy purchased by the amount of energy discharged from storage. Additionally, amount of energy purchased could be increased by deciding to buy energy to add to storage.

$$S_t = S_{t-1} + p_{charge,t} \times .25 - \frac{p_{discharge,t}}{e_{Roundtrip}} \times .25 \tag{1.2}$$

Equation 1.2 determines the amount of energy stored at the end of time step t. The amount of energy added to a storage system is characterized by the efficiency of the storage device and therefore only a percentage of energy input will be stored, but storage is measured before application of round-trip efficiency, so storage is increased by the amount of energy sent to storage (p_{charge_t}). Furthermore, the researchers apply round trip efficiency during discharge and therefore any energy that is discharged from storage during time step t will reduce the amount of energy stored at the end of time step t.

$$HoursOfUse = \frac{\sum_t P_{buy,t}}{4 \times \max_{t \in T} P_{buy,t}} \tag{1.3}$$

Equation 1.3 determines the hours of use. This value is required for the calculation of certain bill structures, such as KCP&L. First, this equation converts the total amount of energy purchased during a billing cycle from kW to kWh. The size of the time steps in this model was 15 minutes and therefore to convert kW to kWh it is divided by 4. The equation then divides by the maximum demand during the billing cycle.

4. Objective Functions

The goal of each heuristic is to reduce the cost of energy purchased from a commercial grid. The cost is a function of the rate structure assigned to a facility by given electric company. From the given rate structures above, the researchers formulated the following objective functions.

PG&E

Equation 1.4 is the objective function that applies to the PG&E rate structures identified in Tables 4 and 5. The variables within the function can be found in the table corresponding to which PG&E rate structure is desired to reproduce.

$$Min\ Z = DailyCost + ConsumptionCost + MaxDemandCost + PeakDemandCost + PartPeakDemandCost \tag{1.4}$$

Equation 1.5 Calculates how many days within a billing period which is then multiplied by the daily meter charge.

$$DailyCost = \left(\frac{T}{96} \times DailyCharge\right) \tag{1.5}$$

Equation 1.6 Calculates the sum of multiplying the demand (kW) of each 15-minute interval with the corresponding time of use charge. This equation converts from kW to kWh by dividing by 4, because the time step size is 15 minutes.

$$ConsumptionCost = \left(\frac{\sum_t P_{buy,t} \times EnergyCharge_t}{4}\right) \tag{1.6}$$

Demand cost for the PG&E rate structures are calculated as described in equations 1.7 to 1.9. For example, if the current billing period is in the summer, then the $MaxDemandCost$, $PeakDemandCost$, and $PartPeakDemandCost$ are calculated as in equations 1.7 to 1.9. During winter, the calculation is similar. However, if the billing period includes days of summer and winter, then $MaxDemandCost$, $PeakDemandCost$, and

PartPeakDemandCost are calculated for summer days and prorated for the number of days of the billing period that are defined as summer days. Then, *MaxDemandCost*, *PeakDemandCost*, and *PartPeakDemandCost* are calculated for winter and prorated for the number of days of the billing period that are defined as winter days.

Equation 1.7 determines the maximum 15-minute interval demand (kW) in a given billing period and multiples it by maximum demand charge.

$$MaxDemandCost = \left(\max_{t \in BillingPeriod} P_{buy,t} \times MaxDemandCharge_t\right) \qquad (1.7)$$

Equation 1.8 determines the maximum 15-minute interval demand (kW) specifically within peak times in a given billing period and multiples it by maximum peak demand charge.

$$PeakDemandCost = \left(\max_{t \in \left\{\begin{matrix} Summer-peak \\ Winter-peak \end{matrix}\right\}} P_{buy,t} \times PeakDemandCharge_t\right) \qquad (1.8)$$

Equation 1.9 determines the maximum 15-minute interval demand (kW) specifically within partial peak times in a given billing period and multiples it by maximum partial peak demand charge.

$$PartPeakDemandCost = \max_{t \in \left\{\begin{matrix} Summer-partpeak \\ Winter-partpeak \end{matrix}\right\}} P_{buy,t} \times PartPeakDemandCharge_t \qquad (1.9)$$

KCP&L

Equation 1.10 is the objective function that applies to the KCP&L rate structure identified in Table 6 and the variables within the function can be found in the table.

$$Min\ Z = MonthlyCharge + TieredConsumptionCost + FacilityDemandCost + MaxDemandCost \qquad (1.10)$$

$$Hours_{Tier\ 1} = \begin{cases} 180 \text{ if } HoursOfUse > 180 \\ HoursOfUse \text{ otherwise} \end{cases}$$

$$Hours_{Tier\ 2} = \begin{cases} 0 \text{ if } HoursOfUse \leq 180 \\ HoursOfUse - 180 \text{ if } 180 < HoursOfUse \leq 360 \\ 180 \text{ otherwise} \end{cases}$$

$$Hours_{Tier\ 3} = \begin{cases} 0 \text{ if } HoursOfUse \leq 360 \\ HoursOfUse - 360 \text{ if } HoursOfUse \ > 360 \end{cases}$$

Equation 1.11 determines the appropriate hourly values for each tier and multiplies by the appropriate tier charge for the season.

$$TieredConsumptionCost = (Hours_{Tier1} \times Tier1Charge_t) + (Hours_{Tier2} \times Tier2Charge_t) + (Hours_{Tier3} \times Tier3Charge_t) \quad \textit{(1.11)}$$

Equation 1.12 determines the maximum 15-minute interval demand (kW) in the past 12 months, including the current billing month, and multiplies by the facility demand charge.

$$FacilityDemandCost = \left(\max_{t \in past\ 12\ months} P_{buy,t} \times FacilityDemandCharge \right) \quad \textit{(1.12)}$$

Equation 1.13 determines the maximum 15-minute interval demand (kW) in a given billing period and multiplies by maximum demand charge.

$$MaxDemandCost = \left(\max_{t \in BillingPeriod} P_{buy,t} \times MaxDemandCharge_t \right) \quad \textit{(1.13)}$$

5. Constraints

Equation 1.14 identifies the amount of energy stored at the beginning of each period and ensures that the amount of energy sent to storage during that period does not result in exceeding the capacity of the storage system.

$$p_{charge,t} \times .25 \leq \frac{MaxCapacity_{storage}}{e_{RoundTrip}} - S_{t-1} \quad \textit{(1.14)}$$

Equation 1.15 ensures the customer does not purchase more than the desired maximum demand to replenish storage. $MaxPurchase$ is the maximum desired demand (kW) as defined by the customer. For example, a PG&E customer may desire to remain under 500kW maximum demand to remain on E-19 rate structure.

$$p_{charge,t} \leq MaxPurchase - Demand_t \tag{1.15}$$

Equation 1.16 limits the amount of energy pulled from storage in each time step as constrained by the maximum discharge power of the storage system.

$$p_{discharge,t} \leq MaxDischarge_{storage} \tag{1.16}$$

Equation 1.17 ensures that the amount of energy used from storage in a given period does not exceed the amount of energy available in storage at the beginning of the given period.

$$\frac{p_{discharge,t} \times .25}{e_{RoundTrip}} \leq S_{t-1} \tag{1.17}$$

G. ENERGY STORAGE HEURISTICS

The researchers developed three heuristics that determine how much energy should be sent to and from storage for each time step. The heuristics are designed to reduce overall energy costs. Each of the following heuristics is subject to the constraints defined in the previous section.

1. Load-Shifting Heuristic

The Load-Shifting heuristic is tailored to rate structures with TOU charges. Equation 1.18 defines the amount of energy that should be sent to storage during off-peak periods. The equation sums the prior day’s amount of energy pulled from storage and then divides that value by 44 (the number of off-peak periods each day). That value is divided by the efficiency rate to take account for the loss that will occur. The Load-Shifting heuristic aims eliminate peak and part-peak consumption and maintains off-peak consumption below a maximum purchase amount defined by the customer. The maximum purchase amount may help customers with rate structures similar to PG&E where maintaining demand below 500 kW allows them to stay on the cheaper E-19 rate structure. During each period, the following equations are applied:

- During off-peak periods:
  - $p_{charge,t} = \left(\frac{\sum_{t}^{t-96} p_{discharge,t}}{44}\right) \div e_{RoundTrip}$ (1.18)
  - Equation 1.18 is constrained by equations 1.14 and 1.15
  - $p_{discharge,t} = 0$
- During peak and partial peak periods:
  - $p_{charge,t} = 0$
  - $p_{discharge,t} = demand_t$, constrained by equations 1.16 and 1.17

2. Averaging Heuristic

The Averaging heuristic is a modification of the Load-Shifting heuristic to tailor it for rate structures without TOU charges. Equation 1.19 defines the target purchase amount which is determined by taking the sum the entire billing period worth of demand (total consumption) and dividing by the number of periods in the billing month, then dividing this value by the efficiency rate to account for loss. Additional energy can be added to storage as safety stock.

$$TargetPurchase = \left[\left(\frac{\sum_{t=1}^{T} demand_t}{T}\right) \div e_{RoundTrip}\right] \times (1 + SafetyStockRate) \quad (1.19)$$

Given an ESS with sufficient capacity and maximum discharge power, the Averaging heuristic is designed to create a constant demand to minimize demand charges. Regardless of time period, the following rules are applied:

- If $demand_t < TargetPurchase$
  - $p_{charge,t} = TargetPurchase - demand_t$, constrained by equation 1.14

- $p_{discharge,t} = 0$

- If $demand_t > TargetPurchase$
  - $p_{charge,t} = 0$
  - $p_{discharge,t} = demand_t - TargetPurchase$, constrained by equations 1.16 and 1.17

- If $demand_t = TargetPurchase$
  - $p_{charge,t} = 0$
  - $p_{discharge,t} = 0$

3. Load-Shifting and Averaging Heuristic

The Load-Shifting and Averaging heuristic is a combination of the two previous heuristics and tailors the Averaging heuristic to use with rate structures with TOU charges. Equation 1.20 defines the target purchase amount to be purchased during off-peak periods only. The target purchase amount is the sum of the entire billing period worth of demand (total consumption) divided by the number of off-peak periods in the billing month, divided by the efficiency rate to account for loss. Additional energy can be added to storage as safety stock.

$$TargetPurchase = \left[\left(\frac{\sum_t demand_t}{T_{Off-Peak}}\right) \div e_{RoundTrip}\right] \times (1 + SafetyStockRate) \qquad (1.20)$$

- During off-peak periods:
  - If $demand_t < TargetPurchase$
    - $p_{charge,t} = TargetPurchase - demand_t$, constrained by equation 1.14
    - $p_{discharge,t} = 0$

- If $demand_t > TargetPurchase$
    - $p_{discharge,t} = demand_t - TargetPurchase$, constrained by equations 1.16 and 1.17
    - $p_{charge,t} = 0$
- During peak and partial-peak periods:
    - $p_{charge,t} = 0$
    - $p_{discharge,t} = demand_t$, constrained by equations 1.16 and 1.17

The Load-Shifting and Averaging heuristic is designed to eliminate peak and part-peak consumption and create constant demand for off-peak periods to minimize TOU demand and consumption charges. It requires an ESS with sufficient capacity and maximum discharge power, and when constraints would be violated by the heuristic, the constraints determine $p_{charge,t}$ and $p_{discharge,t}$.

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IV. ANALYSIS OF RESULTS

The researchers used two different rate structures and two demand profiles to evaluate the impact of the three heuristics discussed in Chapter III. Pacific Gas and Electric (PG&E) and Kansas City Power and Light (KCP&L) have distinctly different combinations of electricity rate structures that allowed the researchers to analyze the impact on the different types of schedules. Additionally, the volatile demand profile from Naval Support Activity (NSA) Monterey and the stable demand profile from Defense Information Systems Agency (DISA) allowed to the researchers to analyze the impact on different energy demand profiles.

Chapter IV is structured to analyze the impact of each of the defined heuristics given a demand profile and an electricity rate structure. First, the researchers analyzed the impact of the heuristics on a volatile demand profile with the PG&E and KCP&L rate structures. Next the team analyzed the impact of the heuristics on the stable demand profile with the PG&E and KCP&L rate structures. Furthermore, the researchers analyzed the impact on each type of energy charge and the total cost for each rate structure.

A. VOLATILE DEMAND PROFILE

The following section analyzes the impact of each heuristic on the volatile demand profile and subsequently the financial impact given the application of either the PG&E or KCP&L rate structure. The researchers utilized the six energy storage system (ESS) configurations defined in Chapter III. Three of the ESS configurations use the Tesla Powerpack and provide 100%, 50%, and 25% coverage. The other three ESS configurations are the UET Uni.System configured for 100%, 50%, and 25% coverage.

1. Total Annual Cost

Figure 22 illustrates the annual total cost of each heuristic and ESS configuration combination applied to the volatile demand profile and the PG&E rate structure. Each combination of ESSs and heuristics achieved overall cost savings. The greatest cost savings in each combination was achieved in the demand charge category. Furthermore, the heuristics that achieved the most cost savings was the Load-Shifting and Averaging heuristic.

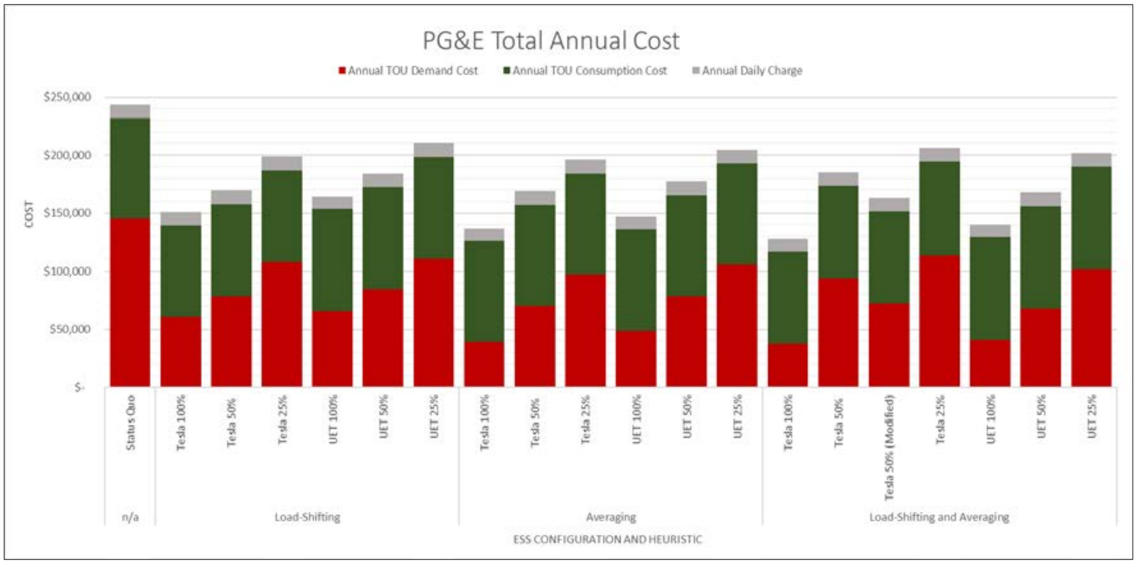

Figure 22. Volatile Profile Annual Total PG&E Cost

Figure 23 illustrates the annual total cost of each heuristic and ESS configuration applied to the volatile demand profile and the KCP&L rate structure. Similar to the PG&E rate structure, each combination also achieved overall cost savings with the demand charge category producing the most cost savings relative to other charges. However, the greatest cost savings under the KCP&L rate structure was achieved with the Averaging heuristic.

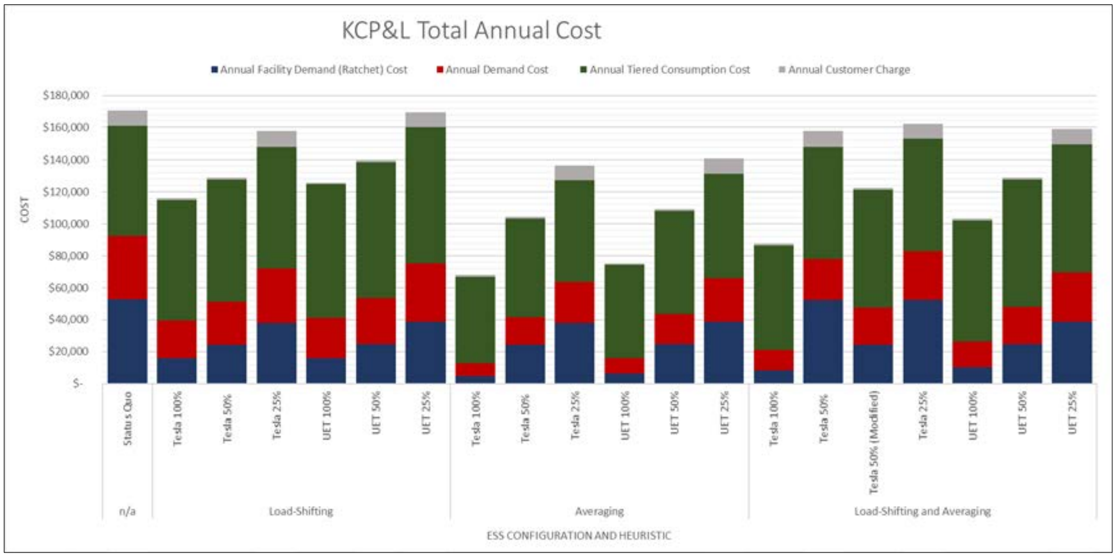

Figure 23. Volatile Profile Annual Total KCP&L Cost

The following sections evaluate the impact each heuristic had on maximum 15-minute interval demand and total consumption in order to further demonstrate how the heuristics reduced total cost.

2. Impact on Maximum 15-Minute Interval Demand

As previously depicted in Figures 22 and 23, the most significant cost savings were achieved in demand charge categories. Monthly maximum 15-minute interval demand drives the demand charges for each billing period. Monthly maximum 15-minute interval demand is defined as the highest consumption (kW) in a 15-minute interval within the billing period. Figure 24 shows the impact each heuristic had on the monthly maximum 15-minute interval demand.

The Load-Shifting heuristic shaved the spikes in demand that are seen in the volatile demand profile. The 100% configurations eliminated all spikes. The 50% and 25% configurations reduced the spikes, but did not completely eliminate them. The 50% and 25% configurations were unable to completely eliminate the spikes even though they had enough stored energy available at the time, because the demand for energy exceeded the maximum discharge power. January to May 2017, each ESS configuration resulted in increased monthly maximum demand with the Load-Shifting heuristic because there were no spikes during these months.

The Averaging heuristic also effectively shaved the spikes in demand that are seen in the volatile demand profile. The 100% configurations eliminated all spikes. Similar to the Load-Shifting heuristic, the 50% and 25% configurations were limited by the maximum discharge power of the ESSs. The Averaging heuristic resulted in not only lower maximum demand than the status quo but also the lowest maximum demand of all three heuristics in every billing period.

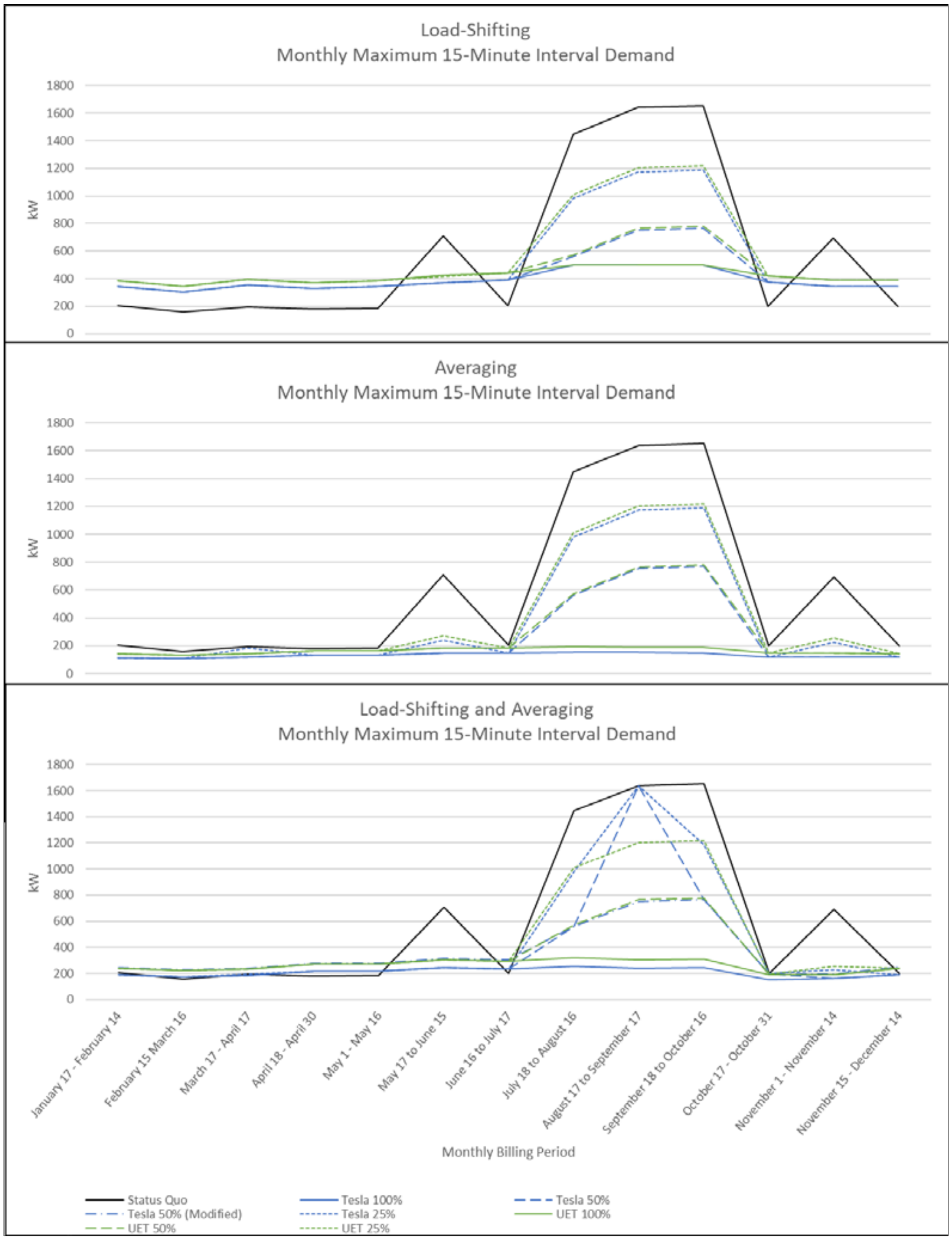

Figure 24. Volatile Profile Monthly Maximum 15-Minute Interval Demand

The results of the Load-Shifting and Averaging heuristic highlight the impact of limited capacity and limited maximum discharge power. The Tesla Powerpack 50% and 25% configurations shaved the demand spikes in May, July, and October, but were unable to shave the peak demand in August due to insufficient stored energy available. However, the 50% (modified) Tesla Powerpack configuration effectively shaved each spike because of the additional energy stored as safety stock to ensure sufficient stored energy was available to meet demand during the spike period. However, the maximum discharge power is still a limitation of the 50% and 25% configurations, regardless of any safety stock applied and therefore the 50% (modified) configuration was unable to completely eliminate the larger spikes. All UET configurations effectively shaved the demand spikes in August because they had enough capacity to avoid purchasing demand during part-peak and peak periods like the 50% and 25% Tesla configurations.

The Load-Shifting and Averaging heuristic was able to shave the spikes in demand while also not significantly increasing demand during months without spikes like the Load-Shifting heuristic. Although the Averaging heuristic resulted in the lowest monthly maximum demand, it is important to note the impact each heuristic had on demand throughout the day. Specifically, it is important to note how the heuristics performed on a day without spikes compared to typical day without spikes. This analysis is significant because some utility companies, such as PG&E apply time-of-use (TOU) demand charges in addition to overall monthly maximum demand charges. Figures 25 and 26 show the impact each heuristic had on the 15-minute interval demand on March 13, 2017 and August 4, 2017, respectively.

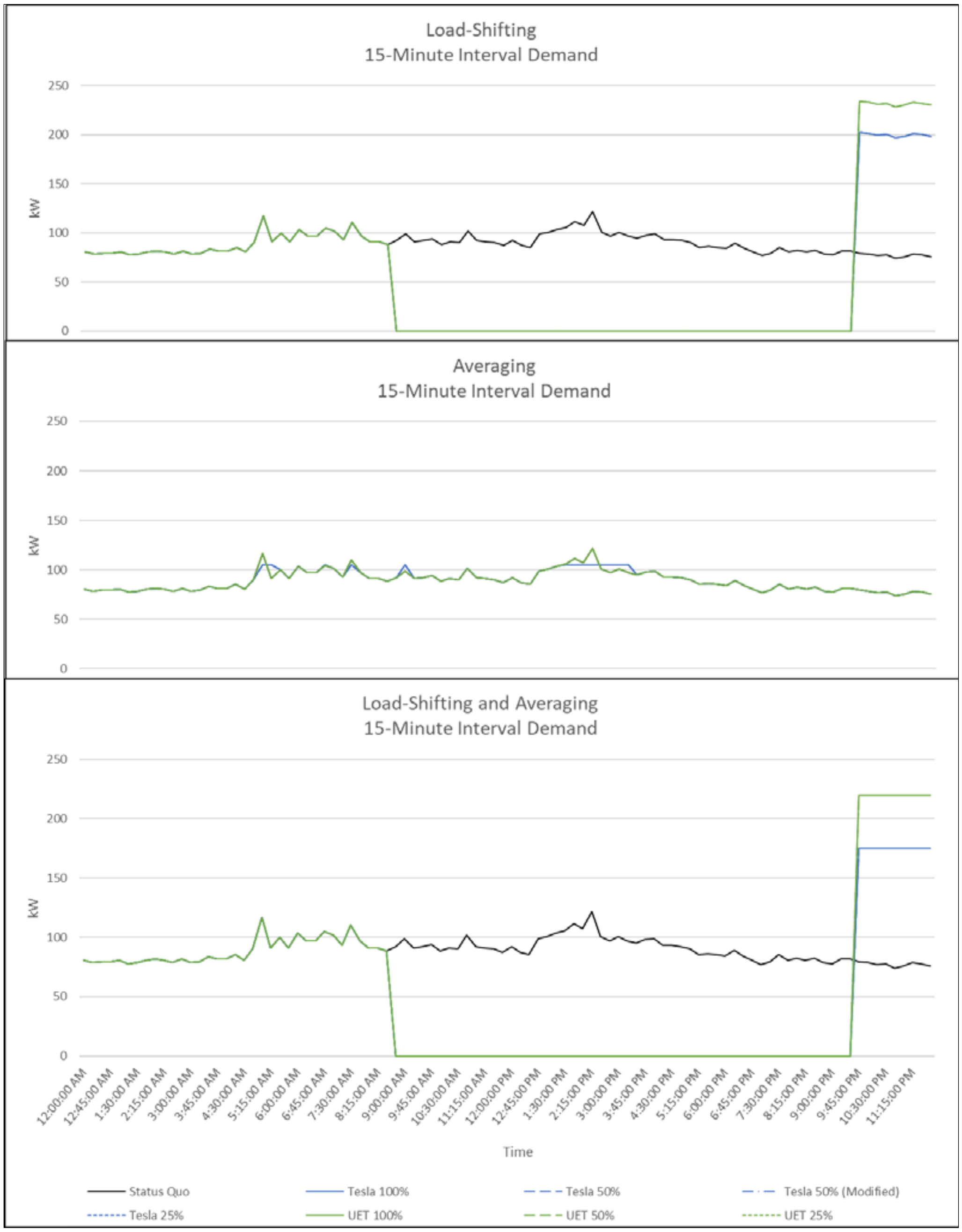

Figure 25. Volatile Profile March 13, 2017, 15-Minute Interval Demand

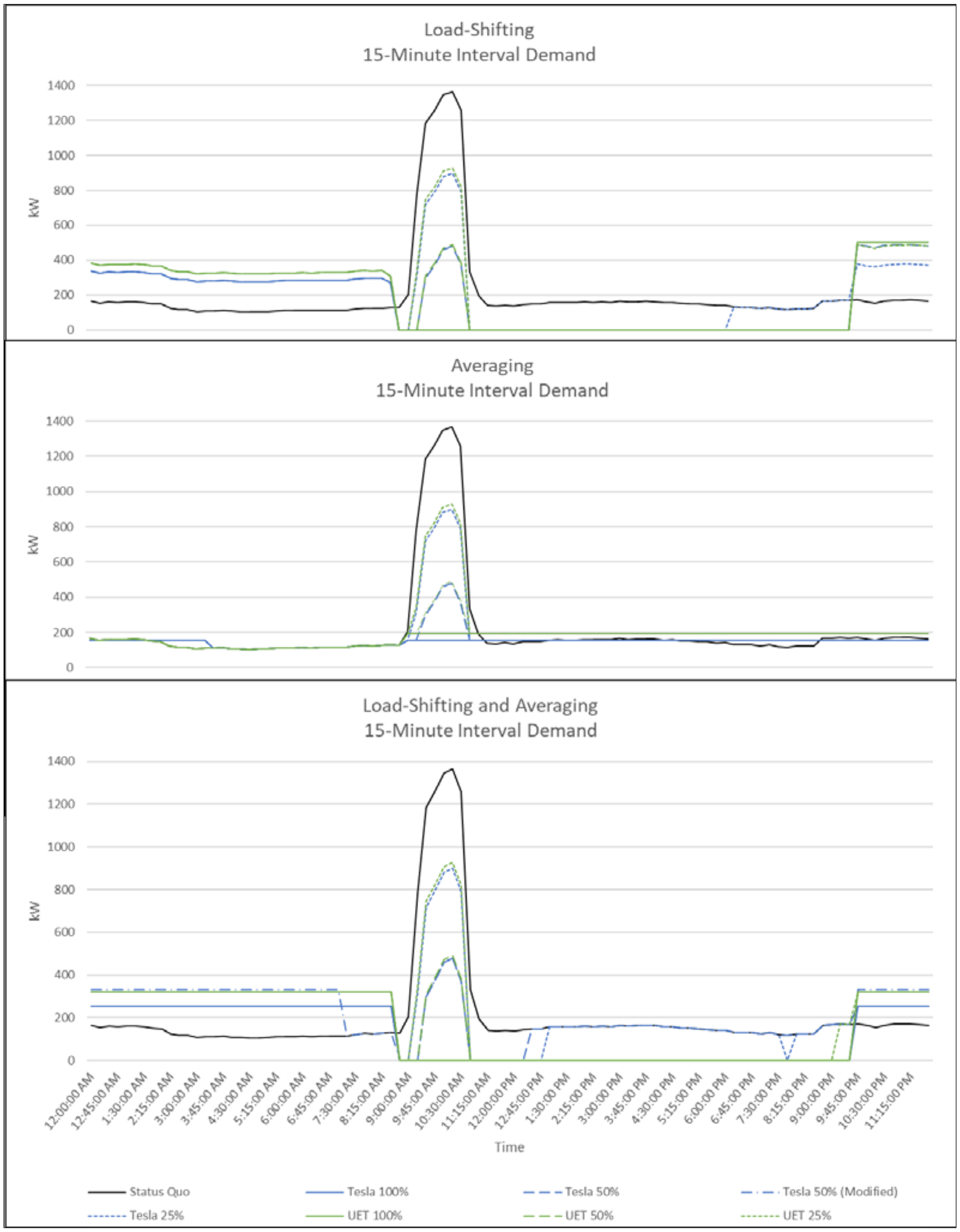

Figure 26. Volatile Profile August 4, 2017, 15-Minute Interval Demand

On a typical day, such as March 13, 2017, the ESS configurations performed similarly under each heuristic. In contrast, on a day with spikes, such as August 4, 2017, the performance of each ESS configuration varied by heuristic. The Load-Shifting heuristic eliminated all peak and part-peak time demand on March 13, 2017, a day without any spikes in demand. Even on August 4, 2017, a day with spikes in demand, the Load-Shifting heuristic eliminated peak and part-peak time demand with the exception of the Tesla Powerpack 25% configuration beginning around 6:00PM. All other configurations effectively shaved the peak as well as possible given the limitation of their maximum discharge power and were still able to service all other peak and part-peak time demand from storage.

The Averaging heuristic did not eliminate peak and part-peak time demand on either day, but it did effectively shave the demand spikes on August 4, 2017.

The Load-Shifting and Averaging heuristic eliminated all peak and part-peak time demand on March 13, 2017. However, on August 4, 2017, the Tesla Powerpack 25% and 50% configurations were unable to service peak and part-peak time demand beginning around 12:00PM due to an insufficient amount of stored energy. However, the 50% configuration modified with a built in safety stock provided a sufficient amount of stored energy to service peak and part-peak time demand.

This analysis revealed that although the averaging heuristic resulted in the lowest monthly maximum demand, it did not eliminate demand during peak and part-peak time periods which can be costly depending on the rate structure. The demand during these periods can influence both TOU demand charges and TOU consumption charges. The impact on total consumption needs to examined before analyzing the impact on cost for different rate structures.

3. Impact on Total Consumption

Total annual consumption is defined as the total kWh consumed during the year. Figure 27 illustrates the impact each heuristic and ESS configuration had on the total annual consumption.

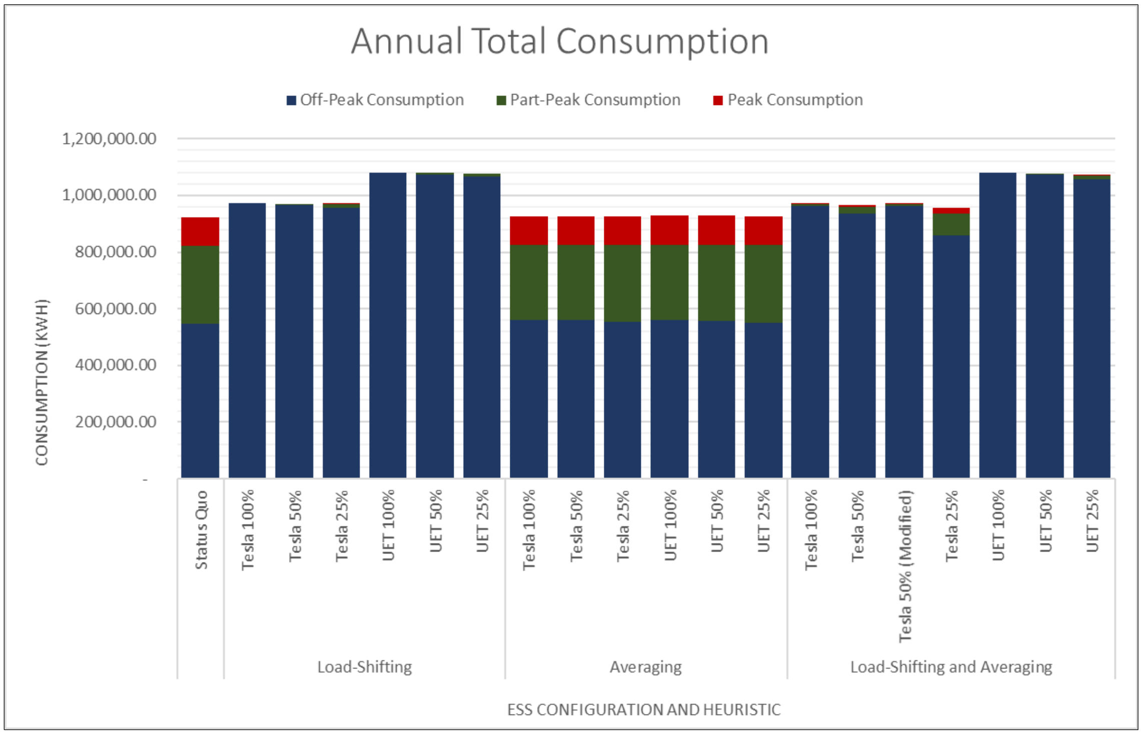

Figure 27. Volatile Profile Annual Total Consumption

As discussed in the previous section on demand, the Load-Shifting and the Load-Shifting and Averaging heuristics effectively shifted peak and part-peak consumption to off-peak time periods. Figure 27 reinforces what was presented in Figure 26, where the insufficient availability of stored energy resulted in some peak and part-peak consumption.

Each heuristic increased total annual consumption. How much consumption increased is a function of both the heuristic utilized and the ESS configuration. For example, the UET ESSs have higher annual total consumption that the Tesla Powerpack configurations because the UET systems have a lower efficiency rate than the Tesla systems. The amount of additional energy that must be purchased to account for efficiency loss may offset some of the savings achieved by load shifting to cheaper periods. This concept is discussed in greater detail in the following sections.

4. Analysis of the Impact on Cost

PG&E Analysis

Table 8 summarizes the annual cost savings achieved with each heuristic for the PG&E rate structure. Every combination of the three heuristics and ESS configurations achieved cost savings. However, the cost of some charge categories increased, despite decreased overall cost. Each specific charge category is examined in detail in the following sections.

(1) Demand Charges

The majority of cost savings were achieved by reducing demand charges. PG&E includes TOU demand charges. Customers are charged a maximum peak demand charge for the maximum demand for any 15-minute period within peak times, a part-peak demand charge for the maximum demand within part-peak times, and an overall maximum demand charge for the maximum demand occurring anytime within the billing period.

The Load-Shifting heuristic resulted in each configuration significantly reducing annual demand costs. The cost savings for the 100% configurations were achieved by eliminating demand altogether for peak and part-peak time periods. However, as illustrated in Figure 24, some of the cost savings achieved during months with large demand spikes was offset by the higher demand during months without spikes.

The Averaging heuristic offered greater cost savings even without eliminating peak and part-peak demand. However, the Load-Shifting and Averaging heuristic exhibited the greatest cost savings in the demand charge category of the PG&E rate structure. This was achieved by not only shaving the large peaks, but also by shifting and eliminating peak and part-peak demand and then averaging that demand over off-peak times.

Table 8. Volatile Profile Annual Total PG&E Cost Summary

		Total		TOU Demand								TOU Consumption								Daily	
Heuristic	Configuration	Annual Total Cost	Change from Status Quo	Annual TOU Demand Cost	Change from Status Quo	Max Demand Cost	Change from Status Quo	Peak Demand Cost	Change from Status Quo	Part-Peak Demand Cost	Change from Status Quo	Annual TOU Consumption Cost	Change from Status Quo	Annual Peak Consumption Cost	Change from Status Quo	Annual Part-Peak Consumption Cost	Change from Status Quo	Annual Off-Peak Consumption Cost	Change from Status Quo	Annual Daily Charge	Change from Status Quo
n/a	Status Quo	**$243,386**	n/a	**$144,992**	n/a	$ 100,780	n/a	$17,489	n/a	$ 26,723	n/a	**$86,517**	n/a	$14,018	n/a	$27,951	n/a	$44,547	n/a	**$11,877**	n/a
Load-Shifting	Tesla 100%	**$150,786**	-38.0%	**$ 60,477**	-58.3%	$ 60,477	-40.0%	$ -	-100.0%	$ -	-100.0%	**$79,402**	-8.2%	$ -	-100.0%	$ -	-100.0%	$79,402	78.2%	**$10,908**	-8.2%
	Tesla 50%	**$169,838**	-30.2%	**$ 78,765**	-45.7%	$ 69,336	-31.2%	$ -	-100.0%	$ 9,429	-64.7%	**$79,196**	-8.5%	$ -	-100.0%	$ 473	-98.3%	$78,723	76.7%	**$11,877**	0.0%
	Tesla 25%	**$199,109**	-18.2%	**$107,925**	-25.6%	$ 87,480	-13.2%	$ 4,175	-76.1%	$ 16,269	-39.1%	**$79,307**	-8.3%	$ 22	-99.8%	$ 1,263	-95.5%	$78,022	75.1%	**$11,877**	0.0%
	UET 100%	**$164,749**	-32.3%	**$ 65,515**	-54.8%	$ 65,515	-35.0%	$ -	-100.0%	$ -	-100.0%	**$88,326**	2.1%	$ -	-100.0%	$ -	-100.0%	$88,326	98.3%	**$10,908**	-8.2%
	UET 50%	**$184,351**	-24.3%	**$ 84,491**	-41.7%	$ 74,913	-25.7%	$ -	-100.0%	$ 9,578	-64.2%	**$87,983**	1.7%	$ -	-100.0%	$ 485	-98.3%	$87,498	96.4%	**$11,877**	0.0%
	UET 25%	**$210,312**	-13.6%	**$110,508**	-23.8%	$ 93,737	-7.0%	$ -	-100.0%	$ 16,771	-37.2%	**$87,928**	1.6%	$ -	-100.0%	$ 1,074	-96.2%	$86,854	95.0%	**$11,877**	0.0%
Averaging	Tesla 100%	**$136,921**	-43.7%	**$ 38,938**	-73.1%	$ 20,295	-79.9%	$14,580	-16.6%	$ 4,064	-84.8%	**$87,075**	0.6%	$14,526	3.6%	$26,658	-4.6%	$45,891	3.0%	**$10,908**	-8.2%
	Tesla 50%	**$168,803**	-30.6%	**$ 70,099**	-51.7%	$ 43,890	-56.4%	$14,742	-15.7%	$ 11,467	-57.1%	**$86,827**	0.4%	$14,446	3.1%	$26,807	-4.1%	$45,574	2.3%	**$11,877**	0.0%
	Tesla 25%	**$196,118**	-19.4%	**$ 97,432**	-32.8%	$ 65,063	-35.4%	$14,742	-15.7%	$ 17,626	-34.0%	**$86,809**	0.3%	$14,346	2.3%	$27,248	-2.5%	$45,216	1.5%	**$11,877**	0.0%
	UET 100%	**$147,060**	-39.6%	**$ 48,735**	-66.4%	$ 25,513	-74.7%	$18,113	3.6%	$ 5,108	-80.9%	**$87,417**	1.0%	$14,666	4.6%	$27,055	-3.2%	$45,696	2.6%	**$10,908**	-8.2%
	UET 50%	**$177,450**	-27.1%	**$ 78,458**	-45.9%	$ 47,987	-52.4%	$18,317	4.7%	$ 12,154	-54.5%	**$87,115**	0.7%	$14,610	4.2%	$27,195	-2.7%	$45,310	1.7%	**$11,877**	0.0%
	UET 25%	**$204,559**	-16.0%	**$105,713**	-27.1%	$ 68,900	-31.6%	$18,317	4.7%	$ 18,496	-30.8%	**$86,969**	0.5%	$14,458	3.1%	$27,555	-1.4%	$44,957	0.9%	**$11,877**	0.0%
Load-Shifting and Averaging	Tesla 100%	**$127,770**	-47.5%	**$ 37,391**	-74.2%	$ 32,655	-67.6%	$ 3,607	-79.4%	$ 1,128	-95.8%	**$79,472**	-8.1%	$ 219	-98.4%	$ 600	-97.9%	$78,654	76.6%	**$10,908**	-8.2%
	Tesla 50%	**$185,654**	-23.7%	**$ 94,104**	-35.1%	$ 65,344	-35.2%	$12,498	-28.5%	$ 16,261	-39.1%	**$79,674**	-7.9%	$ 965	-93.1%	$ 2,457	-91.2%	$76,252	71.2%	**$11,877**	0.0%
	Tesla 50% (Modified)	**$163,581**	-32.8%	**$ 72,405**	-50.1%	$ 58,748	-41.7%	$ 3,701	-78.8%	$ 9,957	-62.7%	**$79,299**	-8.3%	$ 188	-98.7%	$ 622	-97.8%	$78,489	76.2%	**$11,877**	0.0%
	Tesla 25%	**$206,260**	-15.3%	**$113,538**	-21.7%	$ 78,051	-22.6%	$15,132	-13.5%	$ 20,355	-23.8%	**$80,846**	-6.6%	$ 2,812	-79.9%	$ 7,985	-71.4%	$70,049	57.2%	**$11,877**	0.0%
	UET 100%	**$140,179**	-42.4%	**$ 40,943**	-71.8%	$ 40,943	-59.4%	$ -	-100.0%	$ -	-100.0%	**$88,329**	2.1%	$ -	-100.0%	$ -	-100.0%	$88,329	98.3%	**$10,908**	-8.2%
	UET 50%	**$167,761**	-31.1%	**$ 67,908**	-53.2%	$ 58,310	-42.1%	$ -	-100.0%	$ 9,598	-64.1%	**$87,976**	1.7%	$ -	-100.0%	$ 501	-98.2%	$87,475	96.4%	**$11,877**	0.0%
	UET 25%	**$201,705**	-17.1%	**$101,939**	-29.7%	$ 77,718	-22.9%	$ 5,543	-68.3%	$ 18,678	-30.1%	**$87,890**	1.6%	$ 259	-98.1%	$ 1,605	-94.3%	$86,026	93.1%	**$11,877**	0.0%

(2) Consumption Charge

Consumption cost for the Load-Shifting and the Load-Shifting and Averaging heuristics was approximately the same. Consumption costs for the Tesla Powerpack configurations benefited from shifting consumption to the cheaper, off-peak period. The Load-Shifting heuristic completely eliminated peak and part-peak consumption for the 100% configurations. The 50% and 25% configurations incurred consumption cost during peak and part-peak periods under the Load-Shifting heuristic due to not enough maximum discharge power of those configurations.

All configurations also incurred additional consumption cost during high-cost periods with the Load-Shifting and Averaging heuristic because there was an insufficient amount of available stored energy. This was discussed in previous sections and also illustrated in Figure 26. Furthermore, the UET configurations exhibited increased consumption cost for both the Load-Shifting and the Load-Shifting and Averaging heuristics due to the lower efficiency rate. Although the UET configurations were able to effectively load-shift, the lower efficiency rate required more total consumption resulting in increased the total consumption cost.

The Averaging heuristic did not benefit from load-shifting and therefore displayed higher total consumption cost for both Tesla and UET configurations.

(3) Daily Charge

Daily charge savings were achieved with the Tesla and UET 100% configurations for all three heuristics. Daily charge savings were achieved by reducing and maintaining the maximum demand below 500 kW to remain on the PG&E E-19 rate schedule. The 50% and 25% configurations were unable to maintain maximum demand below 500kW and therefore resulted in the move to the PG&E E-20 rate structure and did not see any cost savings.

KCP&L Analysis

Table 9 summarizes the annual cost savings achieved by each heuristic with the KCP&L rate structure. Every combination of the three heuristics and ESS configurations achieved cost savings. Specific charge categories are examined in detail in the following sections.

(1) Facilities Charge

Facilities charge is a demand charge with ratchet adjustment applied to the maximum demand for the previous 12-months, including the current billing period. This is extremely costly for demand spikes presented by the volatile demand profile. Each heuristic displayed cost savings in this charge category for all ESS configurations. The Averaging heuristic exhibited the highest cost savings due to maintaining the lowest maximum 15-minute interval demand as illustrated in Figure 24.

The 50% and 25% configurations exhibited the same cost savings with the application of each heuristic, except for the Load-Shifting and Averaging heuristic and the Tesla configurations due to the constraints of the maximum capacity of those systems. As also seen in Figure 24, the Tesla Powerpack 50% and 25% configurations saw a large spike in August 2017 with the application of the Load-Shifting and Averaging heuristic due to not having enough stored energy available to meet demand at the time. The 50% modified configuration showed this can be mitigated by applying the concept of a safety stock.

(2) Monthly Demand Charge

Monthly demand cost decreased for every heuristic and ESS configuration combination. The Averaging heuristic achieved the greatest cost savings for the same reasons discussed in the previous section and as illustrated in Figure 24. Figure 24 shows how the Averaging heuristic was able to reduce the monthly maximum 15-minute interval demand for each billing period.

Moreover, Figure 24 shows that the Load-Shifting heuristic and the Load-Shifting and Averaging heuristic increased the monthly maximum 15-minute interval demand for billing periods without spikes but effectively shaved the spikes. Shaving the spikes resulted in achieving annual demand cost savings, although some savings were off-set with higher monthly demand costs during months without spikes.

Table 9. Volatile Profile Annual Total KCP&L Cost Summary

		Total		Customer		Facility Demand		Monthly Demand		Tiered Consumption							
Heuristic	**Configuration**	**Total Annual Cost**	**Change from Status Quo**	**Annual Customer Charge**	**Change from Status Quo**	**Annual Facility Demand (Ratchet) Cost**	**Change from Status Quo**	**Annual Demand Cost**	**Change from Status Quo**	**Annual Tiered Consumption Cost**	**Change from Status Quo**	**Annual Tier One Cost**	**Change from Status Quo**	**Annual Tier Two Cost**	**Change from Status Quo**	**Annual Tier Three Cost**	**Change from Status Quo**
n/a	Status Quo	**$170,538**	n/a	**$ 9,499**	n/a	**$52,687**	n/a	**$39,943**	n/a	**$68,408**	n/a	$57,248	n/a	$ 9,366	n/a	$ 1,794	n/a
Load-Shifting	Tesla 100%	**$116,023**	-32.0%	**$ 1,113**	-88.3%	**$15,917**	-69.8%	**$23,502**	-41.2%	**$75,492**	10.4%	$66,472	16.1%	$ 9,020	-3.7%	$ -	-100.0%
	Tesla 50%	**$128,762**	-24.5%	**$ 1,113**	-88.3%	**$24,450**	-53.6%	**$26,861**	-32.8%	**$76,338**	11.6%	$69,583	21.5%	$ 6,755	-27.9%	$ -	-100.0%
	Tesla 25%	**$157,720**	-7.5%	**$ 9,499**	0.0%	**$37,820**	-28.2%	**$34,141**	-14.5%	**$76,259**	11.5%	$69,531	21.5%	$ 6,728	-28.2%	$ -	-100.0%
	UET 100%	**$125,898**	-26.2%	**$ 1,113**	-88.3%	**$15,917**	-69.8%	**$25,414**	-36.4%	**$83,454**	22.0%	$71,960	25.7%	$11,494	22.7%	$ -	-100.0%
	UET 50%	**$139,706**	-18.1%	**$ 1,113**	-88.3%	**$24,800**	-52.9%	**$28,964**	-27.5%	**$84,829**	24.0%	$77,231	34.9%	$ 7,599	-18.9%	$ -	-100.0%
	UET 25%	**$169,588**	-0.6%	**$ 9,499**	0.0%	**$38,743**	-26.5%	**$36,517**	-8.6%	**$84,828**	24.0%	$77,748	35.8%	$ 7,080	-24.4%	$ -	-100.0%
Averaging	Tesla 100%	**$ 68,124**	-60.1%	**$ 1,113**	-88.3%	**$ 4,900**	-90.7%	**$ 7,912**	-80.2%	**$54,200**	-20.8%	$24,979	-56.4%	$15,449	65.0%	$13,772	667.6%
	Tesla 50%	**$104,497**	-38.7%	**$ 1,113**	-88.3%	**$24,450**	-53.6%	**$17,315**	-56.7%	**$61,620**	-9.9%	$42,892	-25.1%	$10,485	11.9%	$ 8,243	359.4%
	Tesla 25%	**$136,661**	-19.9%	**$ 9,499**	0.0%	**$37,820**	-28.2%	**$25,692**	-35.7%	**$63,650**	-7.0%	$46,266	-19.2%	$11,486	22.6%	$ 5,897	228.7%
	UET 100%	**$ 75,349**	-55.8%	**$ 1,113**	-88.3%	**$ 6,160**	-88.3%	**$ 9,947**	-75.1%	**$58,130**	-15.0%	$31,402	-45.1%	$17,281	84.5%	$ 9,447	426.5%
	UET 50%	**$109,128**	-36.0%	**$ 1,113**	-88.3%	**$24,800**	-52.9%	**$18,866**	-52.8%	**$64,350**	-5.9%	$47,739	-16.6%	$11,040	17.9%	$ 5,571	210.5%
	UET 25%	**$140,818**	-17.4%	**$ 9,499**	0.0%	**$38,743**	-26.5%	**$27,294**	-31.7%	**$65,281**	-4.6%	$49,512	-13.5%	$11,332	21.0%	$ 4,437	147.3%
Load-Shifting and Averaging	Tesla 100%	**$ 87,608**	-48.6%	**$ 1,113**	-88.3%	**$ 8,129**	-84.6%	**$12,943**	-67.6%	**$65,424**	-4.4%	$40,746	-28.8%	$20,342	117.2%	$ 4,336	141.7%
	Tesla 50%	**$157,721**	-7.5%	**$ 9,499**	0.0%	**$52,198**	-0.9%	**$25,832**	-35.3%	**$70,192**	2.6%	$55,449	-3.1%	$12,196	30.2%	$ 2,547	41.9%
	Tesla 50% (Modified)	**$122,402**	-28.2%	**$ 1,113**	-88.3%	**$24,450**	-53.6%	**$23,284**	-41.7%	**$73,556**	7.5%	$62,025	8.3%	$11,531	23.1%	$ -	-100.0%
	Tesla 25%	**$162,317**	-4.8%	**$ 9,499**	0.0%	**$52,198**	-0.9%	**$30,829**	-22.8%	**$69,791**	2.0%	$55,406	-3.2%	$12,164	29.9%	$ 2,221	23.8%
	UET 100%	**$103,388**	-39.4%	**$ 1,113**	-88.3%	**$10,219**	-80.6%	**$16,272**	-59.3%	**$75,785**	10.8%	$50,512	-11.8%	$23,795	154.1%	$ 1,478	-17.6%
	UET 50%	**$128,953**	-24.4%	**$ 1,113**	-88.3%	**$24,800**	-52.9%	**$23,104**	-42.2%	**$79,937**	16.9%	$64,509	12.7%	$14,649	56.4%	$ 779	-56.6%
	UET 25%	**$158,844**	-6.9%	**$ 9,499**	0.0%	**$38,743**	-26.5%	**$30,728**	-23.1%	**$79,873**	16.8%	$65,072	13.7%	$14,044	49.9%	$ 757	-57.8%

(3) Tiered Consumption Charges

KCP&L includes tiered consumption charges. KCP&L bills customers in tiers based on the number of billing hours. Billing hours are determined by dividing total consumption by the maximum demand for the billing period. Furthermore, the first 180 billing hours are the most expensive, the second 180 hours are the second most expensive, and any hours over 360 are the least expensive\ Therefore, a higher number of billing hours allows customers to spread their consumption into the cheaper tiers. Increasing consumption and/or decreasing maximum demand will increase the number of billing hours. Figure 28 shows the impact of each heuristic on the number of billing hours per billing period.

Under the Load-Shifting heuristic and the Load-Shifting and Averaging heuristic, each configuration resulted in fewer billing hours during months without demand spikes because monthly maximum demand was higher than the status quo in these months. However, in months with demand spikes, the number of billing hours was greater than the status quo. As a result, annual consumption costs increased for each configuration. Specifically, the costs increased due to the decrease in billing hours coupled with the increase in total consumption which meant more consumption was being charged at the higher tier rates.

However, the application of the Averaging heuristic combined with each ESS configuration resulted in more billing hours for each billing period. Monthly maximum demand was lower than the status quo and total monthly consumption increased every month. Annual consumption costs decreased for each configuration. Specifically, billing hours increased, which allowed more of the consumption to be spread over the cheaper tiers two and three. Thus, costs decreased because the billing hours increased.

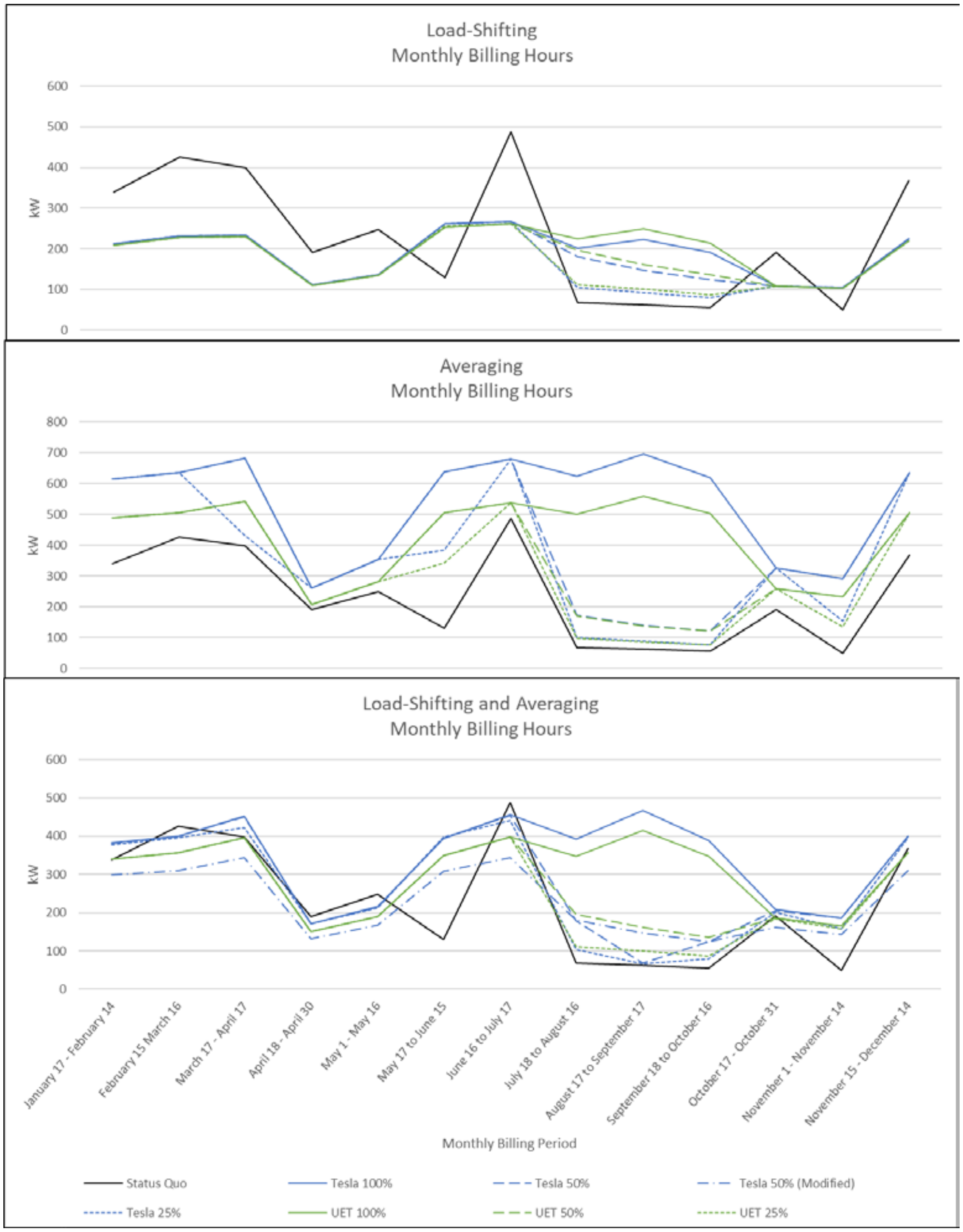

Figure 28. Volatile Profile Monthly Billing Hours

(4) Customer Charge

For each heuristic, annual cost savings for the 100% and 50% configurations was achieved by remaining under 1,000 kW facility demand (maximum annual demand). The 25% configurations resulted in an annual maximum demand above 1,000 kW and therefore did not achieve any cost savings in this category.

B. STABLE DEMAND PROFILE

The following section analyzes the impact of each heuristic on the stable demand profile utilizing the PG&E and KCP&L rate structures.

1. Total Annual Cost

Figure 29 illustrates the annual total cost of each heuristic and ESS configuration combination applied to the stable demand profile and the PG&E rate structure. Tesla Powerpack 100% configurations achieved cost savings with each heuristic, and the greatest cost savings was achieved with the Load Shifting and Averaging heuristic. In contrast, the UET Uni.System configurations resulted in cost increases for each heuristic. For each heuristic the researchers omitted ESS configurations with less efficiency and/or less capacity if a configuration with higher capacity or efficiency resulted in increased cost.

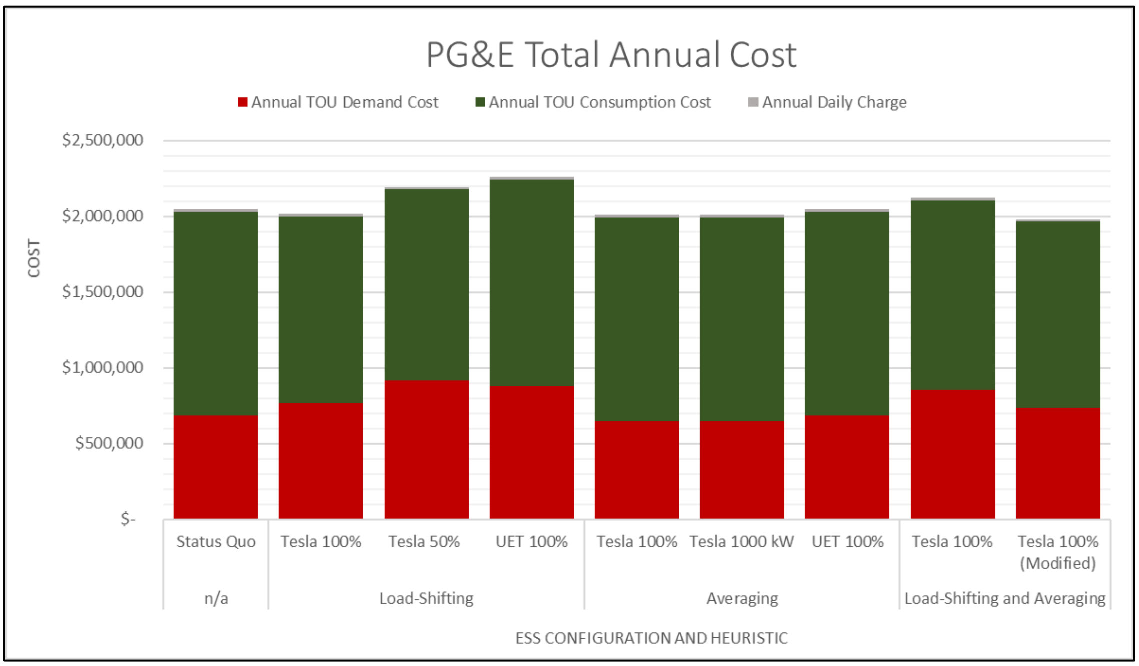

Figure 29. Stable Profile Annual Total PG&E Cost

Figure 30 illustrates the annual total cost of each heuristic and ESS configuration combination applied to the stable demand profile and the KCP&L rate structure. In contrast to the results for the PG&E rate structure, only the Tesla Powerpack configurations achieved overall cost savings and only with the application of the Averaging heuristic. Furthermore, each Tesla Powerpack configuration achieved the same cost savings with the application of the Averaging heuristic. In fact, a Tesla Powerpack configuration with 1000kW capacity could achieve the same cost savings as the 100% configuration.

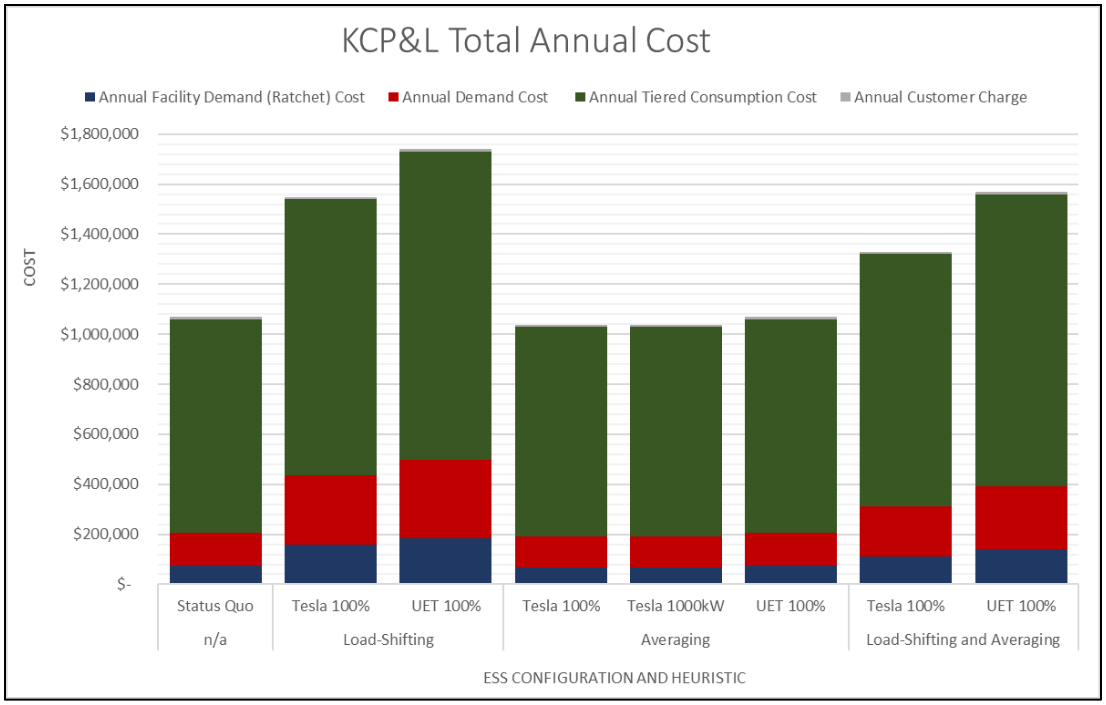

Figure 30. Stable Profile Annual Total KCP&L Cost

The following sections evaluate the impact each heuristic had on maximum 15-minute interval demand and total consumption. Changes in demand and consumption impacted the total annual cost savings for each combination of demand profiles, heuristics, and ESS configurations.

2. Impact on Maximum 15-Minute Interval Demand

Figure 31 shows the impact each heuristic had on the monthly maximum 15-minute interval demand. The Load-Shifting and the Load-Shifting and Averaging heuristics resulted in each ESS configuration having higher monthly maximum demands for each billing period. Shifting consumption to off-peak periods resulted in more than doubling the maximum demand of the status quo because of the characteristics of the stable demand profile. The maximum demand more than doubled to account for efficiency loss.

The Averaging heuristic combined with the Tesla Powerpack configurations effectively smoothed and reduced the maximum monthly demand. The averaging heuristic resulted in a lower maximum demand in every billing period compared to the Load-Shifting heuristic. Each Tesla Powerpack configuration resulted in the same impact on maximum monthly demand. However, as a result of lower efficiency, the UET Uni.Systems result did not differ from the status quo.

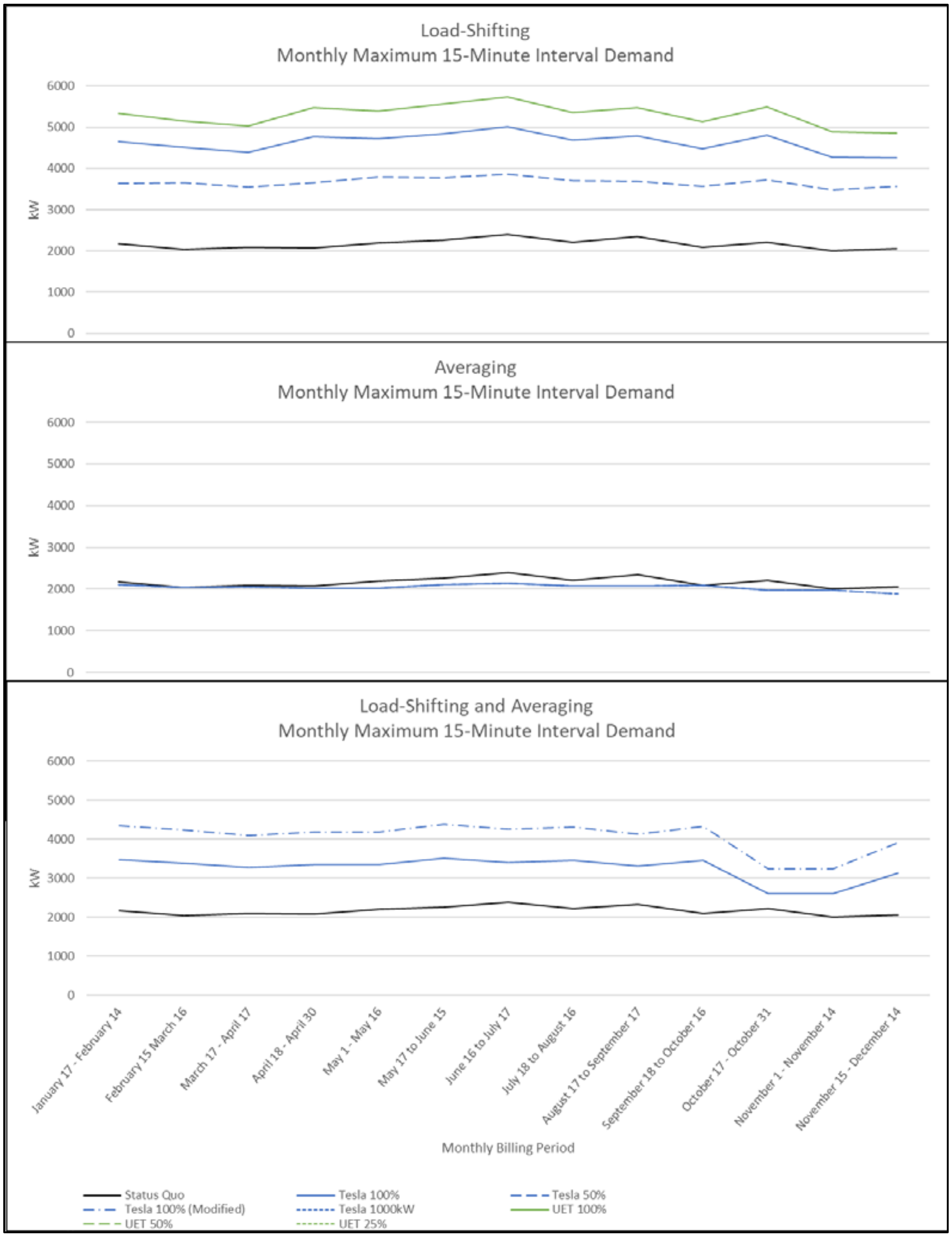

Figure 31. Stable Profile Monthly Maximum 15-Minute Interval Demand

As discussed with the volatile profile, it is also important to analyze the daily impact of demand. Figures 32 shows the impact each heuristic had on the 15-minute interval demand on August 4, 2017. Due to each day of the stable profile having similar characteristics, it was only necessary to show the impact on August 4, 2017.

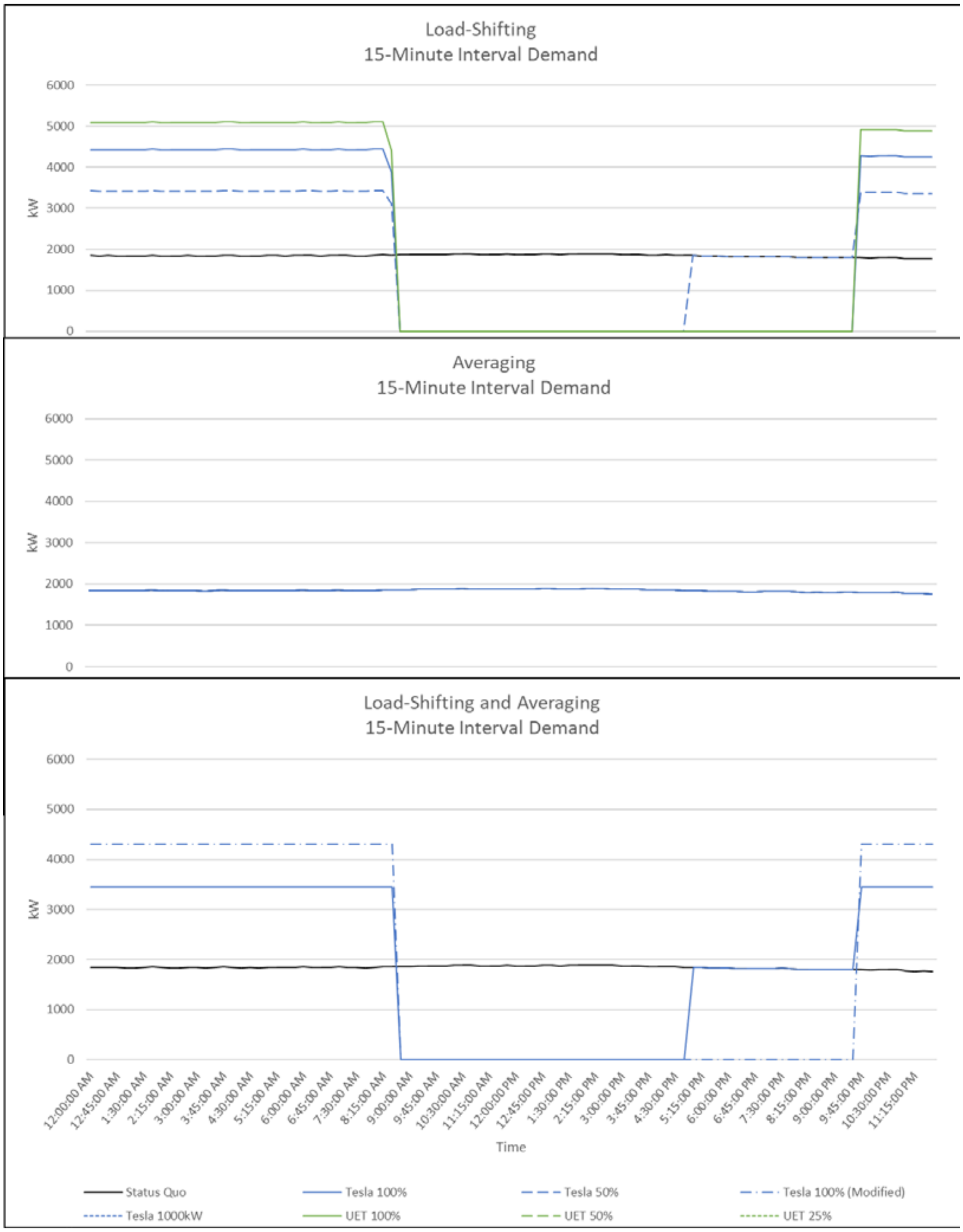

Figure 32. Stable Profile August 4, 2017, 15-Minute Interval Demand

Given a stable demand profile, load-shifting results in more than doubling off-peak demand. In both the Load-Shifting and the Load-Shifting and Averaging heuristics, the impact of insufficient capacity is illustrated by peak and part-peak consumption beginning around 5:00PM. This was mitigated with the Load-Shifting and Averaging heuristic by applying a 25% safety stock to the 100% configuration. This level of analysis provides insight for how each heuristic influences TOU demand charges and TOU consumption charges. The next section ex the impact on total consumption.

3. Impact on Total Consumption

Total annual consumption is defined as the total kWh consumed during the year. Figure 33 illustrates the impact each heuristic and ESS configuration combination had on the total annual consumption.

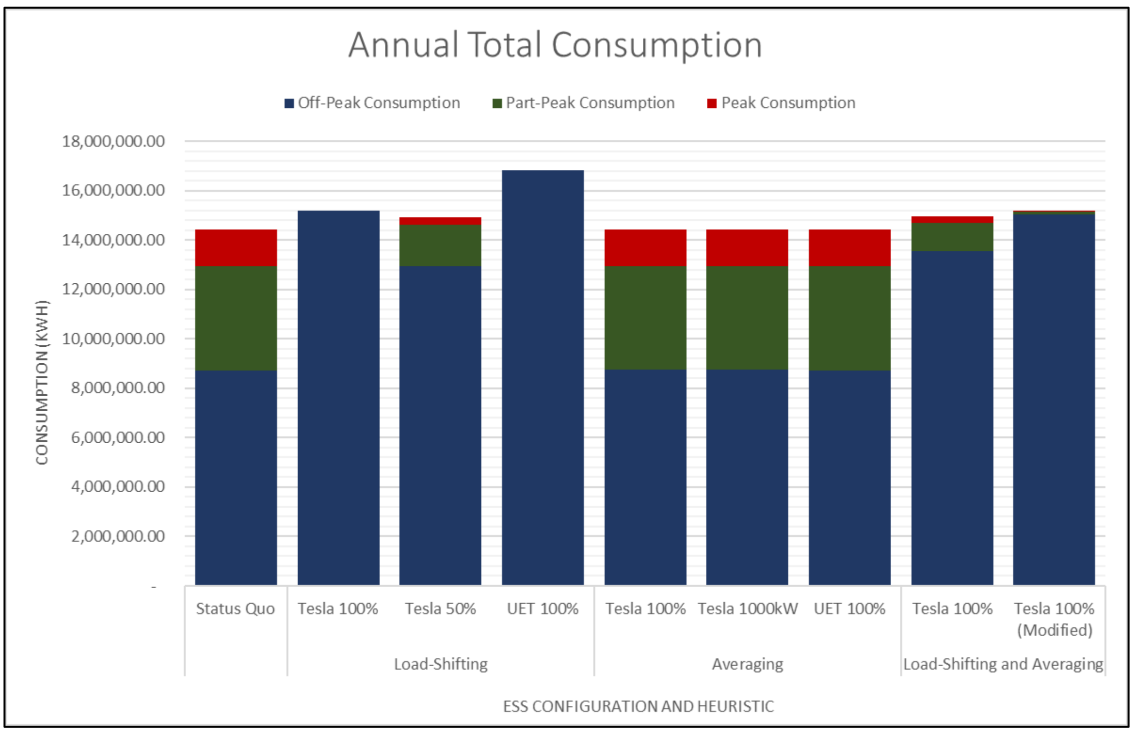

Figure 33. Stable Profile Annual Total Consumption

As discussed in the previous section on demand, the Load-Shifting and the Load-Shifting and Averaging heuristics shifted peak and part-peak consumption to off-peak time periods. When analyzing the Load-Shifting and the Load-Shifting and Averaging heuristics, Figure 33 reinforces what was seen in Figure 32; the insufficient availability of stored energy resulted in some peak and part-peak consumption.

Each configuration increased total annual consumption except the UET Uni.Systems and the Averaging heuristic, which did not differ from the status quo. UET configurations did not differ from the status quo because with an efficiency rate of 70%, the target purchase amount was greater than the demand in every time-step. Therefore, the Averaging heuristic did not use storage at all and because the researchers assume each system begins fully charged, there was no change from the status quo. An increase in consumption is a function of the configuration of the heuristic and the ESS. The impact of increased consumption on total cost will be analyzed in the following section.

4. Analysis of the Impact on Cost

PG&E Analysis

Table 10 summarizes the annual cost savings achieved by each heuristic with the PG&E rate structure. The combination of all Tesla Powerpack ESSs and heuristics achieved cost savings. Each heuristic had varying impacts of the different types of charges in the PG&E rate structure. The greatest cost savings was achieved with the application of the Load Shifting and Averaging heuristic utilizing a Tesla Powerpack 100% configuration with a 25% safety stock.

(1) Demand Charges

In contrast to the volatile demand profile, the majority of cost savings were not achieved by reducing demand charges across the board. For example, the Load-Shifting and the Load-Shifting and Averaging heuristics resulted in each configuration increasing annual demand costs. The overall demand cost increases were a result of more than doubling off-peak maximum demand. Although the 100% configuration eliminated peak and part-peak demand charges, off-peak demand charge increases more than offset the cost savings achieved in those categories. However, the Averaging heuristic achieved cost savings in all demand charge categories as a result of monthly maximum demand smoothing exhibited in Figures 31 and 32.

Table 10. Stable Profile Annual Total PG&E Cost Summary

		Total		TOU Demand								TOU Consumption							
Heuristic	Configuration	Annual Total Cost	Change from Status Quo	Annual TOU Demand Cost	Change from Status Quo	Max Demand Cost	Change from Status Quo	Peak Demand Cost	Change from Status Quo	Part-Peak Demand Cost	Change from Status Quo	Annual TOU Consumption Cost	Change from Status Quo	Annual Peak Consumption Cost	Change from Status Quo	Annual Part-Peak Consumption Cost	Change from Status Quo	Annual Off-Peak Consumption Cost	Change from Status Quo
n/a	Status Quo	**$2,046,176**	n/a	**$686,879**	n/a	$ 361,021	n/a	$255,344	n/a	$ 70,514	n/a	**$1,342,936**	n/a	$214,854	n/a	$420,341	n/a	$ 707,742	n/a
Load-Shifting	Tesla 100%	**$2,014,345**	-1.6%	**$768,152**	11.8%	$ 768,152	112.8%	$ -	-100.0%	$ -	-100.0%	**$1,229,831**	-8.4%	$ -	-100.0%	$ -	-100.0%	$1,229,831	73.8%
	Tesla 50%	**$2,193,316**	7.2%	**$916,306**	33.4%	$ 608,493	68.5%	$239,884	-6.1%	$ 67,929	-3.7%	**$1,260,649**	-6.1%	$ 43,468	-79.8%	$168,224	-60.0%	$1,048,957	48.2%
	UET 100%	**$2,259,697**	10.4%	**$879,253**	28.0%	$ 879,253	143.5%	$ -	-100.0%	$ -	-100.0%	**$1,364,083**	1.6%	$ -	-100.0%	$ -	-100.0%	$1,364,083	92.7%
Averaging	Tesla 100%	**$2,008,837**	-1.8%	**$649,540**	-5.4%	$ 341,071	-5.5%	$242,475	-5.0%	$ 65,993	-6.4%	**$1,342,936**	0.0%	$214,782	0.0%	$420,179	0.0%	$ 707,975	0.0%
	Tesla 1000kW	**$2,008,837**	-1.8%	**$649,540**	-5.4%	$ 341,071	-5.5%	$242,475	-5.0%	$ 65,993	-6.4%	**$1,342,936**	0.0%	$214,782	0.0%	$420,179	0.0%	$ 707,975	0.0%
	UET 100%	**$2,046,176**	0.0%	**$686,879**	0.0%	$ 361,021	0.0%	$255,344	0.0%	$ 70,514	0.0%	**$1,342,936**	0.0%	$214,854	0.0%	$420,341	0.0%	$ 707,742	0.0%
Load-Shifting and Averaging	Tesla 100%	**$2,123,636**	3.8%	**$854,908**	24.5%	$ 548,759	52.0%	$237,932	-6.8%	$ 68,217	-3.3%	**$1,252,367**	-6.7%	$ 38,096	-82.3%	$114,894	-72.7%	$1,099,377	55.3%
	Tesla 100% (Modified)	**$1,981,534**	-3.2%	**$732,910**	6.7%	$ 685,948	90.0%	$ 20,686	-91.9%	$ 26,275	-62.7%	**$1,232,263**	-8.2%	$ 3,697	-98.3%	$ 10,094	-97.6%	$1,218,472	72.2%

(2) Consumption Charges

Consumption cost for the Load-Shifting and the Load-Shifting and Averaging heuristics was approximately the same. Consumption costs for the Tesla Powerpack configurations benefited from shifting consumption to the cheaper, off-peak period. The Load-Shifting heuristic eliminated peak and part-peak consumption for the 100% configurations. The 50% configuration incurred consumption cost during peak and part-peak periods under the Load-Shifting heuristic due to insufficient capacity.

The Tesla Powerpack 100% configuration with the Load-Shifting and Averaging heuristic also incurred consumption cost due to insufficient amount of available stored energy, as discussed in previous sections and illustrated in Figure 32. However, the insufficient amount of stored energy was mitigated with the use of a 25% safety stock, as illustrated with the 100% modified configuration.

Although the Averaging heuristic did not benefit from load-shifting, it was able to maintain the same consumption costs as the status quo.

(3) Daily Charges

The cost of daily charges did not change for any heuristic.

KCP&L Analysis

Table 11 summarizes the annual cost savings achieved by each heuristic with the KCP&L rate structure. The Averaging heuristic was the only heuristic to achieve overall cost savings. The greatest cost savings was achieved with Tesla Powerpack 1000 kW ESS configuration. Each specific charge category is examined in detail in the following sections.

Table 11. Stable Profile Annual Total KCP&L Cost Summary

		Total		Customer		Facility Demand		Monthly Demand		Tiered Consumption							
Heuristic	Configuration	Total Annual Cost	Change from Status Quo	Annual Customer Charge	Change from Status Quo	Annual Facility Demand (Ratchet) Cost	Change from Status Quo	Annual Demand Cost	Change from Status Quo	Annual Tiered Consumption Cost	Change from Status Quo	Annual Tier One Cost	Change from Status Quo	Annual Tier Two Cost	Change from Status Quo	Annual Tier Three Cost	Change from Status Quo
n/a	Status Quo	**$1,068,328**	n/a	**$ 9,499**	n/a	**$ 76,163**	n/a	**$129,668**	n/a	**$ 852,997**	n/a	$415,473	n/a	$243,696	n/a	$193,828	n/a
Load-Shifting	Tesla 100%	**$1,548,587**	45.0%	**$ 9,499**	0.0%	**$159,744**	109.7%	**$276,060**	112.9%	**$1,103,283**	29.3%	$824,362	98.4%	$278,921	14.5%	$ -	-100.0%
	UET 100%	**$1,739,020**	62.8%	**$ 9,499**	0.0%	**$182,419**	139.5%	**$315,979**	143.7%	**$1,231,123**	44.3%	$936,508	125.4%	$294,615	20.9%	$ -	-100.0%
Averaging	Tesla 100%	**$1,038,319**	-2.8%	**$ 9,499**	0.0%	**$ 68,168**	-10.5%	**$121,386**	-6.4%	**$ 839,265**	-1.6%	$391,320	-5.8%	$238,439	-2.2%	$209,506	8.1%
	Tesla 1000kW	**$1,038,319**	-2.8%	**$ 9,499**	0.0%	**$ 68,168**	-10.5%	**$121,386**	-6.4%	**$ 839,265**	-1.6%	$391,320	-5.8%	$238,439	-2.2%	$209,506	8.1%
	UET 100%	**$1,068,328**	0.0%	**$ 9,499**	0.0%	**$ 76,163**	0.0%	**$ 9,947**	-92.3%	**$ 852,997**	0.0%	$415,473	0.0%	$243,696	0.0%	$193,828	0.0%
Load-Shifting and Averaging	Tesla 100%	**$1,330,092**	24.5%	**$ 9,499**	0.0%	**$111,707**	46.7%	**$198,797**	53.3%	**$1,010,088**	18.4%	$641,104	54.3%	$309,251	26.9%	$ 59,733	-69.2%
	UET 100%	**$1,569,409**	46.9%	**$ 9,499**	0.0%	**$140,432**	84.4%	**$249,917**	92.7%	**$1,169,561**	37.1%	$794,378	91.2%	$357,875	46.9%	$ 17,308	-91.1%

(1) Facility Demand Charges

In contrast to the volatile demand profile, the stable demand profile did not achieve cost savings for facility demand charges across the board. The Load-Shifting and the Load-Shifting and Averaging heuristics resulted in each configuration increasing facility demand costs. The cost increases were caused by more than doubling annual maximum demand. On the other hand, the Averaging heuristic achieved cost savings in this category by decreasing annual maximum demand, as illustrated in Figure 31.

(2) Monthly Demand Charges

The Load-Shifting and the Load-Shifting and Averaging heuristics also resulted in each configuration increasing annual demand costs. The cost increases were a result of more than doubling monthly maximum demand. Again, the Averaging heuristic achieved cost savings this category as a result of reducing monthly maximum demand exhibited in Figure 31.

(3) Tiered Consumption Charges

Figure 34 shows the impact of each heuristic on the number of billing hours per billing period. Under the Load-Shifting heuristic and the Load-Shifting and Averaging heuristic, each configuration resulted in less billing hours because monthly maximum demand was higher than the status quo in these months. As a result, annual consumption costs increased for each configuration. Specifically, the costs increased due to the decrease in billing hours coupled with the increase in total consumption which meant more consumption was being charged at the higher tier rates.

However, the Averaging heuristic and each ESS configuration resulted in more billing hours for each billing period because monthly maximum demand was lower than the status quo and total monthly consumption increased every month. Annual consumption costs decreased for each configuration. Specifically, the costs decreased due to the increase in billing hours which allowed more of the consumption to be spread over the cheaper tiers, two and three.

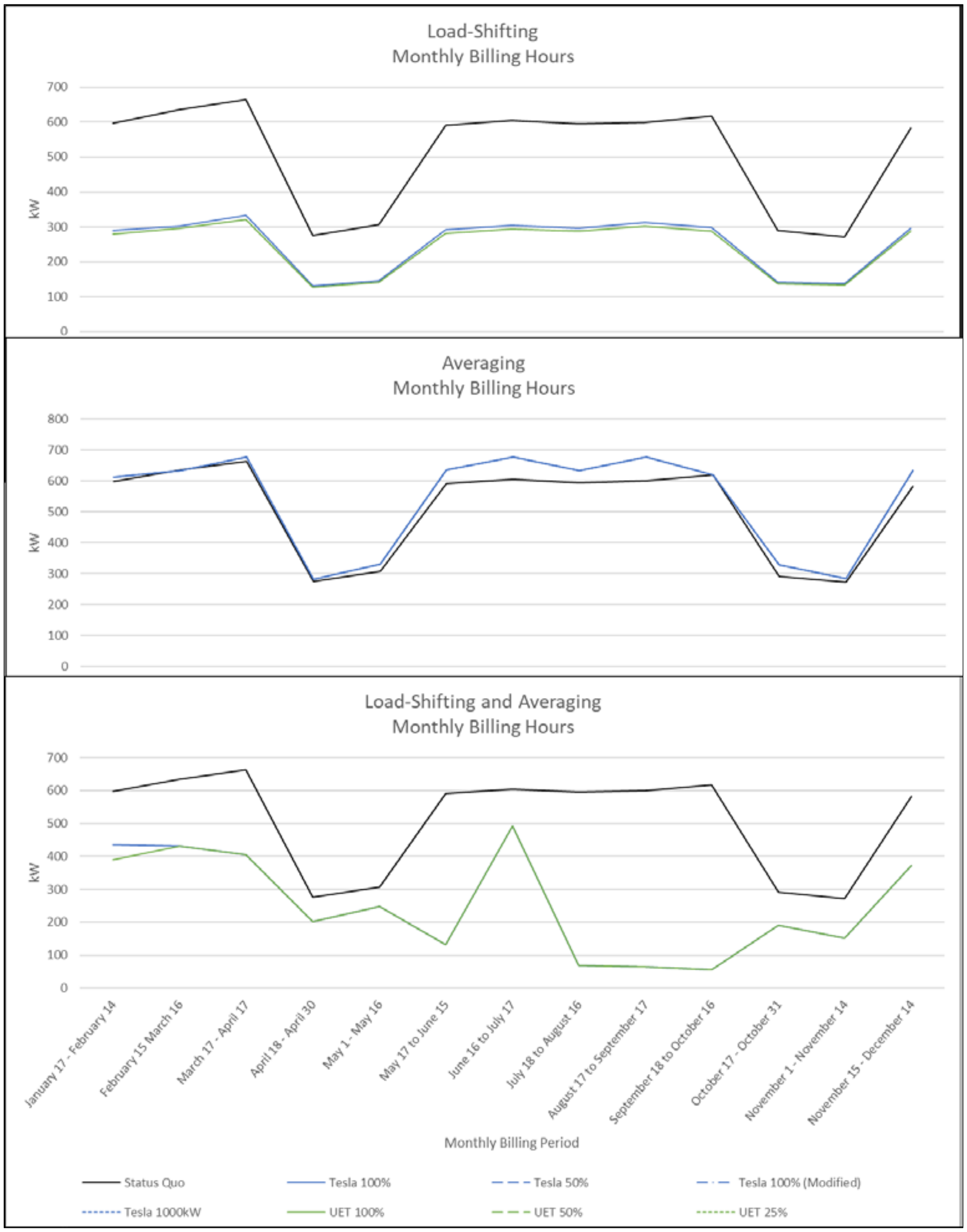

Figure 34. Stable Profile Monthly Billing Hours

(4) Customer Charges

All configurations resulted in an annual maximum demand above 1,000 kW and therefore did not achieve any cost savings in this category.

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V. CONCLUSION

There are many benefits of energy storage systems (ESSs). They include back-up power to increase resilience, the integration of renewable resources, and the ability to time shift to reduce costs. The ideal investment is to procure renewable generation assets and storage systems to eliminate the reliance and vulnerability of the commercial grid. However, such large of an investment may not be possible in fiscally constrained environments. Investing in only the renewable generation assets or the energy storage system is a potential solution. ESSs can still provide back-up power and reduce costs as stand-alone systems. However, there is a trade-off between having back-up power when needed to increase energy assurance and reducing costs. Energy or installation managers can choose whether to employ ESSs to achieve cost savings or resiliency as they desire.

This research focused on the cost reduction benefit and found that ESSs reduce overall energy costs in volatile demand environments, and can to a lesser extent in stable demand environments. Annual cost savings achieved by employing an ESS was a function of the characteristics of the ESS and the implementation of different heuristics. Chapter V summarizes how to determine the most beneficial heuristic and ESS configuration given various situations.

A. HEURISTIC DETERMINATION

The Load-Shifting and Averaging heuristic should be used when users are subject to time-of-use (TOU) energy charges. Shifting demand from more expensive billing periods to cheaper periods is the primary goal of this heuristic. For example, Pacific Gas and Electric (PG&E) charges customers based on consumption and maximum monthly demand during peak, part-peak, and off-peak time periods. Moving consumption to off-peak periods, eliminates consumption and demand charges during peak and part-peak time periods and shifts it to the cheaper, off-peak period.

The Load-Shifting heuristic follows a similar logic but does not average the shifted energy over all off-peak time periods in the month. This heuristic is beneficial when users desire to completely restore the ESS to full charge each day. This heuristic may be appropriate when reliable back-up power is necessary and/or when the operational cost of not having available stored energy is high. However, the Load-Shifting and Averaging heuristic averages the shifted consumption over all off-peak billing periods throughout the month, resulting in lower maximum demand and subsequently lower costs compared to the Load-Shifting heuristic.

The Averaging heuristic should be used when users are not subject to TOU energy charges. In these instances, demand charges can be reduced by smoothing demand and purchasing energy at constant rate. For example, the facility charge for Kansas City Power and Light (KCP&L) is a demand charge with ratchet adjustment that multiplies the maximum demand over the previous 12 months by this rate. The Averaging heuristic reduces the maximum demand the most and thus reduces the cost of the facilities charge the most. This concept also applies to monthly demand charges.

B. ENERGY STORAGE SYSTEM SELECTION

The ESS configurations utilized during this research provided several insights to potential users interested in investing in an appropriate storage system. The following sections summarize those insights.

1. Efficiency Rate

The Tesla Powerpack configurations achieved greater cost savings than the UET Uni.System because of the higher efficiency rate of the Tesla Powerpack. Higher efficiency rates require less energy to be purchased to account for efficiency loss. For example, PG&E customers would benefit from using a storage system to shift consumption from peak and part-peak periods to off-peak periods. The potential savings can be calculated given any TOU charges with equation below:

$$Savings = \left[kWh_{moved} \times Peak_{TOU\ Charge}\right] - \left[\frac{kW_{moved}}{Efficiency\ Rate} \times OffPeak_{TOU\ Charge}\right] \qquad (1.21)$$

Table 12 summarizes the potential savings of moving a kWh of consumption from peak an part-peak periods to off-peak. Tesla Powerpack’s 88% efficiency rate produces savings by moving demand from any peak and part-peak to off-peak periods. However, UET Uni.System's 70% efficiency rate actually costs money to move from part-peak to off-peak periods.

Table 12. PG&E Savings per kWh

ESS	Efficiency	Savings per kWh
Tesla PowerPack	88%	$.05233/kWh moving from Peak to Off Peak, Summer
		$.01395/kWh moving from Part-Peak to Off Peak, Summer
		$.00185136/kWh moving from Part-Peak to Off Peak, Winter
UET Uni.System	70%	$.029364/kWh moving from Peak to Off Peak, Summer
		-$.01395/kWh moving from Part-Peak to Off Peak, Summer
		-$.02290/kWh moving from Part-Peak to Off Peak, Winter

Table 13 summarizes the required efficiency rates to achieve zero additional cost and zero savings per kWh. These values were calculated by setting the equation 1.21 equal to zero and solving for the efficiency rate. The solution is termed the 'savings indifference efficiency rate.' The savings indifference rates for the PG&E rate structure are 76% and 86% in part-peak to off-peak summer and winter respectively. Therefore, it does not make sense to load shift from part-peak to off-peak during summer or winter with the UET Uni.System because it is only 70% efficient.

Table 13. PG&E Savings Indifference Efficiency Rates

Savings Indifference Efficiency Rate	Load Shifting
55%	Peak to Off Peak, Summer
76%	Part-Peak to Off Peak, Summer
86%	Part-Peak to Off Peak, Winter

Nonetheless, total cost savings can still be achieved with a 70% efficient system because other charges such as demand charges offset the increase in consumption costs. The key take-away is that a utility rate structure can be used to determine the required efficiency rate to generate cost savings.

2. Maximum Discharge Power

The demand profile will also influence the decision of which ESS to employ. For example, the volatile demand profile required an ESS with a maximum discharge power large enough to service the largest spike in energy demand, which was 1,655 kW. All the ESS configurations required 1,655 kW of discharge power to effectively shave the demand spikes. On the other hand, with the stable demand profile, heuristics were not limited by the maximum discharge power of the ESSs.

3. Capacity

The maximum capacity of the ESS can be a limitation. However, the researchers also found that capacity limitations can be mitigated with the application of a safety stock. Demand profiles will also require different capacities. The stable demand profile was influenced more by the capacity of the ESS. For example, under the PG&E rate structure, the stable demand profile required the use of the Tesla Powerpack 100% configuration with the addition of a 25% safety stock to provide enough stored energy to cover peak and part-peak periods. However, rate structure is also an important factor into how much capacity is required. For example, with the KCP&L rate structure, a 1000 kW ESS provided sufficient enough energy to reduce costs with the Averaging heuristic.

C. APPLICATION OF DETERMINATION CRITERIA:

Using the decision criteria outlined in the previous section, potential users can define the required characteristics required of an ESS and determine which heuristic will provide the greatest cost savings. For example, the researchers would recommend the following for the LabRec area at the Naval Postgraduate School:

- An ESS with at least 1,655 kW of maximum discharge power
- An ESS that has at least 86% round-trip efficiency and
- The use of the Load Shifting and Averaging heuristic.

D. RESEARCH QUESTIONS SUMMARY

This research was guided by the following question:

1. How can ESSs reduce energy costs in DoD installations?

ESSs can reduce utility costs by peak shaving and time-shifting consumption to purchase energy when it is cheapest. Tables 8 and 9 display the cost savings achieved with a volatile demand profile and tables 10 and 11 show the savings achieved with a stable demand profile.

To answer this, the research incorporated the following additional questions to enrich understanding:

2. How are other industries incorporating alternative energy storage technologies to reduce overall energy costs? How can the DoD adopt such practices?

Many industries are incorporating energy storage solutions to reduce their overall energy costs. For example, Tesla's Powerpack was implemented by Advanced Microgrid Solutions, Target, Jackson Family Wines, Vector, and PowerSmart solar ("Tesla Powerpack," n.d.). Additionally, Tesla supplied a 52 MWh BESS to SolarCity in their project to meet the peak demand on the Hawaiian island Kauai (Kelley, 2016). Similarly, The Uni.System was implemented at a Bronx hospital in October 2017 to help reduce costs and improve resiliency (UniEnergy Technologies, n.d.-a). The research analyzed two installation energy demand case studies that demonstrated the cost savings potential of ESSs for DoD installations. ESSs can also increase resiliency of DoD installations, but this research limited the analysis to the cost savings benefits of ESSs.

3. How do characteristics of ESSs impact cost savings?

The efficiency, capacity and maximum discharge power of a given ESS all impact the cost savings possible. Section V.B discusses how each of these characteristics impacted cost savings.

4. How does volatility in energy demand profiles influence the ESS required?

Volatile demand profiles require greater maximum discharge power to effectively shave the spikes in demand. Stable demand profiles can reduce maximum demand with much smaller ESSs.

5. How do rate structures influence how ESSs are employed?

Demand charges are a common charge utilities companies apply to the maximum 15-minute interval demand in billing period. These demand charges amount to a large portion of the overall utility bill. Reducing maximum demand by employing the ESS to peak-shave demand can result in significant cost savings.

Customers with rate structures that apply time-of-use charges can also benefit from time-shifting consumption to purchase energy when it is cheapest.

6. What energy storage heuristics can be applied to the energy demand data to determine how and when to move energy to and from storage to estimate cost savings?

The researchers developed three heuristics that determine how and when to move energy to and from storage. The rate structure determines which heuristic should be applied to a given demand profile. Section V.A summarizes how to choose which heuristic to use.

E. RECOMMENDATIONS FOR FUTURE RESEARCH

The researchers recommend the following future research:

- A study to apply ESSs in a tactical environment. For example, a study analyzing the deployment of batteries with generators to capture excess energy and reduce the number of hours the generator runs and the amount of fuel consumed.

- A study to analyze the impact of renewable energy on utility bills with each heuristic. The research could determine what size energy storage system and how much renewable energy generation would be necessary to eliminate reliance on the energy grid for a given demand profile and renewable generation profile.

- A complete cost benefit analysis of various ESSs given the cost savings demonstrated in this study.

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