FINAL REPORT

Comprehensive Microgrid Energy Storage Designs with Guaranteed Optimality

ESTCP Project EW19-5054

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ACRONYMS AND ABBREVIATIONS

AFMC	Air Force Materiel Command
CMES	Comprehensive Microgrid Energy Storage solution
CDF	Cumulative Density Function
DAM	Day Ahead Market
DoD	U.S. Department of Defense
DOD	Depth Of Discharge
ESS	Energy Storage System
FY	Fiscal Year
IRR	Internal Rate of Return
LCC	Life Cycle Costs
LMP	Locational Marginal Price
MG	Microgrid
NPV	Net Present Value
NTV	Non-Tactical Vehicles
PDF	Probability Density Function
SOC	State of Charge
TDSP	Transmission and Distribution Service Provider
ToU	Time of Usage
UEP	Urban Electric Power

ABSTRACT

Improving reliability of a microgrid (MG) by incorporating Battery Energy Storage (BES)can be a cost-effective solution, hence, it should be properly assessed. A Comprehensive Microgrid Energy Storage (CMES) solution that improves both reliability and cost performance of a MG is proposed in this report. The solution is implemented in a test MG system and the corresponding reliability, cost analysis results and potential electricity market participation of BES are presented. The results show the effectiveness of CMES solution for microgrid applications.

EXECUTIVE SUMMARY

Siemens and Urban Electric Power (UEP) have developed a comprehensive microgrid energy storage solution (CMES) that addresses both reliability and cost performance of a microgrid. The key benefits of the solution are through offline and online optimization modules:

i) offline optimizer to **estimate most optimal storage size** that best meets the site requirements while **minimizing lifecycle costs** (LCC) of the storage and maximizing system reliability.
ii) online optimizer that generates **optimal battery operation actions** once storage has been included in the site and market participation mechanisms have been determined.

Our CMES solution consists of an optimization and control software, UEP battery, commercial-off-the-shelf inverter and control hardware, as described below.

Battery: We plan to use low-cost zinc manganese oxide $ZnMnO_2$ rechargeable batteries manufactured by UEP (1). A comprehensive battery degradation model was developed using experimental results provided by UEP. UEP batteries can provide 20 to 50 deep cycles when discharged to 60%-100% depth of discharge (DOD) (Resilience mode), and 300-1000 cycles when operated DOD < 40% (Economic Operation mode).

Inverter: For a given battery size, a commercial-off-the-shelf inverter will be used.

Storage Control Box (SCB): a Siemens industrial rack PC SIMATIC IPC847D would house the optimization and control software. This box would be located near the energy storage and would be interfaced with the inverter through Modbus communication protocol. The box can also support TCP/IP and OPC communication protocols.

Optimization software: The optimization software consists of two main modules:

Offline Optimizer: Figure 2 shows the high-level approach for the offline optimizer developed in Phase 1 of the project.

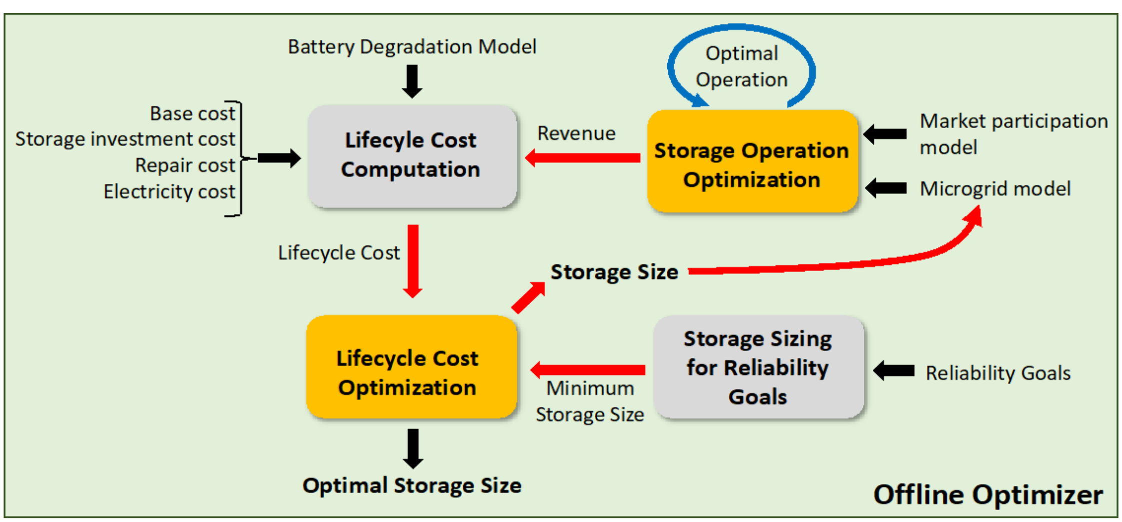


Figure 2. Approach for Offline Optimizer

First, the minimum storage size that meet the reliability goals and requirements is computed. This size serves as a lower bound on the storage size variable used in the lifecycle cost optimization process. Then, for a given storage size, consisting of battery and inverter sizes, the storage operation optimization module determines the optimal operation of storage and other generation sources such that revenue earned through market participation is maximized while meeting all the operating constraints and load requirements of the site. Lifecycle cost is computed based on the determined revenue, optimal operation of storage and generation sources, and storage size. Final output of the offline optimization module is the storage size, including - number of battery cells, inverter size, and topology for each battery size, for the MG site (with the MG being modeled with a determined location of the storage) that meets the reliability goals and minimizes the lifecycle cost.

Online Optimizer: This module was proposed to be developed in Phase 2, which was not awarded. This module determines the optimal operation of the storage to minimize LCC. Figure shows the approach for Online Optimizer. The Online Optimizer works in two modes:

Grid tied operation: In grid-tied operation, battery operation has to be optimized in real-time. Unlike the offline optimization, where the load condition is known, optimization in real-time has to predict load conditions. In Figure 6, we show a moving horizon based online optimization method, whereby prediction of load distribution is fed into a stochastic optimization framework for making optimal operation decisions under uncertainty. We will leverage our prior work (1) for this online operation. In this prior work, the team developed an online optimization approach and demonstrated how battery electrical storage could be used synergistically in conjunction with a commercial building's other demand response capabilities, namely curtailment and load shifting. We will adapt and integrate this mature tool in our CMES solution.

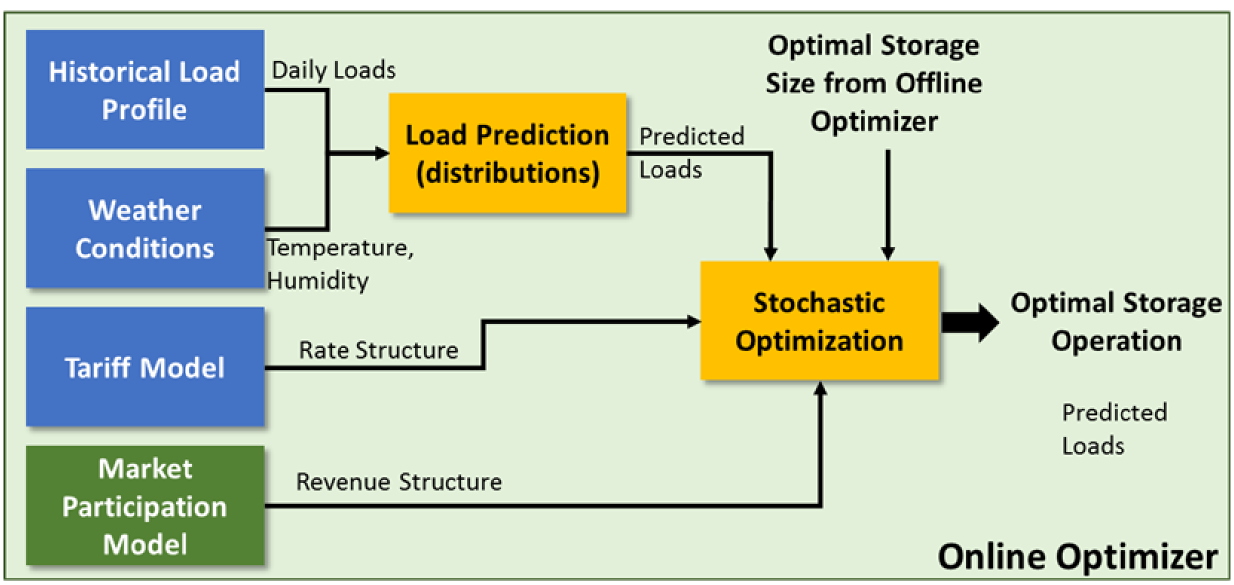


Figure 6. Approach for Online Optimization

Islanded operation: In islanded operation mode, the online optimizer would work the same way except that market participation will not be considered and the available resources are only used to serve active loads.

MG model/system: Information about the topology of the site is required to model the MG system, including the storage model. The model will be utilized to simulate various operational scenarios of the storage and other MG components and participation of the MG in market programs.

Reliability computation: The reliability model evaluates the survival rate of sites under a specific combination of infrastructures (generator, battery, UPS, etc.). The analysis becomes input to the lifecycle analysis.

Lifecycle computation: The LCC model takes into account all possible costs, including storage investment, O&M and repair of various assets in the MG, tariff, and other operational costs. It also includes revenue earned through any market participation activities.

In Phase 1 of the project, the offline module was used to optimally size UEP's batteries and commercial off-the-shelf inverters for five sites – NAS Corpus Christi, March ARB, Holloman AFB, Fort Bliss and NAS Patuxent River. In a first step, the offline optimizer was used to determine minimum battery and inverter sizes required to maintain close to 100% reliability requirements and serve critical load at each site (Table 6). Efficient operation of the UEP battery was considered between 100% and 60% depth of discharge. We examined the survival curve against different LCC and plotted out different battery size installations and their impact on survival rate.

Table 6. Minimum Battery and Inverter Size to Maintain Close to 100% Reliability Requirements

Site	100% Reliability	
	Battery Size (kWh)	Battery Power/Inverter Size (kW)
Fort Bliss	1992.3	164.4
Holloman AFB	2180.2	197.4
March ARB	118.3	5.6
NAS Corpus Christi	912.7	110.1
NAS Patuxent River	2541.7	258.4

In a second step, the minimum battery and inverter sizes identified in Table were used in the offline optimizer to determine the optimal operation of storage and other generation sources such that revenue earned through market participation is maximized while meeting all the operating constraints and load requirements of the site. The results of LCC analysis across the different sites are shown in Table 2. Expenses considered here were battery and inverter installation costs, annual electricity bill for each site, and battery degradation cost. Savings are primarily obtained through reduction of the peak demand electricity bill when the battery is in operation. In 4 out of 5 sites, net present value (NPV) of net savings is positive. In three sites, the number of years needed to break even and recover investment cost ranges between 2-6 years. For the March ARB and Fort Bliss sites, the investment recovery period is 10 and 20 years respectively.

This is due to their respective tariff structure. Both sites are charged a fixed rate for minimum demand, even when actual consumption is lower than minimum demand. This reduces possible savings from battery operation by a large amount. Finally, further savings from possible market participation (e.g., 1-day ahead market and/or ancillary market) were also evaluated for the resultant optimally sized battery-inverter combinations. Summarize findings are given below in Table 8.

Table 8. Estimated Annual Costs and LCC Analysis for 20-year Lifetime

	NAS Corpus Christi	**NAS Patuxent River**	**Holloman AFB**	**March ARB**	**Fort Bliss**
Annual electricity bill before optimization	$7,127,185	$17,749,463	$ 6,066,698	$ 4,353,485	$ 20,749,629
Battery size after optimization (kWh)	1600	4500	4000	1000	3500
Battery power/Inverter size after optimization (kW)	600	600	600	300	1000
Battery & inverter installation cost	$140,000	$285,000	$260,000	$80,000	$275,000
Annual battery degradation cost	$3,575	$7,967	$11,491	$4,669	$5,247
Est. Annual electricity bill after optimization	$7,051,996	$17,682,167	$5,952,039	$4,328,007	$20,731,143
Est. Annual savings with accounting for battery degradation	$71,614	$59,329	$103,167	$20,807	$13,239
Internal Rate of Return	44%	20%	39%	26%	0%
NPV of savings over 20 years	**$843,204**	**$529,540**	**$1,156,403**	**$205,663**	**-$93,234**
Years to recover investment	3	6	2	13	> 20 years

1.0 INTRODUCTION

Siemens and Urban Electric Power have developed a comprehensive microgrid energy storage solution that addresses both reliability and cost performance of a microgrid. The developed solution was tested with data from five sites – NAS Corpus Christi, March ARB, Holloman AFB, Fort Bliss and NAS Patuxent River. This report describes the results from the reliability and life cycle cost analyses performed for those sites.

1.1 BACKGROUND

In recent years, the United States Department of Defense (DoD) has focused increasingly on the ways in which energy affects its operations and the opportunities to improve its performance through the development and adoption of innovative energy technologies and practices (2). The American Recovery and Reinvestment Act of 2009 required federal agencies to set reduction targets for greenhouse gas emissions and achieve them by FY 2020. Percentage reductions were to be considered across several contributing factors such as energy intensity in buildings, increasing use of renewable energy, and/or reduction in the use of fossil fuels in vehicles. Approximately eighty percent of total Federal energy consumption was attributed to the DoD operational and installation energy consumption, more than sixteen times the total energy consumption of the next closest Federal agency, the United States Postal Service (3). In fiscal year 2018, DoD spent approximately $91 million to supply fuel to the fleet of NTVs and $3.49 billion on installation energy, which included $3.40 billion to power, heat, and cool buildings (4).

Commercial power supplies carry a risk associated with a variety of events ranging from physical and cyber-attacks on infrastructure to natural hazards. Increasing power outages have pressed DOD to focus on increasing resilience. In FY 2018, DoD Components reported a decrease in the number of events related to utility outages from 1,205 in FY 2017 to 562. These utility outages lasted eight hours or longer and were due for the majority (88%) to electrical disruptions. Of the 562 reported outage events lasting longer than eight hours, the services provided financial impacts for 223 of them (4). The combined length of outages was 1,695 days. The estimated financial impact was $23,342,102 or $13,771 per outage day. However, from a financial perspective, AFMC reported the most substantial costs at about $4.75 million ($338,708/electrical incident). Overall, the Air Force had a financial impact of $5.36 million ($22,213/all incidents) or, when factoring out AFMC electrical outages, $614,710 ($2,732/all incidents) (5).

A variety of technical solutions such as microgrid and distributed power generation and energy storage, have the potential to promote energy resilience in the form of energy generation and infrastructure hardening for DoD missions on fixed installations. Title 10 U.S.C. section 2911(g) established a goal for DoD to produce or procure not less than fifteen percent by FY 2018, and twenty percent of the total quantity of facility energy it consumes within its facilities by FY 2025 and each FY thereafter from renewable energy sources. DoD progress toward the title 10 U.S.C. section 2911(g) renewable energy goal in FY 2018 was 15.76%.

The Energy Policy Act of 2005 goal considers total renewable electricity consumption as a percentage of total facility electricity consumption, with the goal of 7.5% by 2013 and every FY thereafter. Renewable electricity consumption subject to these requirements was 5.9% of DoD total electricity consumption, falling short of the 7.5% goal.

National Defense Authorization Act of 2010, section 2842, beginning in 2025, DoD should produce or procure 25 percent of its total facility energy use from renewable sources (6).

1.2 OBJECTIVE OF THE DEMONSTRATION

Objective of Phase 1 of this project is to develop methods for optimal design and operation of a novel low-cost zinc manganese oxide $ZnMnO_2$ rechargeable battery by minimizing life-cycle costs and maximizing microgrid reliability. The developed methods were tested with data from five sites – NAS Corpus Christi, March ARB, Holloman AFB, Fort Bliss and NAS Patuxent River. We consider stochastic factors, such as weather, load, tariff, etc., and optimize energy storage design parameters for the maximum economic benefits in the 20-year term using a multi-level optimization approach.

1.3 REGULATORY AND MARKET DRIVERS

The increasing penetration of renewable energy sources, power consumption and electrification of the transportation sector have created opportunities to deploy various energy storage solutions to help deal with high levels of variable renewable energy inflow. In 2018, the United States had more than 25 gigawatts of electrical energy storage capacity, of which ninety four percent was in the form of pumped hydroelectric storage, and six percent was in the form of battery, thermal storage, compressed air, and flywheel (7). Several nation-wide and state-specific regulatory and market drivers have facilitated the uptake of utility-scale energy storage solutions as well as residential / behind-the-meter installations.

Several U.S. states have taken a keen interest in energy storage installations, and their policies can serve as inspiration for others (8).

- **Hawaii** has been at the forefront of the transition to renewables and energy storage since importing fossil fuels is very costly. Two recent Hawaiian Electric Industries projects come in at 8 cents per kilowatt-hour, half as much as the price for fossil fuel generation in the state.
- **Massachusetts** had set a goal for 1,000 MWh of energy storage by the end of 2025 by passing the H.4857 in July of 2018.
- **New York** had set a goal of reaching 1,500 MW's worth of energy storage by 2025. Under this directive, New York Green Bank has agreed to invest $200 million towards energy storage technologies.
- **California's** three largest electric cooperatives have been mandated to develop a combined energy storage capacity of 1,825 MW by the end of 2024.

- **Oregon** passed HB 2193 which mandates 5 MWh of energy storage integrated into the grid by 2020.
- **New Jersey** passed A3723 in 2018 that sets New Jersey's energy storage target at 2,000 MW by 2030.
- **Arizona** has proposed a target of 3,000 MW in energy storage by 2030

The participation of electric storage resources in the capacity, energy and ancillary services markets operated by Regional Transmission Organizations and Independent System Operators has become easier since the Federal Energy Regulatory Commission (FERC) removed several barriers. FERC'S order No. 841 issued in 2018 (9), directs all Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) in the US to propose updates to their pricing schemes and develop new strategies to incorporate all storage technologies interconnected to the transmission system, distribution system, or behind-the-meter on a nondiscriminatory basis in their wholesale energy, capacity and ancillary services markets. Storage resources that are currently participating in demand-response programs can continue doing so under the new rule.

Order 841 mandates that:

- Wholesale market participation for storage should be able to recover costs through both cost-based and market-based rates.
- The physical and operational characteristics of different storage technologies should be considered in the proposed bidding parameters.
- General pricing rules for energy resources are applied to storage. Storage would participate both as wholesale buyers and wholesale sellers, and should be able to set the wholesale market clearing price. The buying and selling prices of energy storage should be the locational marginal price, or the price specific to a given location.
- The minimum required size must not exceed 100 kW to participate in the wholesale market.

Order 841 broadly directs grid operators to create market mechanisms that accommodate batteries' unique abilities to both charge and discharge from the grid and ramp up and down at speeds that traditional generators can't match.

Payment allocations and federal-state coordination between different jurisdictions and interconnection levels will be a major challenge for energy storage participation in the grid. While interstate transmission is under Federal regulation, the distribution system is under States regulation. Because of its multiple applications, energy storage can participate at transmission or distribution levels. Market manipulation and unclear pricing schemes are the two concerns raised by this new FERC rule. The Transmission Access Policy Study Group (TAPS) has proposed that distributed-connected storage resources should be required to bid exclusively in one market, either wholesale or retail. TAPS is concerned that market manipulation can occur if a distributed storage service purchases energy from one market and then discharges it in another market. This is due to the difficulty in verifying the source of any particular amount of energy discharging to the grid.

Before the FERC Order, several ISO/RTOs had implemented rules for energy storage to participate in the markets, but only for a limited number of energy or ancillary services and as a new category of resources separate from generation. Minimum capacity requirements varied from 100 kW to 5 MW. With FERC's order 841, mandating that minimum capacity requirement for storage to participate in wholesale markets be no higher than 100 kW, grid operators expressed concerns about the influx of small energy storage operators in the wholesale market. They allege that energy storage resources of 100 kW in capacity are difficult to manage due to their small size and limitations to current software. Midcontinent Independent System Operator (MISO) has commented that this new threshold would require extensive software reprogramming.

2.0 TECHNOLOGY DESCRIPTION

2.1 TECHNOLOGY OVERVIEW

Siemens and Urban Electric Power have developed a comprehensive microgrid energy storage solution (CMES) that addresses both reliability and cost performance of a microgrid. The CMES solution consists of optimization and control software, battery, inverter and control hardware, as described below.

a) Components and System

Battery**:** UEP developed low-cost, non-toxic, low maintenance $ZnMnO_2$ batteries, which can be used for thousands of cycles at a moderate depth of discharge (equivalent to 70Wh/L) to manage energy and peak load in the microgrid, more than 1500 cycles for normal discharge, and 50-100 cycles at very deep discharge (equivalent to 400Wh/L) to respond to occasional emergency situations. The technology is based on the alkaline rechargeable $ZnMnO_2$ chemistry. Since the battery is solid with no toxic chemical, it is maintenance free and has no fire safety hazard (Li-ion batteries have fire and exploration risks).

UEP battery characteristic curve is shown in Figure 1. The x-axis is Depth of Discharge (DOD), the y-axis is number of cycles at 100% capacity (no fade). The curve indicates that the cycle number is a function of the depth of the discharge.

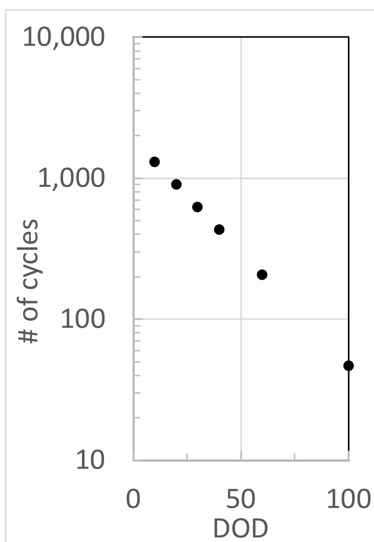


Figure 1. UEP Battery Cells.

The area in the top right is for normal operations and the area in the bottom right is for emergency situations.

A comprehensive battery degradation model was developed using experimental results. System performance will be tested in two operational modes: revenue and resilience. UEP batteries can provide 50 deep cycles when discharged to 100% DOD (Resilience mode), and 300-1000 cycles when operated at a depth of discharge (DOD) < 40% (Operation mode).

***Inverter*:** For a given battery size, a commercial-off-the-shelf (grid-tied or UPS) inverter designed for Li-ion or Lead-Acid batteries can be used. The average cost of a large commercial invert (grid-tied or UPS) is of about $0.10-$0.15/W. For the analysis, the low bound ($100/kW) has been considered. The cost of installations is based on space and AC connections being available.

***Storage Control Box (SCB)*:** We will utilize Siemens industrial rack PC SIMATIC IPC847D which will house the optimization and control software. This box will be located near the storage and will be interfaced with the inverter through Modbus communication protocol. The box can also support TCP/IP and OPC communication protocols.

***Optimization software*:** The optimization software consists of two main modules:

Offline Optimizer: Figure 2 shows the high-level approach for the offline optimizer. Final output of the offline optimization module will be the storage size for the MG site including - number of battery cells, inverter size, and topology for each battery size. MG site is modeled with a determined location of storage. The minimum storage size is determined in Reliability mode to increase resilience of the electric system by assuming that 50 cycles (100% DOD) are adequate. For a given storage size, consisting of battery and inverter sizes, the storage optimization module determines the optimal operation of storage and other generation sources such that lifecycle cost of the microgrid is minimized while meeting all the operating constraints and load requirements of the site. Lifecycle cost is computed based on the revenue earned through market participation, optimal operation of storage and generation sources, and storage size. Reliability metrics are also computed for a given storage size. Then the LCC optimization module optimizes the reliability metrics and LCC by varying the storage (battery and inverter) size. A battery degradation model is used to determine the degradation of the battery to ensure that the battery can respond to outage events. The various modes of operation of the Optimizer are described below.

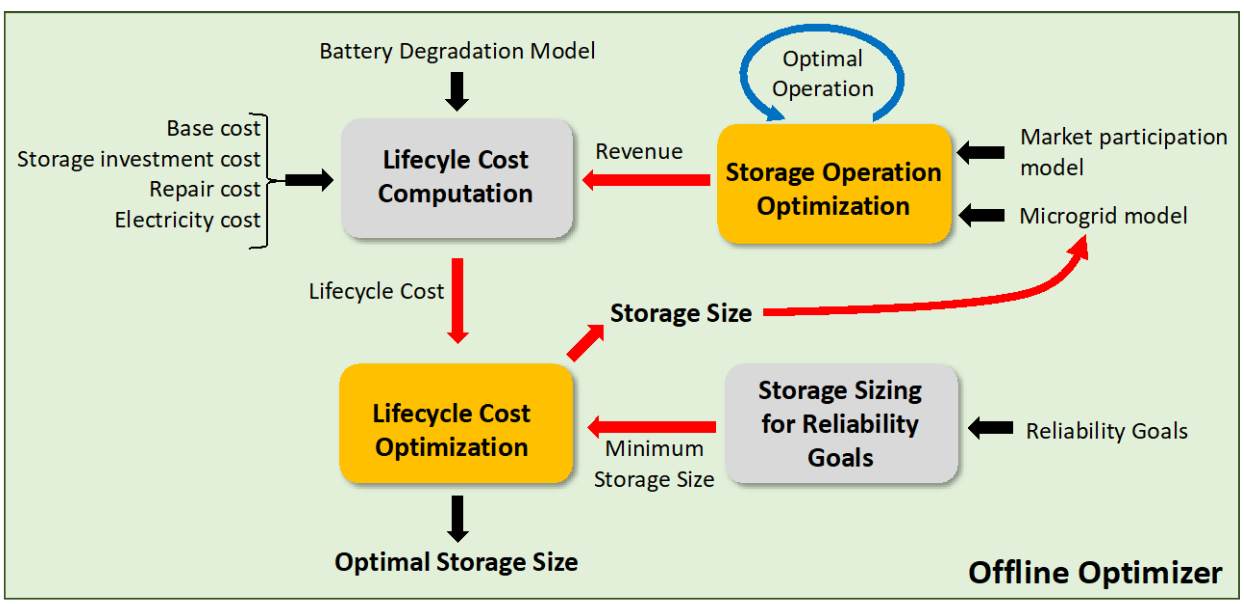


Figure 2. Approach for Offline Optimizer.

<u>*Online Optimizer:*</u> This module determines the optimal operation of the storage to minimize LCC. Details of this module are given in next section.

<u>MG model/system</u>: Information about the topology of the site is required to model the MG system, including the storage model. The model will be utilized to simulate various operational scenarios of the storage and other MG components and participation of the MG in market programs.

<u>Tariff Model / Economic Model:</u> In order to participate the energy market, we need to capture the utility tariff in analytical models. The term tariff in this proposal refers to the *energy bill* charging policies by utility companies. In order to analyze the economic impacts for different market participation strategies, we need to build analytical tariff models for the convex optimization process. We will start building tariff model from text in energy contracts, including energy price, demand charge, demand response incentives, etc. For example, we built New York Small Commercial type 9 (SC9) tariff model to the form in 3, where we employ a set of lines to capture the tariff method. The left chart in Figure 3 shows Time of Usage (ToU) energy price, similar to the TOU-8 tariff for the Ford Bliss base and March Air Reserve base, etc. The right chart in Figure 3 is the SC9 monthly peak demand charge, i.e., use monthly peak power (kW) multiply a charge rate. This notion is similar to the "peak demand charges" found in Transmission and Distribution Service Provider (TDSP) schedule found in Naval Air Station Corpus Christi base, Ford Bliss base, Holloman Air Force base, March Air Reserve base, and Westover Air Reserve base, etc.

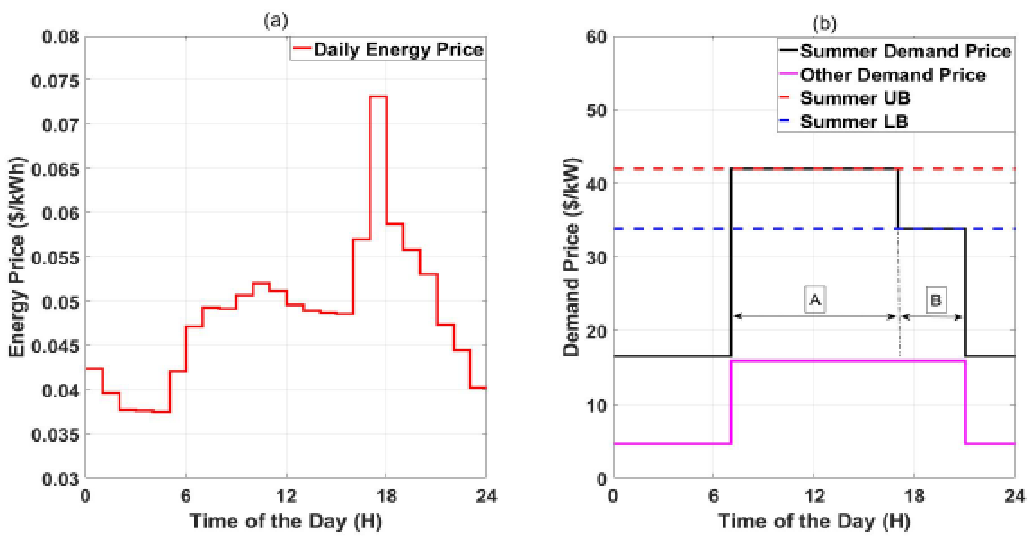


Figure 3. Simplified SC9 Tariff Models.

(left) TOU energy price. (right) demand price.

<u>Weather and load model:</u> In order to derive the coverage probability curves, we need to convert the raw weather data and load data to probability models. One example of our previous work (1) is shown in Figure 4, where we convert raw weather and load data to daily peaks. For New York commercial buildings, we conclude from the plot (B) that we can only use batteries at 5 peak days per month, while most existing works use batteries much more often and introduce necessary battery degradation costs. We will analyze the raw data from the 5 DoD sites and compute the *number of peak days,* in order to minimize battery degradation and maximize the economic benefit.

In plot (C), we calculate probability density function (PDF) and cumulative density function (CDF) of the load with a confidence interval. The runtime charge or discharge decisions for batteries depend on these probabilistic models. They are the foundation for the final coverage probabilistic curves.

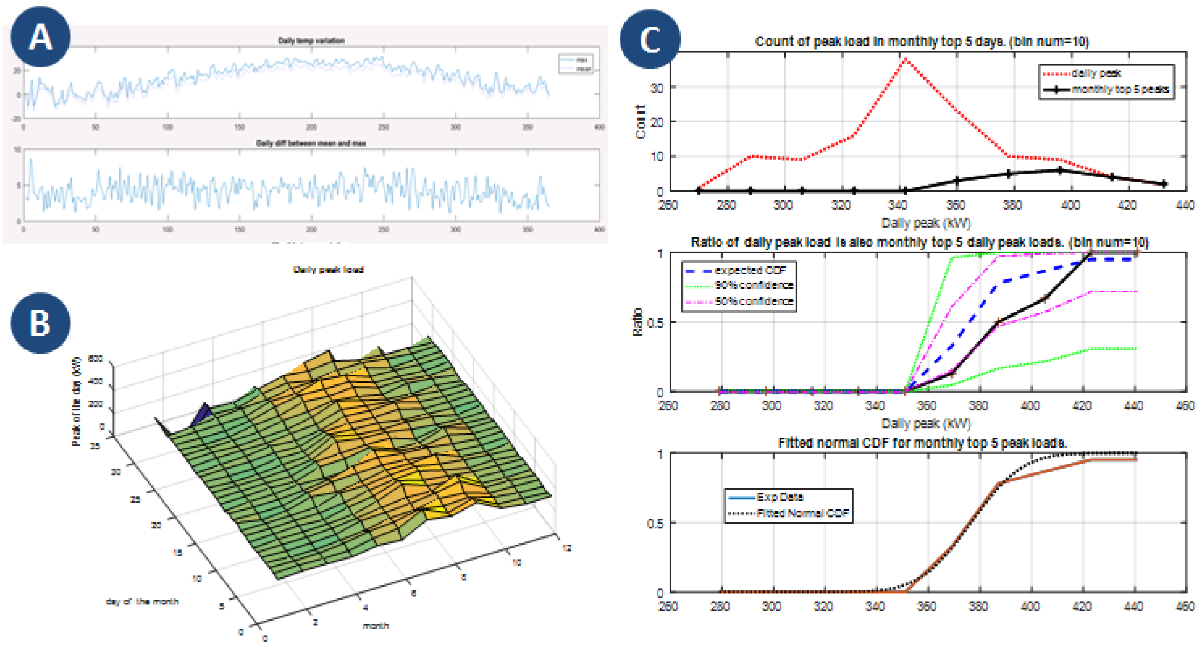


Figure 4. Weather and Load Model Reduction: (A) Raw Data (B) Daily Peaks (C) CDF and PDF.

<u>Reliability computation</u>: The reliability model evaluates the survival rate of sites under a specific combination of infrastructures (generator, battery, UPS, etc.). The analysis becomes input to the lifecycle analysis.

<u>Lifecycle computation</u>: The LCC model takes into account all possible costs, including storage investment, O&M and repair of various assets in the MG, tariff, and other operational costs. It also includes revenue earned through any market participation activities.

b) System Operation

There are two different Energy Storage System (ESS) topologies that can be used to provide power backup and participate in market programs. In one topology, displayed on the left of Figure 5, batteries are used for power backup (UPS systems) but can still be used to reduce demand by regulating the *AC in* current to the rectifier. In the other topology, displayed on the right of Figure 5, systems are grid-tied. UPS systems can only power loads connected to the inverter, but they are active at all times, including when grid power is lost. Grid-tied systems are required by UL 1741 to sense a valid frequency to operate or they will disconnect but can contribute power to all the loads on the grid.

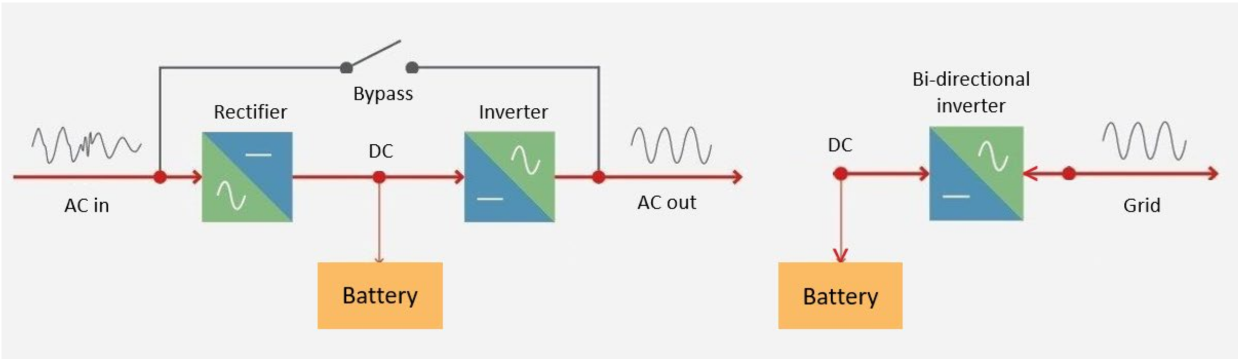


Figure 5. On the Left, the UPS Inverter Is Connected between the Grid and the Load.

The batteries are charged from the grid and directly connected to the inverter. On the right, the batteries are connected to a grid-tied bi-directional power converter.

Grid tied operation: In grid-tied operation, we face the problem of optimizing battery operation in real-time. Unlike the offline optimization in Phase 1, where the load condition is known, optimization in real-time has to predict load conditions. In Figure 6, we show a Moving Horizon based online optimization method, whereby prediction of load distribution is fed into a stochastic optimization framework for making optimal operation decisions under uncertainty. We will leverage our prior work (1) for this online operation. In this work the team has developed an online optimization approach and demonstrated how battery electrical storage could be used synergistically in conjunction with a commercial building's other demand response capabilities, namely curtailment and load shifting. We will adapt and integrate this mature tool in our CMES solution.

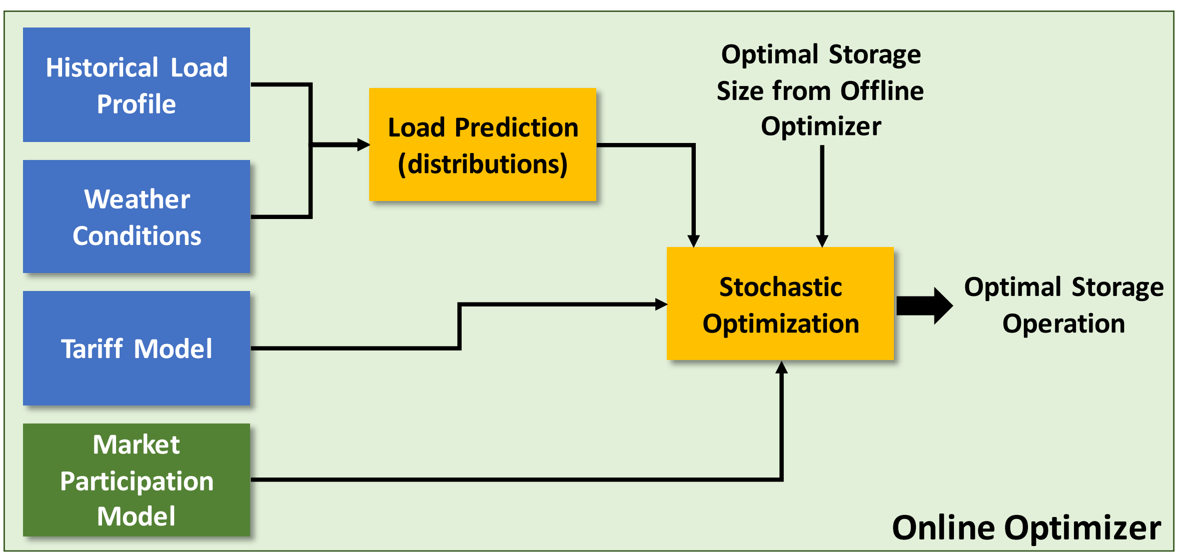


Figure 6. Approach for Online Optimization

Islanded operation: In islanded operation mode, the online optimizer would work the same way except that market participation will not be considered and the available resources are only used to serve active loads.

c) System Schematics

The schematic of Figure 7 shows the components of a microgrid as they could be deployed in any of the modeled installations. Battery systems can be tied with banks of gensets, UPS, critical loads, and non-critical loads. The Microgrid controller control sections of the load connected to the microgrid and the amount of power supplied by batteries connected to grid-tied inverters and UPS inverters. The controller has two types of switches: Type 1: Sections of the load are cut. Type 2: The amount of power provided by the battery is modulated. Sections of Critical Loads are always connected to generators, grid-tied inverters, and solar systems (CLA). The installation network may have some critical loads (CLB) at the end of a feeder that includes large non-critical loads. In this case, UPS inverters are used to ensure that critical loads like CLB are served even if non-critical sections of the load need to be disconnected. The battery labeled Starter Battery, is always present to provide a frequency for the microgrid if the generators all fail. Such frequency allows grid-tied inverters and solar panels to still produce power.

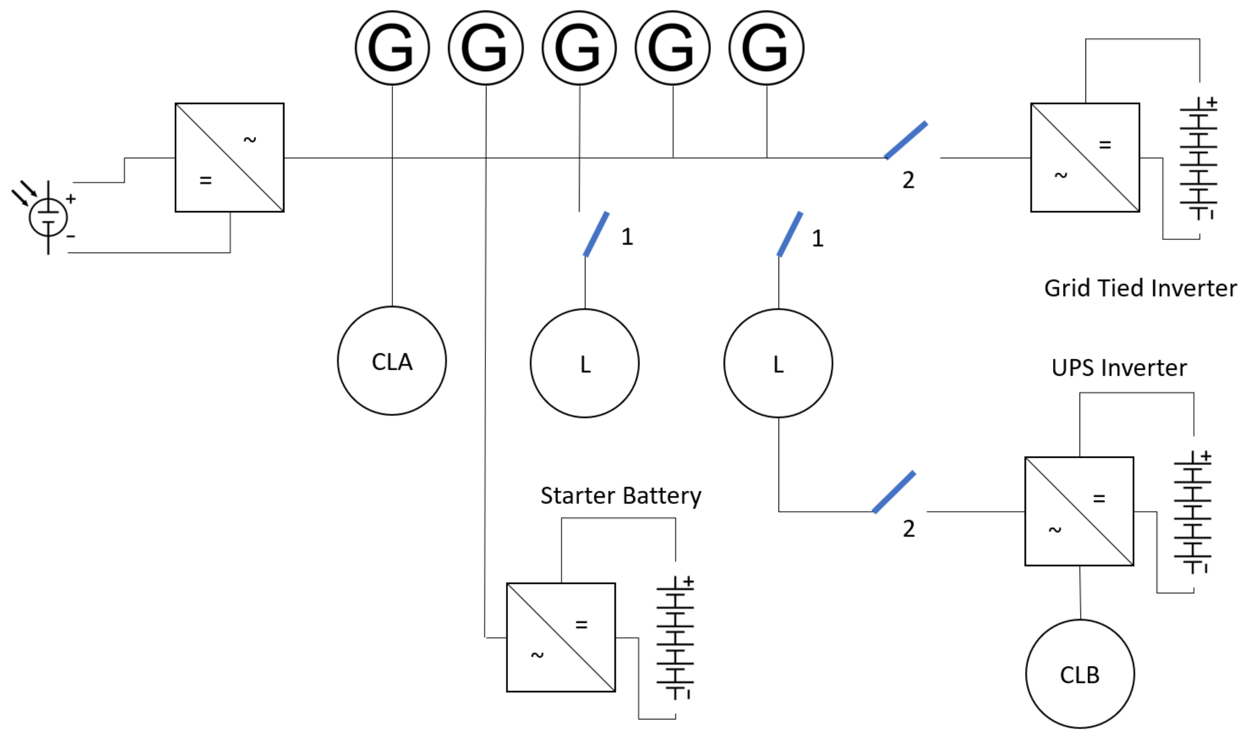


Figure 7. Schematics of the Typical Integration of Solar and Batteries in an Installation.

2.2 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY

Some of the advantages of the technologies that we are using are:

- The UEP battery packs can operate in a temperature range of 0ºC to 50ºC and therefore do not require dedicated temperature control.
- The UEP batteries do not require cell balancing as they can charge efficiently in a wide voltage range. Li-ion batteries need to be precisely charged with a Constant Current (CC), Constant Voltage (CV) profile that requires detailed cell voltage balancing and monitoring. The UEP cells can be charged in a voltage range from 1.67V to 2V and at a current of 2A to 10A.
- The UEP batteries can be charged in 4 hours while lead acid batteries need 12+ hours to charge. In case of emergency, if only solar and batteries are available, the UEP batteries can be fully recharged during a typical solar day. Lead Acid batteries can only be charged up to 50% during a solar day. Therefore, the cost of delivered lead acid capacity in these emergency situations double (because only half of the capacity can be used).
- Li-ion batteries can be used for market-driven applications as their cost at-scale is projected to be about $100-$150/kWh. Li-ion batteries require thermal control and cell-level battery management system that end up decreasing the discharge capacity and increase the cost of the system. In extreme cases of blackouts in very hot weather -- a situation not uncommon in states like California, the Li-ion cells can get permanently damaged when they are completely discharged, and no power is available for air conditioning units.
- In Figure 8 and Figure 9, we report a comparison for lead-acid, Li-ion, and $ZnMnO_2$ batteries for backup applications in datacenters. The data is for a 6-minute, 30-minute, and 1-hour discharge (duration typical of datacenter). The UEP batteries take about the same space of Li-ion batteries for < ½ of the cost for durations longer than 30 minutes.

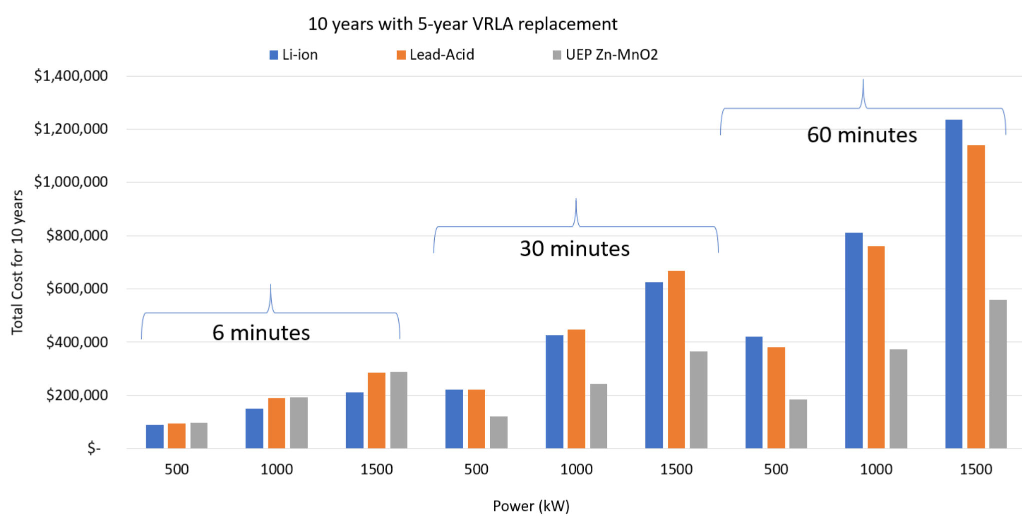


Figure 8. The Cost of the UEP Batteries is Comparable to the Cost of Li-ion and Lead-Acid Batteries for a 6-minute Discharge.

The cost of the UEP batteries is about ½ the cost of Li-ion and Lead-Acid batteries for 30-minutes and 60-minutes discharges

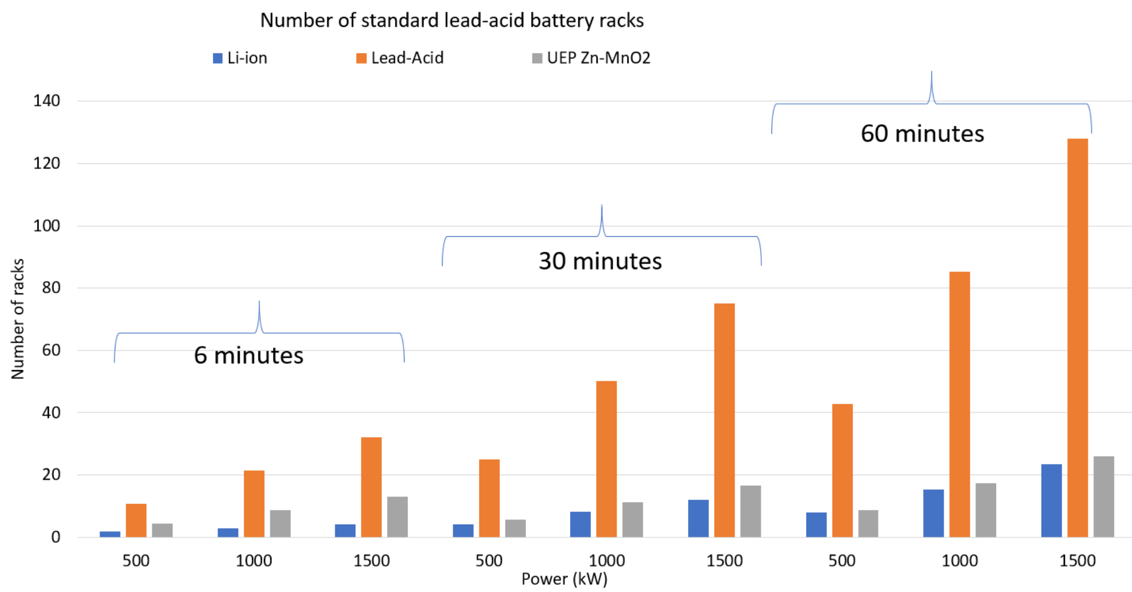


Figure 9. The Space Needed by the UEP Batteries Is 2x the Space Required by Li-ion Batteries and ½ the Space Required by Lead-Acid Batteries for a 6-minute Discharge and Is About the Same of Li-ion for 30-minute or 1-hour Discharge

Some of the limitations of the technologies that we are using are:

- The online optimization module is dependent on prediction weather and electrical load. As such, if the electrical load is incorrectly estimated then storage operation will be sub-optimal.

2.3 RISKS ASSOCIATED WITH THE TECHNOLOGY

The UEP $ZnMnO_2$ batteries are currently being produced in Pearl River, New York and have been installed in commercial and large residential sites to provide power backup. UEP has recently been awarded a contract to supply a 1MW/4MWh system to a large data center in California. UEP has been supplying a power backup solution to commercial and residential customers since 2018. The modular unit is designed to provide up to 16kW of power for up to 48 hours (800kWh). The Technology Readiness Level (TRL) for the CMES energy storage sizing tool is 4-6.

The battery cells use most of the same components of primary rechargeable Alkaline batteries (Like those sold on Amazon Basic). The cost at scale of primary cells is <$15/kWh. The cost of the UEP cells is higher because of the additional current collector and carbons utilized to improve rate performances. The details of the cell fabrication are illustrated in Figure 10 that shows top and cross section of the cell. Anode, separator, and cathode are stacked and wound in a cylindrical jelly roll that is inserted in an ABS can. The ratio energy/power can be tuned for different applications by changing the thickness of the electrodes and the type of separator.

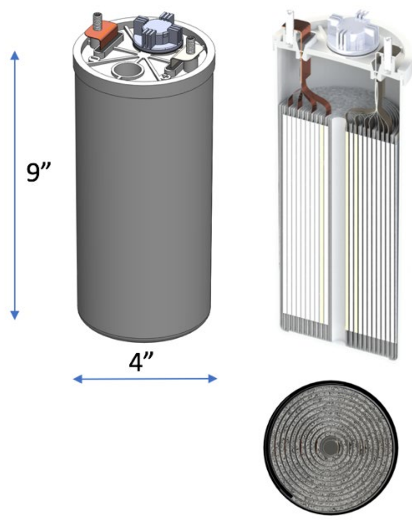


Figure 10. Cell Geometry with Top, Side, and External View

The number of cycles that the battery generates varies with the Depth of Discharge or the ratio Power to Energy. As illustrated in Figure 11, the UEP Batteries can provide ~50 deep cycles when discharged to 80%-100% DOD (Resilience mode), and ~1000 cycles when operated at a DOD ~ 10% (Revenue Generation Mode.)

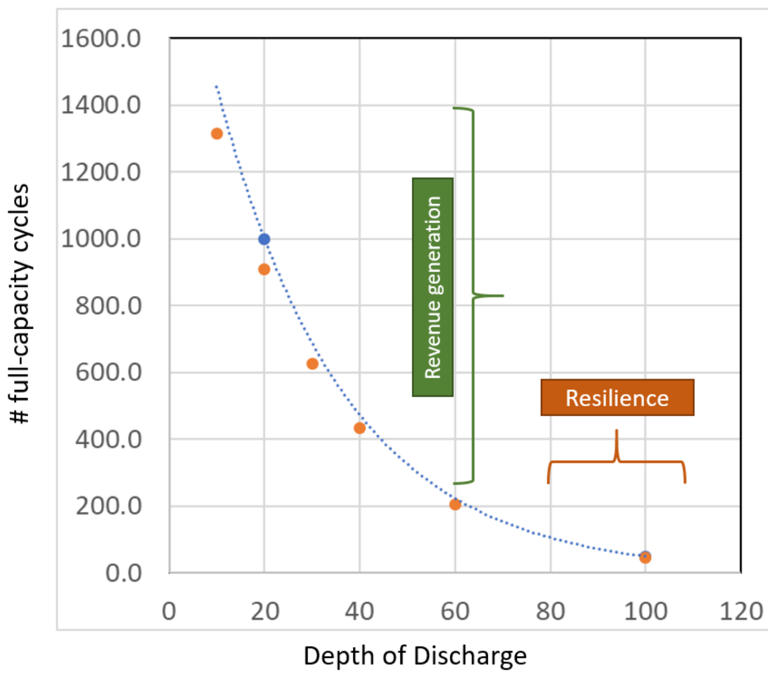


Figure 11. Relationship between Depth of Discharge (DOD) and the Number of Cycles for the Cylindrical Cell

A depth of discharge of 100% corresponds to about 50% of material utilization. In the same condition, the cost of a primary would be \$15/kWh x 2 = \$30/kWh for about 50 cycles. The UEP batteries, as discussed are more expensive than primaries. The pack cost is expected to drop to \$50/kWh by 2022 from the current \$250/kWh. The cost of going from battery packs to DC Battery systems includes the cost of racking (currently at \$50/kWh with DC cabling), of the container, and of the AC/DC Power converters (\$0.15-\$0.20/kW). The UEP batteries, like lead-acid batteries, do not require a BMS or expensive monitoring to operate. The cost projections are for sustained current rates of 10 hours or slower for 100% DOD (C/10 rate) with current spikes (<30 mints) of 1C. The cost is about 50% higher for a sustained C/5 (2X) rate.

UEP charges maintenance contracts tailored to the type of application and size of the installation that are comparable to the maintenance costs of lead-acid batteries.

The information in Figure 11 is used to account for the battery degradation in the simulation. Testing results for a combination of short and long discharges is being collected and will be available in 2020. The inverters have a lifetime of 10 years and may have to be replaced to achieve a 20-year lifetime. To reduce degradation, cells will need to be replaced periodically. The maintenance costs will depend on the size, location, and configuration of the installations.

3.0 PERFORMANCE OBJECTIVES

We have performed reliability analysis for the five DoD sites. The primary results are summarized in the tables below. The methodologies taken are documented in Section 5 and further results are presented in Section 6. Table 1 summarizes the evaluation metrics in detail and analysis results for Fort Bliss.

Table 1. Performance Objectives

Performance Objectives	Metric	Requirements	Success Criteria	Results
1. Reliability to Meet 100% of Installation Critical and Ride-through Load	Critical and ride-through load served during outage	Performance measured for outages of any duration between 1 hour and 168 hours	Meets or exceeds reliability probability curve from baseline microgrid	Met
2. Reliability to Meet 130% of Installation Critical and Ride-through Load			Meets or exceeds reliability probability curve from baseline microgrid specifically for 24- and 168-hour outages.	Met
3. Reliability to Meet 10% and 30% of Installation Critical and Ride-through Load when no Diesel Fuel is Available		Performance measured for outages of any duration between 1 hour and 24 hours	Meets or exceeds reliability probability curve from baseline microgrid for 24- outages.	Met
4. Expected Load Loss and Maximum Power Loss		Calculated expected load loss and maximum power loss during an outage	Values indicates the minimum battery and inverter installations to boost the reliability to 100%	1992.3 kWh 164.4 kW
5. Net Life-cycle Costs of Deployment and Operation (corresponding to technical objective 1 above)		Calculate per methodology distributed with baseline microgrid data and results	Net cost (per kW of critical load) is at or below level of baseline microgrid in current and future volatile scenarios	-$93,234

To conserve space, evaluation metrics that are identical in all sites are ignored. Only results are shown in Table 2 in which contains the analysis results for all sites. For detailed evaluation metrics, refer Table 1.

Table 2. Results for All Sites Against Performance Metrics

Sites	1. Reliability to meet 100% of installation critical and ride-through load	2. Reliability to meet 130% of installation critical and ride-through load	3. Reliability to meet 10% and 30% of installation critical and ride-through load when no diesel fuel is available	4. Expected load loss and maximum power loss		5. Net life-cycle costs of deployment and operation (correspond-ding to technical objective 1 above)	6. Averaged cost ($/kW) of critical load
				kWh	kw		
Holloman AFB	Met	Met	Met	2180.2	197.4	$1,156,403	21.4
March ARB	Met	Met	Met	118.3	5.6	$205,663	10.8
NAS Corpus Christi	Met	Met	Met	912.7	110.1	$843,204	12.8
NAS Patuxent River	Met	Met	Met	2541.7	258.4	$529,540	19.1
Fort Bliss	Met	Met	Met	1992.3	164.4	-$93,234	9.3

Detailed analyses are presented in later sections.

4.0 FACILITY/SITE DESCRIPTION

In this section we describe the five sites – NAS Corpus Christi, March ARB, Holloman AFB, Fort Bliss and NAS Patuxent River.

4.1 FACILITY/SITE LOCATION AND RELEVANT CHARACTERISTICS

Table 3 summarizes the characteristics of each installation site, including data on diesel generator and UPS capacities, electricity costs and market participation opportunities.

Table 3. Facility Characteristics

A summary of the significant features of the tariff model for each site is shown in Table 4.

Table 4. Tariff Model Analysis for Each Site

	NAS Corpus Christi	NAS Patuxent River	Holloman AFB	March ARB	Fort Bliss
Monthly fixed cost	✔	✔	✔	✔	✔
Season-based energy costs (generation, distribution and transmission)	✘	✔	✔	✔	✔
Season-based monthly peak demand costs	✘	✘	✔	✘	✔
Assumed minimum energy demand	✘	✘	✘	✔	✔
Aggregate taxes on energy/peak charges	✘	✔	✔	✘	✔
Discounts on energy/peak charges	✔	✘	✘	✘	✔

Among the multiple cost components, only the energy and peak demand costs provide room for savings. Thus, a battery can supply power during the peak loads and reduce the peak demand cost that is incurred. Afterwards, it can be recharged during periods of low demand when the costs are low, thus resulting in significant overall savings. Some sites even have different energy and peak demand charges for summer and winter.

In March ARB and Fort Bliss, the utility charges for a minimum fixed amount of energy even if the actual usage is lower. Exceeding this minimum energy threshold incurs additional charges. This can be a challenge as the room for cost saving is much less compared to the other sites.

4.2 FACILITY/SITE ASSUMPTIONS AND INITIAL CONDITIONS

A multi-level offline optimization is performed on the battery and inverter sizes at the upper level, and the hourly battery power output at the lower level. Both levels aim to reduce the total cost incurred, which includes the battery and inverter installation costs, the annual electricity bill, and battery degradation cost. All costs are modelled as convex functions of the decision variables. Commercially available GUROBI 9.0 (10) solver is used to perform the optimization. The optimization is performed over the entire year, and thus the number of decision variables is high (above 8000).

Some assumptions made in the model and the optimization process are as follows:

- The hourly load for the full year is assumed to be known beforehand and is obtained from the 2018 data available for all sites.
- Load distribution is assumed to be the same over 20 years.
- The battery is fully charged at the beginning and end of each day. The reason is two-fold: a) Market clearance is usually on a daily basis; b) Resetting the battery to fully charge every day significantly reduces the problem size. The degradation costs implicit in this operating procedure were included in our economic modeling
- A battery efficiency of 98% is assumed which represents the energy loss during charging or discharging. The typical AC/AC efficiency is 90%.
- Loss of charge in the battery due to multiple charge-discharge cycles is not considered as the degradation model includes the degradation per cycle, including charging after a discharge cycle.
- The fuel cost and the O&M cost for the generator is not considered during the market analysis.
- Reliability for solar generation, inverter operation and battery is considered to be 100%.
- Reliability of the battery is considered to be 100% because a) before the battery is shipped, testing will be carried out to ensure that it is 100% reliable; b) the battery is made of a series of paralleled battery cells. Even if some battery cells fail to function, they will not impact the usability of the overall battery.
- Due to their smaller size, the UPS at the site were not considered in the reliability analysis.
- The probability of an outage throughout a year is a uniform distribution.

5.0 METHODOLOGY

5.1 CONCEPTUAL METHODOLOGY

The team has developed a comprehensive microgrid energy storage solution (CMES) that addresses both reliability and cost performance of a microgrid. The key benefits of the solution are through offline and online optimization modules Figure 12: i) offline optimizer to estimate most optimal storage size that meets the site reliability requirements while minimizing lifecycle costs (LCC) of the storage; ii) online optimizer that generates optimal battery operation actions once storage has been included in the site and a market participation mechanism has been determined. Details for the optimizers are given in Section 2. In Phase 1, only Offline Optimizer was implemented.

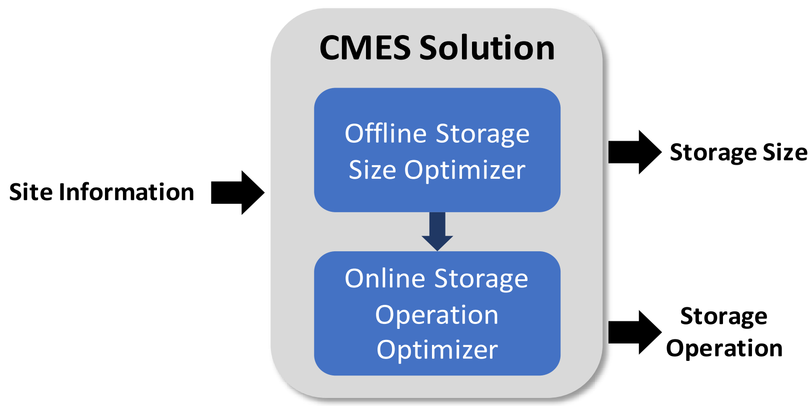


Figure 12. CMES Solution

Figure 13 below shows the process flow diagram for the Offline Optimizer module. First, the site data information and an estimated battery size information is used to compute reliability metrics. If the reliability metrics don't meet the reliability goals, then new battery size is generated, and reliability metrics are recomputed. If the requirements are met, then the battery size serves as a lower bound (minimum) on the storage size variable used in the subsequent lifecycle cost optimization process. For a given minimum battery size, a minimum inverter size is estimated. Then, for a given storage size, consisting of battery and inverter sizes, and operation of storage the market participation revenue for each site is computed using site specific tariff information. Using this revenue and the site information, lifecycle cost of the microgrid is computed over the course of 20 years. The storage operation optimization module determines the optimal operation of storage and other generation sources such that the lifecycle cost of the microgrid is minimized while meeting all the operating constraints and load requirements of the site. Final output of the offline optimization module is the storage size, including - number of battery cells, inverter size, and topology for each battery size, for the MG site (with the MG being modeled with a determined location of the storage) that meets the reliability goals and minimizes the lifecycle cost.

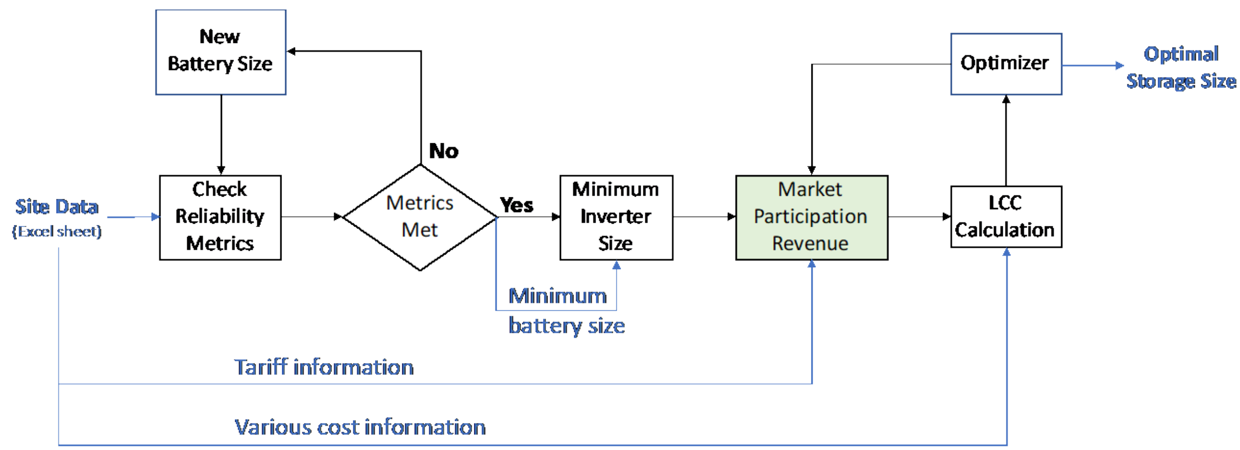


Figure 13. Process Flow Diagram for Offline Optimizer

In Phase 1, the offline process shown in Figure 13 was executed for each site. The process steps for all sites were same except the Market Participation Revenue computation step, which was customized for each site. The offline optimizer module was used to optimally size batteries and inverters for five sites – NAS Corpus Christi, March ARB, Holloman AFB, Fort Bliss and NAS Patuxent River. Results are summarized in Table, which shows minimum battery and inverter sizes that guarantee 100% and 130% reliability of critical load at each site based on the reliability analysis of expected load loss and maximum power loss. We considered the battery operation between 100% to 60% depth of discharge (DOD) for efficient operation as well as to derive revenues through market participation.

5.2 REVIEW OF BASELINE MICROGRID MODELING

For the reliability analysis, we follow the reliability analysis method as provided by the program committee in the document - "Calculating the Reliability of a Backup System with Parallel Generators". Specifically, we follow the analysis in the article to generate "likelihood of survival" and "expected lost load". The "likelihood of survival" illustrates the expected survival rate for a specific duration of outage.

We start the derivation from making important assumptions. We see the operation of parallel generators as a Markovian process, i.e., the states at time $t = t_k$ depends only on time $t = t_{k-1}$. Assuming there are N generators available and α is the likelihood of Fail-to-Start and λ is the likelihood of Fail-to-Run.

We use $P(d, g)$ for probability g generators available after d outage hours. $p(g, g')$ denotes given g generators, chance of g' available generators next period.

Given each generator has a capacity K, the minimum number of generators required to meet critical load can be denoted $\widetilde{g_t}(h)$, where the required number of generators is the critical load divided by generator capacity rounded up:

$$\widetilde{g_t}(d) = \left\lceil \frac{C_t(d)}{K} \right\rceil$$

Where $C_t(d)$ is critical load in given hour.

Given a number of generators g, denote the probability that g generators will run until the next period as $p(g, g')$. Using the assumption of generator Fail-to-Start being independent events, the distribution of generators which start can be calculated using the binomial distribution:

$$P(0, g) = \binom{N}{g} (1 - \alpha)^g (\alpha)^{N-g}$$

where N denotes the number of generators at the facility. Using the assumption that Failure-to-Run events are uncorrelated provides a similar equation for the transition of one period to the next:

$$p(g, g') = \binom{N}{g} (1 - \lambda)^{g'} (\lambda)^{g-g'}$$

We subsequently define the transition matrix as follows:

$$\begin{bmatrix} 1 & \cdots & p(N,0) \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p(N,N) \end{bmatrix}^d \begin{bmatrix} P(0,0) \\ \dots \\ P(0,N) \end{bmatrix} = \begin{bmatrix} P(d,0) \\ \dots \\ P(d,N) \end{bmatrix}$$

a) Calculating likelihood of survival

The backup system survives the outage if the available capacity for each outage hour is greater than the critical load for that hour. Given an outage which starts in hour t and is at current duration d, then for all $g < \widetilde{g_t}(d)$, the chance of survival, ending with g generators $s_t(d, g) = 0$. The initial condition for survival is given by:

$$s_t(0, g) = \begin{cases} 0 & g < \widetilde{g_t}(0) \\ P(0, g) & g \geq \widetilde{g_t}(d) \end{cases}$$

We calculate the chance of survival for each subsequent procedure by the following two steps

$$\begin{bmatrix} s_t'(d+1,0) \\ \dots \\ s_t'(d+1,N) \end{bmatrix} = \begin{bmatrix} 1 & \cdots & p(N,0) \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p(N,N) \end{bmatrix} \begin{bmatrix} s_t(d,0) \\ \dots \\ s_t(d,N) \end{bmatrix}$$

$$s_t(d+1, g) = \begin{cases} 0 & g < \widetilde{g_t}(d+1) \\ s_t'(d+1, g) & g \geq \widetilde{g_t}(d+1) \end{cases}$$

We first calculate the distribution of generators in period d+ 1 given the system has survived to period d and then set the survival probability of all distribution which have less than the required number of generators to zero.

The likelihood of surviving an outage starting in hour t and lasting for D hours is denoted $S_t(D)$, where:

$$S_t(D) = \sum_{g=0}^{N} s_t(D,g)$$

The average likelihood of survival for an outage of duration D with the distribution of outage starts Q is denoted $\bar{S}(D,Q)$

$$\bar{S}(D,Q) = \sum_{t=0}^{T} q_t S_t(D)$$

In our case, Q follows an even distribution and $q_t = \frac{1}{T}$.

b) Calculating expected lost load

The lost load in a given hour is zero if more generators are available than the minimum required and is the difference between critical load and available capacity if an insufficient number of generators are available. Expected lost load can be calculated as follows:

$$l_t(d,g) = P(d,g)\max(0, C_t(d) - g * K)$$

Where $l_t(d,g)$ is expected dropped load, ending with g generators. $C_t(d)$ is the critical load, g is the number of available generators, and K is the capacity of the generators.

The expected lost load in outage hour d, with g generators remaining available, is the likelihood that g generators will remain available in hour d times the lost load given g available generators. We can then calculate the expected lost load for an outage duration D and a distribution of outage starts Q as:

$$\bar{L}(D,Q) = \sum_{t=0}^{T} q_t \left(\sum_{d=1}^{D}\sum_{g=0}^{N} \max(0, C_t(d) - g * K)\right)$$

Again, in our case, Q follows an even distribution and $q_t = \frac{1}{T}$.

c) Calculating maximum power loss

The "expected lost load" is a measurement of the insufficient energy if using diesel generators alone for outage. The maximum value of this curve naturally shows the desired battery capacity to make the site 100% secured for a given duration of outage. Furthermore, based on the "expected lost load" analysis, we could further derive the "maximum power loss" for an outage duration D, where $C_t(d)$ is the critical load in the given hour *t*. $d \in [0, D]$ is the current duration of outage.

$$P(D) = \max\{\max(0, C_t(d) - g * K)\}_{g\in[0,N], d\in[0,D], t\in[0,T]}$$

The equation above first compares the critical load with available generation capacity with 0. In case the number is positive, it shows an expected loss of load it the specific hour. It further selects the maximum of loss of load through all combinations of g, d and t. Thus, $P(D)$ is the maximum power loss for any hour during a duration. The physical meaning of this value is the minimum inverter size needed in order to bring survival rate to 100% given using a battery at the size of "expected lost load". Through reliability analysis, it shows us the minimum size of battery and inverters.

Weather and solar model: The weather conditions are incorporated by calling the APIs: https://www.renewables.ninja/api/. With the correct geographic information and installation size, the API generates solar generation with weather variations.

In the reliability analysis, we have made the following assumptions about key parameters used in the simulation (Table 5).

Table 5. Assumptions Used in the Reliability Analysis

Availability	Failure-to-Start	Mean Time Between Failure	Diesel Fuel Conversion Factor
99.9%	0.2%	1700 hours	1 gallon = 137,381 Btu

We also made the following assumptions:

- Reliability for solar generation, inverter operation and battery is considered to be 100%.
- Reliability of the battery is considered to be 100% because a) before the battery is shipped, testing will be carried out to ensure that it is 100% reliable; b) the battery is made of a series of paralleled battery cells. Even if some battery cells fail to function, they will not impact the usability of the overall battery.
- Due to their smaller size, the UPS at the site were not considered in the reliability analysis.
- The probability of an outage throughout a year is a uniform distribution.

5.3 STORAGE-ENABLED MICROGRID MODELING

The storage-enabled microgrid modeling is casted as an optimization problem. It is shown as the following equations:

$$\min_{P_{bat}, S_{bat}, S_{inv}} f(S_{bat}, S_{inv}) + \sum_{i=1}^{20} (C(E_{bill})) + C(Deg_{bat})))$$

s.t.

$$-S_{inv} \leq P_{bat} \leq \beta_{charge} \times S_{inv}$$

$$\boldsymbol{SOC_{min}} \leq \boldsymbol{SOC(t)} \leq \boldsymbol{SOC_{max}}$$

$$\boldsymbol{E_{bat}(t+1)} = \boldsymbol{E_{bat}(t)} + \boldsymbol{\tau} \times \boldsymbol{P_{bat}(t)} \times \Delta \boldsymbol{t}$$

$$\boldsymbol{C(E_{bill})} = \boldsymbol{g(P_{Energy})} + \boldsymbol{h(P_{Demand})}$$

where $f(S_{bat}, S_{inv})$ is the initial investments on battery and inverter. S_{bat} and S_{inv} are the sizing of battery and inverter. $C(E_{bill})$ is the electricity cost. And $C(Deg_{bat})$ is the degradation of the battery. In the constraints, we have further modelled the constraints on power and State-of-Charge. Without loss of generality, we have showed the electricity cost is composed of two parts: $g(P_{Energy})$ stands for the cost for energy usage. And $h(P_{Demand})$ is the cost for demand price. Every utility and service territory have different tariff model, and therefore $g(P_{Energy})$ and $h(P_{Demand})$ is different from site to site. All other assumptions are considered the same for all the sites.

6.0 PERFORMANCE ASSESSMENT

In this section, we perform a detailed analysis of major results presented in section 3. The analysis is based on the battery and inverter sizing shown in Table 6. The base case for generators is the number of generators given by the program committee.

Table 6. Minimum Battery and Inverter Size to Maintain Close to 100% Reliability Requirements

Site	100% Reliability	
	Battery Size (kWh)	Battery Power/Inverter Size (kW)
Fort Bliss	1992.3	164.4
Holloman AFB	2180.2	197.4
March ARB	118.3	5.6
NAS Corpus Christi	912.7	110.1
NAS Patuxent River	2541.7	258.4

6.1 RELIABILITY TO MEET 100% OF AN INSTALLATION'S CRITICAL AND RIDE-THROUGH LOAD

We ran the simulations according to the methodology described in Section 5. Essentially, this project follows the "reliability of paralleled generators" as the method in calculating the reliability curve. We used Markov Chain approach for this analysis. We compared our results with the baseline case provided by the program committee. The results are documented in figures 11-20 below.

a) Without Battery

In Figure 14, Figure 16, Figure 18, Figure 20, Figure 22, we plot not only the generated expected survival curve for the critical loads, but also the distribution of survival rates in pink shaded area. Each point (for example, t=100hrs) in the generated curve is actually an average of the distribution (for example, pink shaded zone where t=100hrs).

We have compared the generated results with two baseline curves provided, namely fixed load baseline and variable load baseline. The generated curve matches well with the variable baseline, which is expected as we follow the analysis provided. When we compare our generated curve with fixed load baseline curve, they align very well, all showing the worst-case performance using different analysis. The above results demonstrate the correctness of our simulation.

b) With battery

We use the battery and inverter sizing detailed in a later section. As expected, the battery and inverter can keep the reliability curve at each site close to 100% (Figure 15, Figure 17, Figure 19, Figure 21, Figure 23). Note the 100% reliability calculation uses mathematical expectations. That is the reason why there is still a small chance that the battery system cannot meet 100% reliability. As ride-through load is a subset of the critical load and the critical load has met the baseline, the ride through load naturally meets the baseline requirement.

Based on the analysis, we see this performance metric has been met.

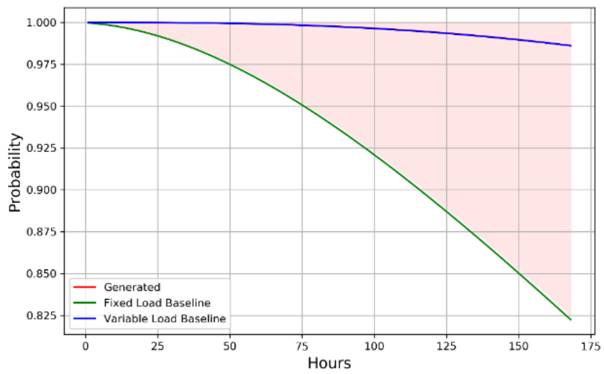


Figure 14. Reliability Curve to Meet 100% of Critical Load for Fort Bliss without Battery

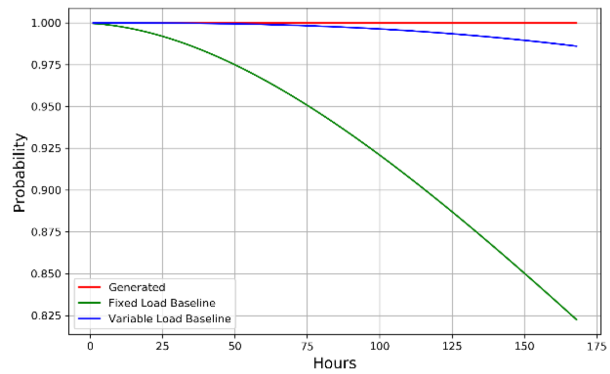


Figure 15. Reliability Curve to Meet 100% of Critical Load for Fort Bliss with Battery

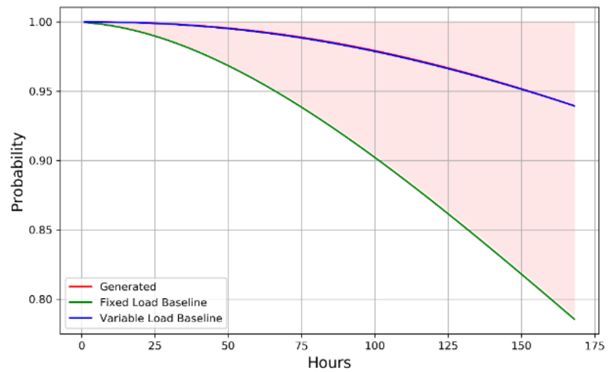


Figure 16. Reliability curve to meet 100% of critical load for Holloman AFB without Battery

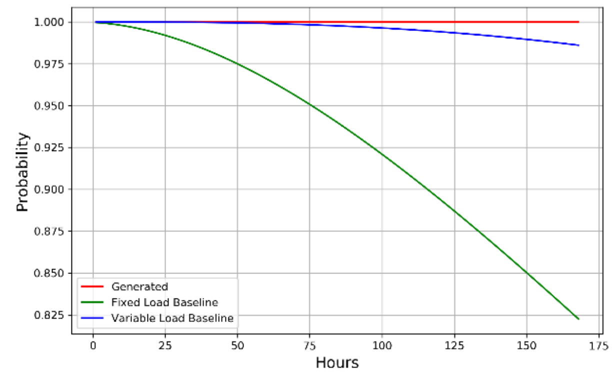


Figure 17. Reliability curve to meet 100% of critical load for Holloman AFB with Battery

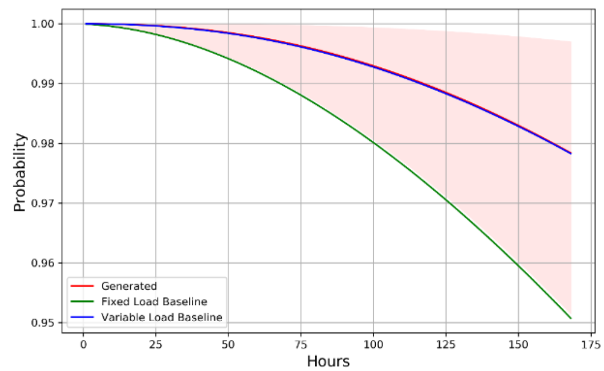


Figure 18. Reliability Curve to Meet 100% of Critical Load for March ARB without Battery

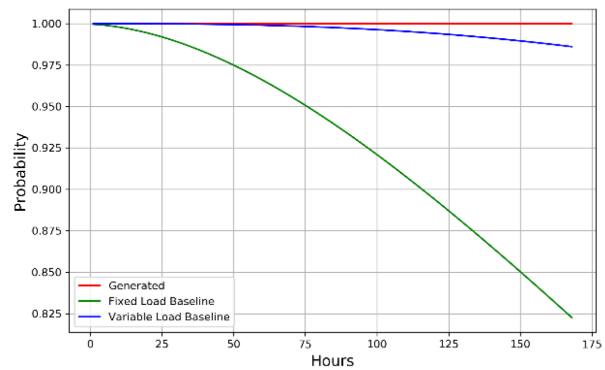


Figure 19. Reliability Curve to Meet 100% of Critical Load for March ARB with Battery

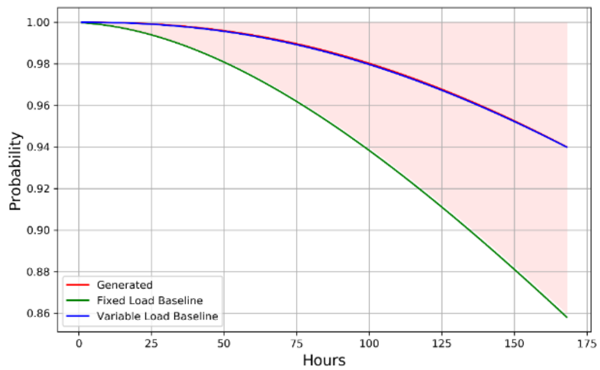


Figure 20. Reliability Curve to Meet 100% of Critical Load for NAS Corpus Christi without Battery

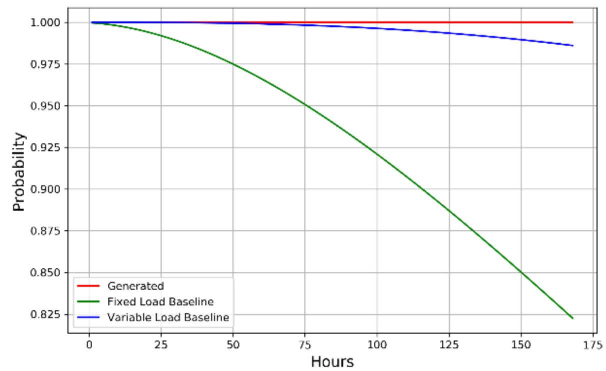


Figure 21. Reliability Curve to Meet 100% Critical-load for NAS Corpus Christi with Battery

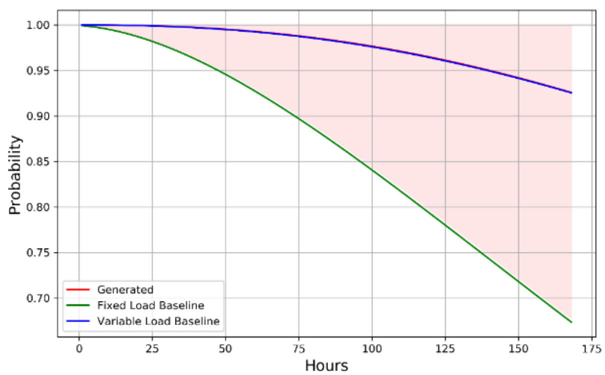


Figure 22. Reliability Curve to Meet 100% of Critical Load for NAS Patuxent River without Battery

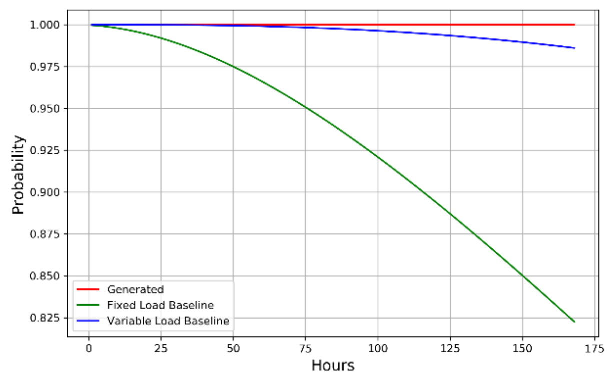


Figure 23. Reliability Curve to Meet 100% of Critical Load for NAS Patuxent River with Battery

6.2 RELIABILITY TO MEET 130% OF AN INSTALLATION'S CRITICAL AND RIDE-THROUGH LOAD

a) Without Battery

In analogy to results presented in Section 6.1, we then increased the loads to 130% and performed simulation. Results are summarized in Figure 24, Figure 26, Figure 28, Figure 30, Figure 32. We observed significant decay in reliability for all sites, in particular NAS Corpus Christi and NAS Patuxent River.

b) With Battery

We utilized the battery sizing showed in Section 6.4 for simulation. Results show very promising results: all five sites beat the baseline with a 30% increase in load. The battery enabled storage has maintained 100% reliability to the last few hours of outage, dropping only slightly in the last few hours. As ride-through load is a subset of critical load and critical load has met the baseline, ride through load meets the baseline requirement. Based on the analysis, we observe that this performance metric was met.

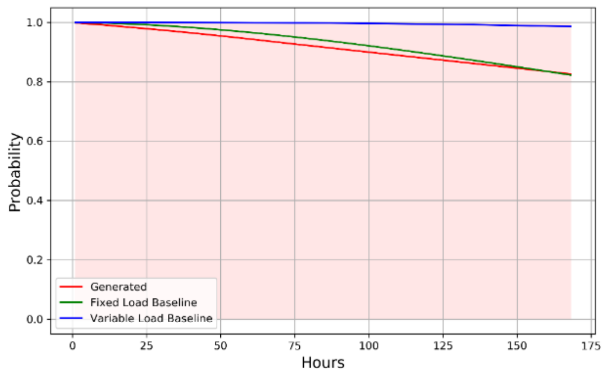


Figure 24. Reliability Curve to Meet 130% of Critical Load for Fort Bliss without Battery

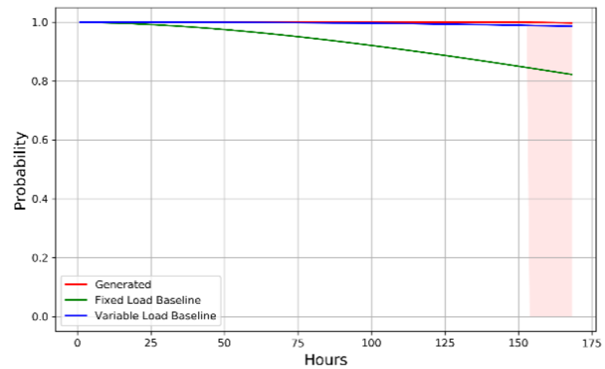


Figure 25. Reliability Curve to Meet 130% of Critical Load for Fort Bliss with Battery

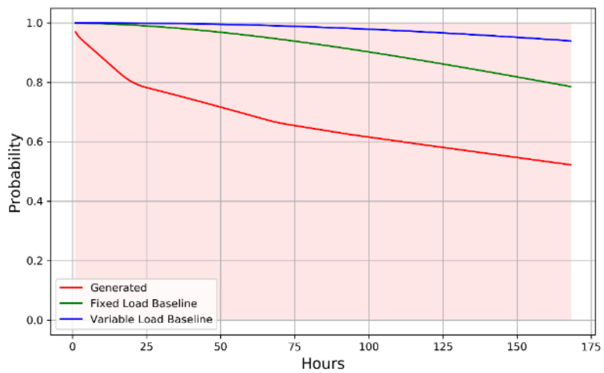


Figure 26. Reliability Curve to Meet 130% of Critical Load for Holloman AFB without Battery

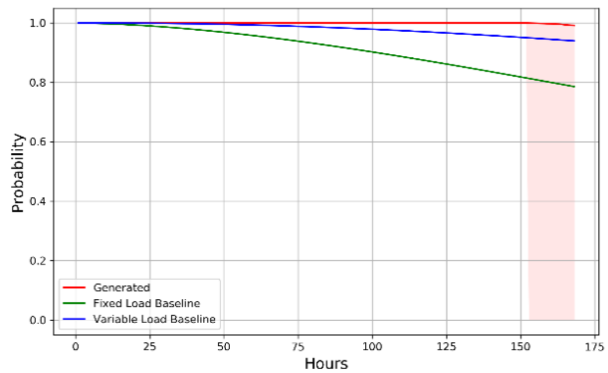


Figure 27. Reliability Curve to Meet 130% of Critical Load for Holloman AFB with Battery

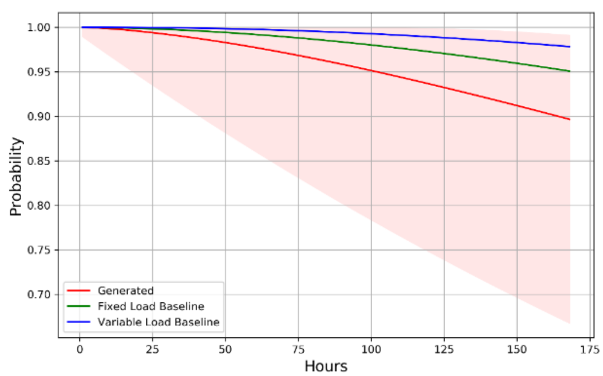


Figure 28. Reliability Curve to Meet 130% of Critical Load for March ARB without Battery

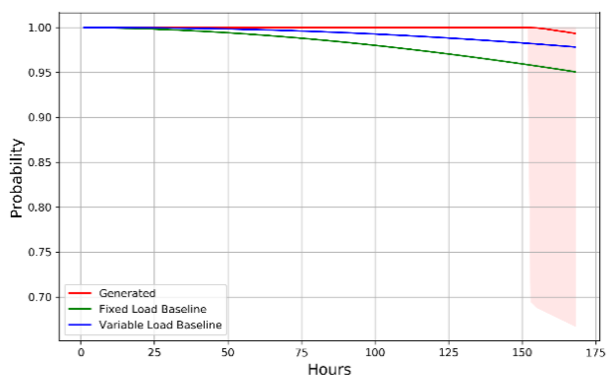
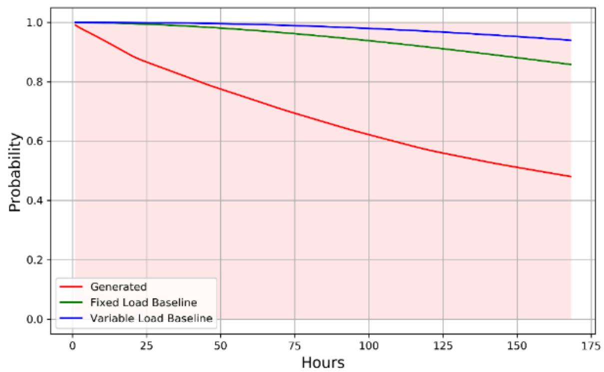


Figure 29. Reliability Curve to Meet 130% of Critical Load for March ARB with Battery



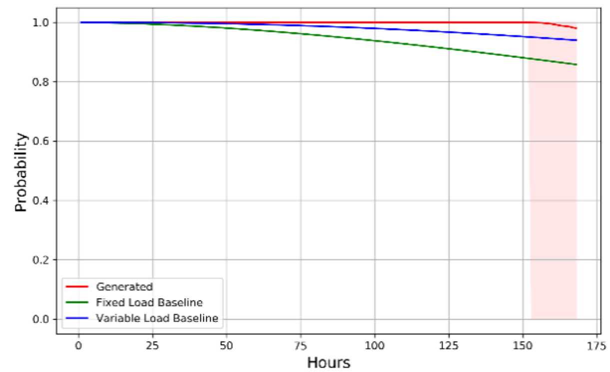
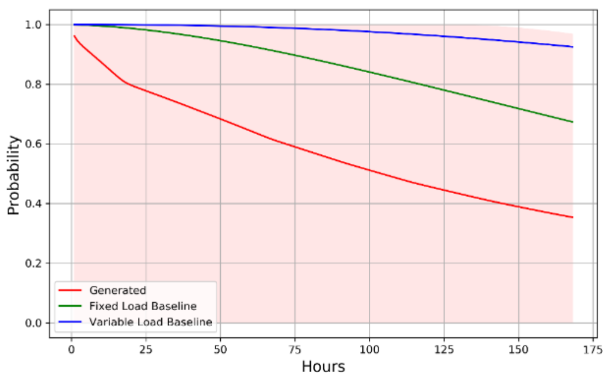


Figure 30. Reliability curve to meet 130% of critical load for NAS Corpus Christi without Battery

Figure 31. Reliability curve to meet 130% of critical load for NAS Corpus Christi with Battery



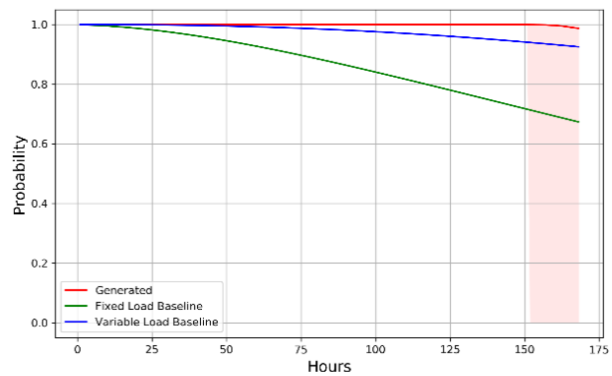


Figure 32. Reliability Curve to Meet 130% of Critical Load for NAS Patuxent River without Battery

Figure 33. Reliability Curve to Meet 130% of Critical Load for NAS Patuxent River with Battery

6.3 RELIABILITY TO MEET 10% AND 30% OF AN INSTALLATION'S CRITICAL AND RIDE-THROUGH LOAD WHEN NO DIESEL FUEL IS AVAILABLE

a) With diesel generation only

We performed analysis using diesel generators alone to meet 10% and 30% of critical load for a duration of 24 hours. Simulation shows that the survival rate for both cases in all five sites is 100% with no fuel refill available. As ride-through load is a subset of critical load and critical load has met the baseline, ride through load also meets the baseline requirement.

b) With battery only (no diesel generator at all)

We examined the reliability curve to meet 10% and 30% of the critical load using battery sizing specified in Section 6.4. Results from the analysis are shown in Figures 34-43 below.

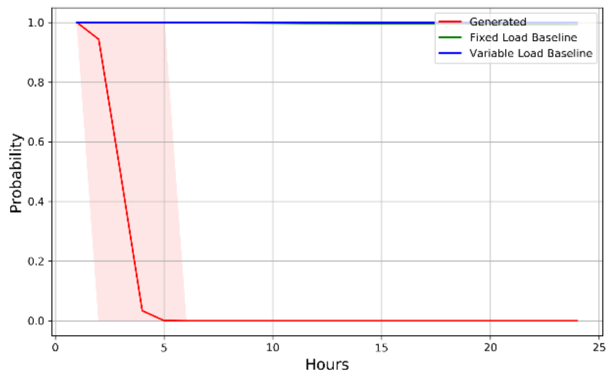


Figure 34. Reliability Curve to Meet 10% of Critical Load with Battery for Fort Bliss

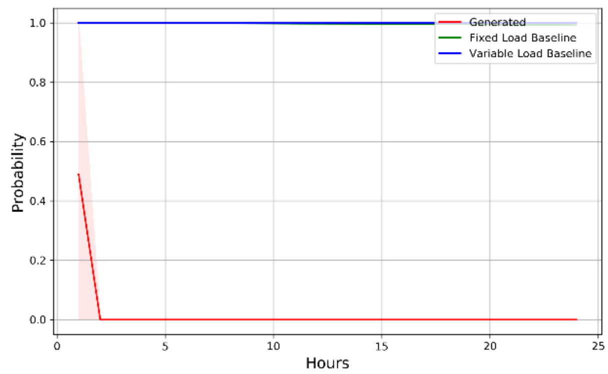


Figure 35. Reliability Curve to Meet 30% of Critical Load with Battery for Fort Bliss

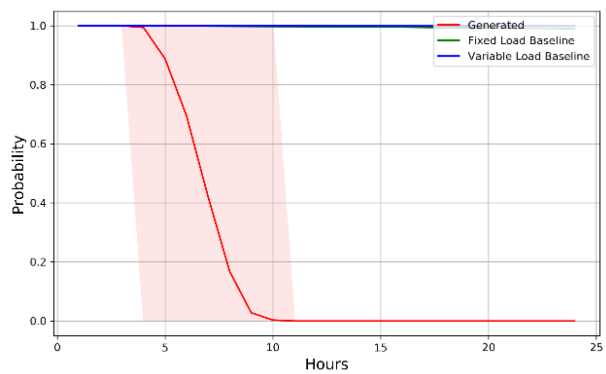


Figure 36. Reliability Curve to Meet 10% of Critical Load with Battery for Holloman AFB

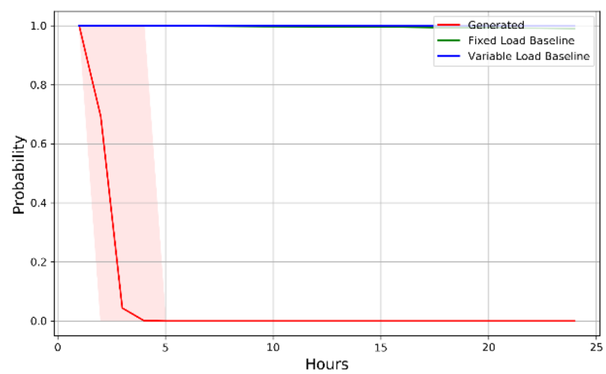


Figure 37. Reliability Curve to Meet 30% of Critical Load with Battery for Holloman AFB

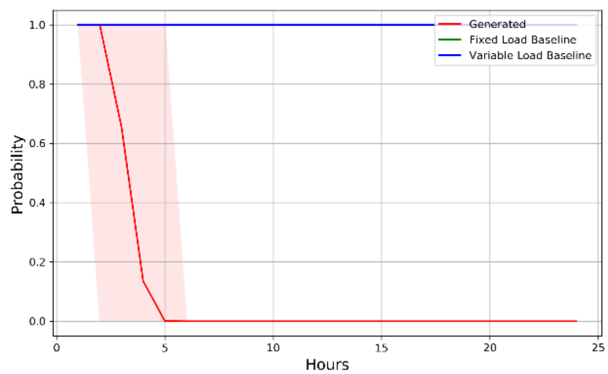


Figure 38. Reliability Curve to Meet 10% of Critical Load with Battery for March ARB

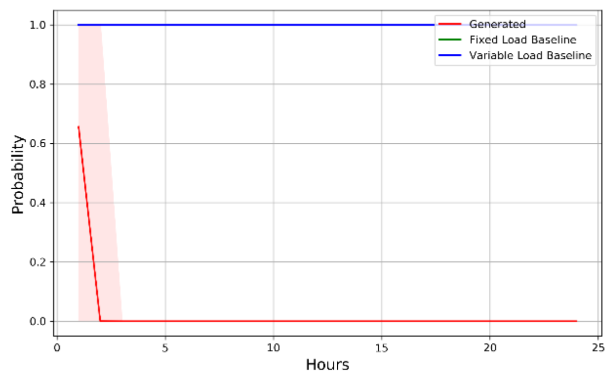


Figure 39. Reliability Curve to meet 30% of Critical Load with Battery for March ARC

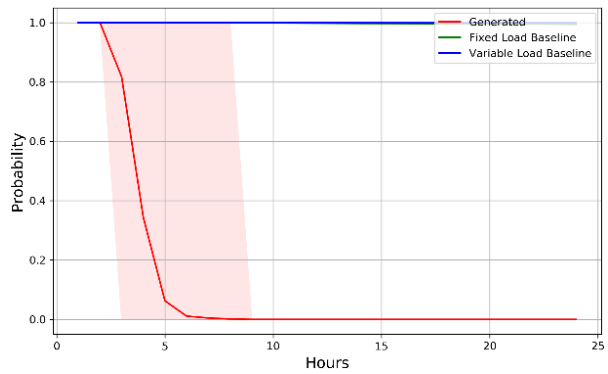


Figure 40. Reliability Curve to Meet 10% of Critical Load with Battery for NAS Corpus Christi

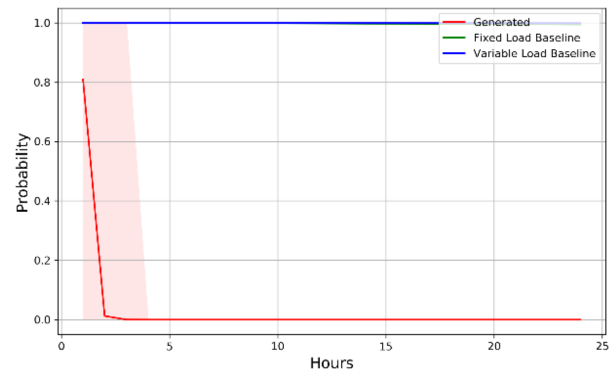


Figure 41. Reliability Curve to Meet 30% of Critical Load with Battery for NAS Corpus Christi

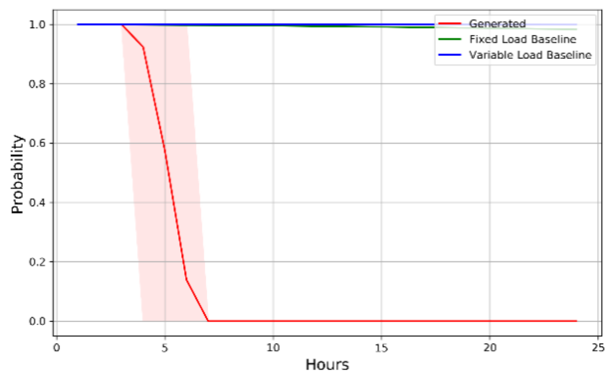


Figure 42. Reliability Curve to Meet 10% of Critical Load with Battery for NAS Patuxent River

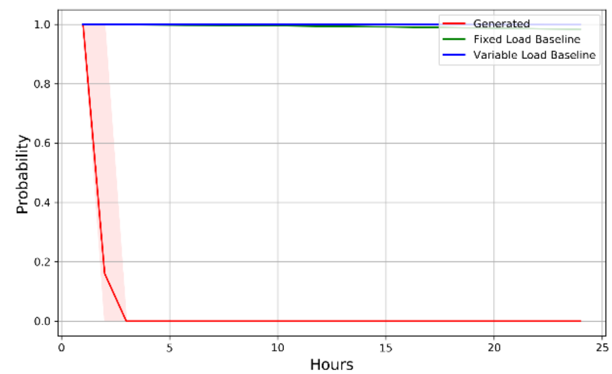


Figure 43. Reliability Curve to Meet 30% of Critical Load with Battery for NAS Patuxent River

Analysis results show a significant reliability curve drop a few hours into the outage. It can be concluded that with battery alone, it is not sufficient to meet reliability requirements of the military bases.

6.4 EXPECTED LOAD LOSS AND MAXIMUM POWER LOSS

We analyzed the expected load loss and maximum power loss according to the method described in section 5. The expected load loss is calculated by averaging expected load loss during an outage. Expected maximum power loss is the maximum of hourly power loss. Therefore, seemingly small numbers are a result of mathematical expectations. In Figures 44-53, we plotted the distribution of expected load loss as well as maximum power loss for each hour for each site.

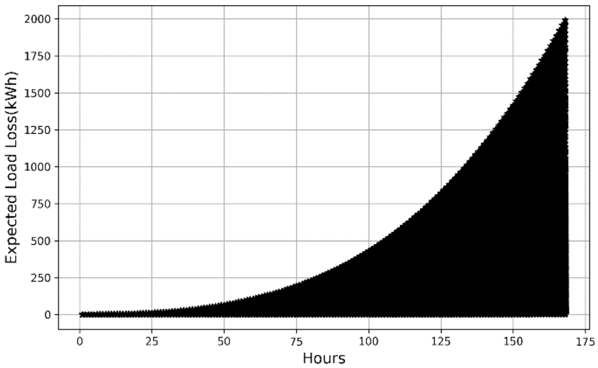


Figure 44. Expected Load Loss for Fort Bliss

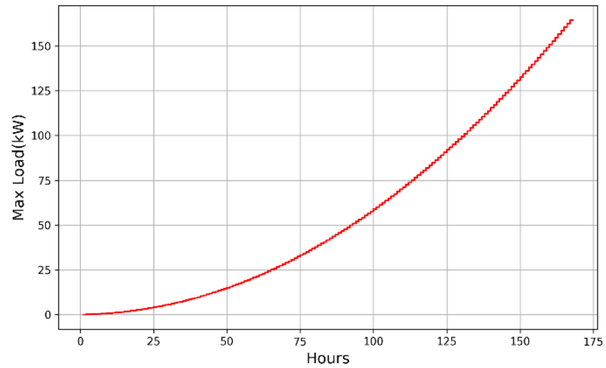


Figure 45. Maximum Power Loss for Fort Bliss

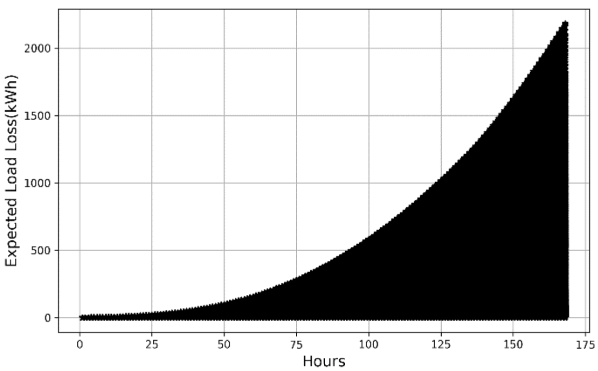


Figure 46. Expected Load Loss for Holloman AFB

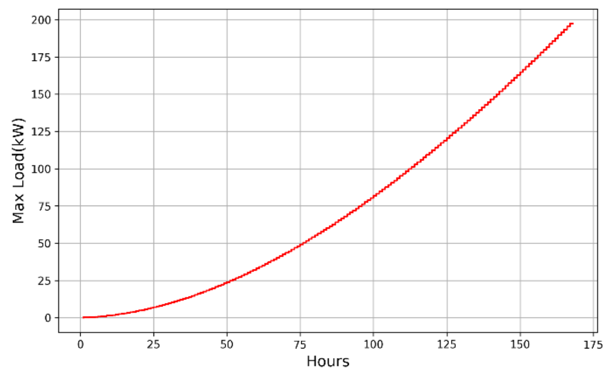


Figure 47. Maximum Power Loss for Holloman AFB

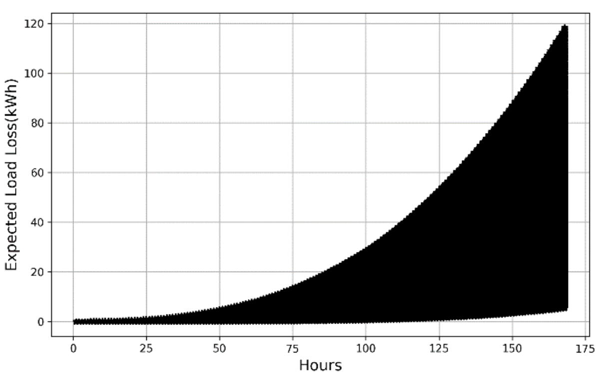


Figure 48. Expected Load Loss for March ARB

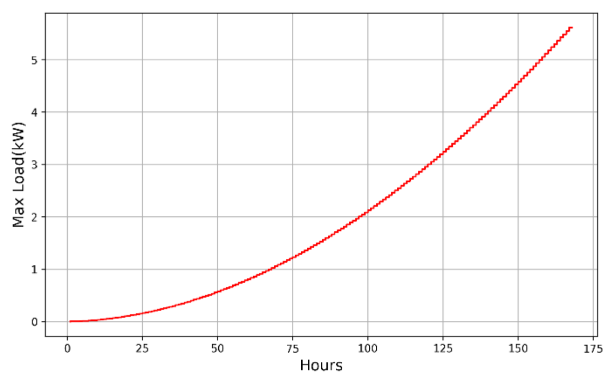


Figure 49. Maximum Power Loss for March ARB

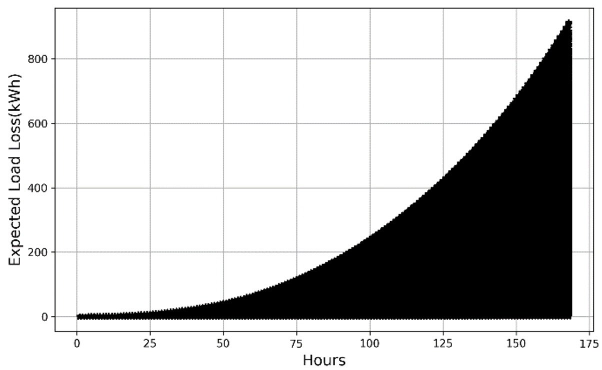


Figure 50. Expected Load Loss for NAS Corpus Christi

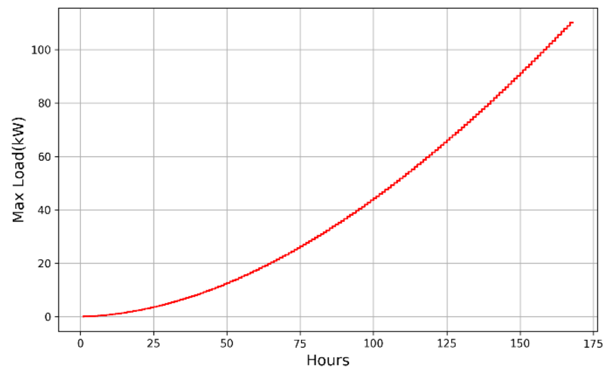


Figure 51. Maximum Power Loss for NAS Corpus Christi

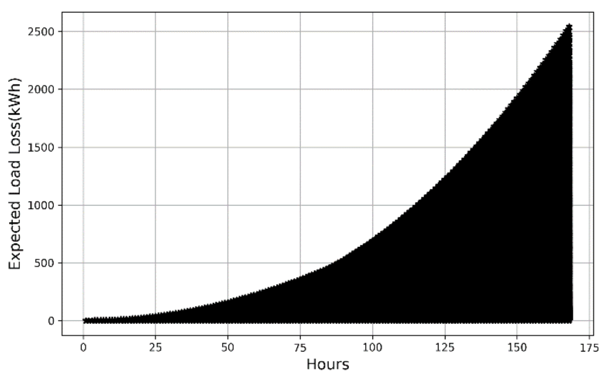


Figure 52. Expected Load Loss for NAS Patuxent River

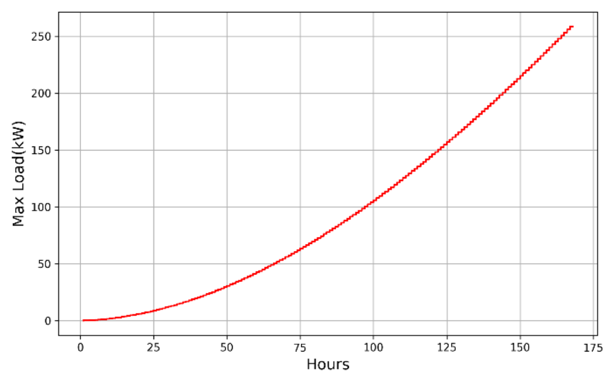


Figure 53. Maximum Power Loss for NAS Patuxent River

The maximum load loss (the maximum point in 168hrs) shows the battery size needed in order to operate the site with 100% reliability. Similarly, maximum power loss shows the deficiency of power. The point at 168hrs in maximum power loss shows the inverter size needed for each site in order to operate the site with 100% reliability. Table 7 below further summarizes the battery and inverter sizes needed.

Table 7. Minimum Battery and Inverter Size to Maintain Close to 100% Reliability Requirements

Site	Battery Size (kWh)	Inverter Size(kW)
Fort Bliss	1992.3	164.4
Holloman AFB	2180.2	197.4
March ARB	118.3	5.6
NAS Corpus Christi	912.7	110.1
NAS Patuxent River	2541.7	258.4

6.5 RELIABILITY WITH LOSS OF GENERATORS

a) Loss of Generators

We also examined the impact of losing diesel generators. We plotted the reliability curve for each site when losing 1 or 2 generators (Figure 54, Figure 56, Figure 58, Figure 60, Figure 62). In figures 51-60, we marked the equivalent power loss when losing one generator.

In Figures 54-63, we show, in sequence, how no loss, loss of one generator and loss of two generators impact the reliability curves. With every generator loss, reliability is reduced. However, reliability performance decay due to the loss of one generator is not as significant as for the loss of two generators. The results are largely due to N+1 redundancy. Further, we show that by replacing one generator with the battery and inverter (sized the same as the one to promote reliability to 100% in the baseline), reliability performance is still far better than the fixed critical load baseline.

b) Replacement of Generator with Battery

We have further examined using battery size to replace one generator. The results are promising. In all five sites, the reliability curve is very close to 100%. This result concludes that we may be able to reduce a generator at each site and replace it with storage system without significant change in reliability. This means, that the reliability benefits caused by one generator can be compensated by the energy storage that we have sized and introduced as solution at each installation. However, this conclusion cannot be extended to market and economic analysis as we use the generators only for backup power during a blackout.

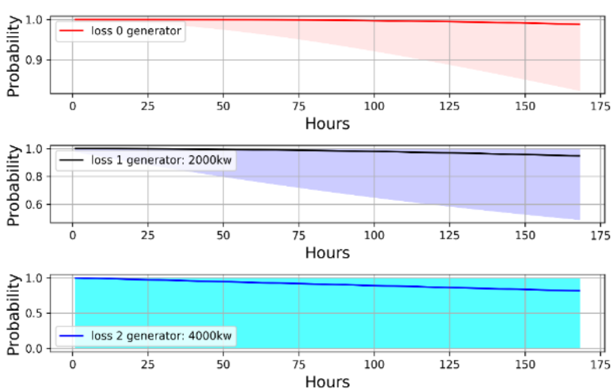


Figure 54. Reliability Decay Due to the Loss of 1 or 2 Generators at Fort Bliss (no Battery)

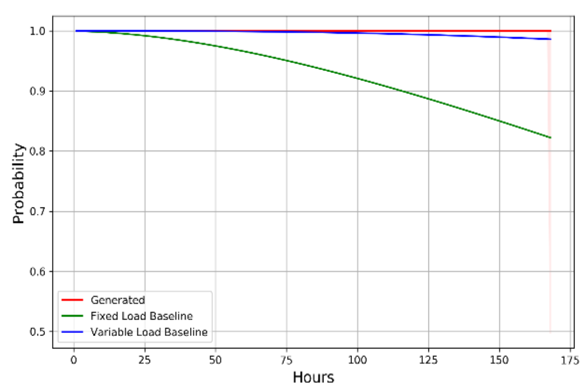


Figure 55. Reliability Curve for Fort Bliss with Loss of One Generator and with Battery

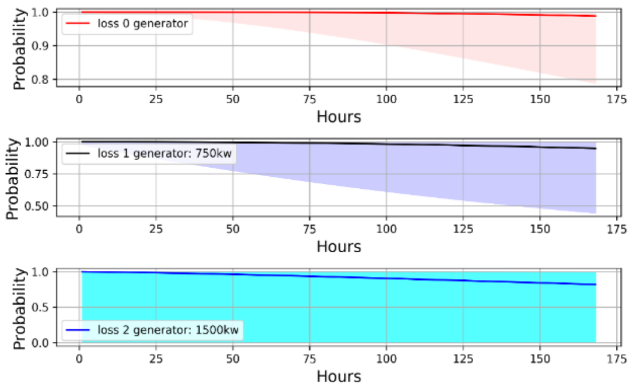


Figure 56. Reliability Decay Due to the Loss of 1 or 2 Generators at Holloman AFB (No Battery)

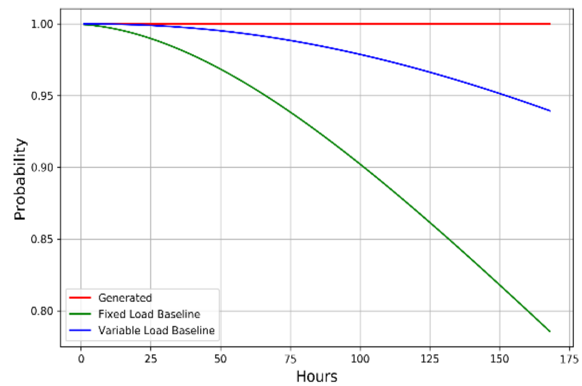


Figure 57. Reliability Curve f or Holloman AFB with Loss of One Generator and with Battery

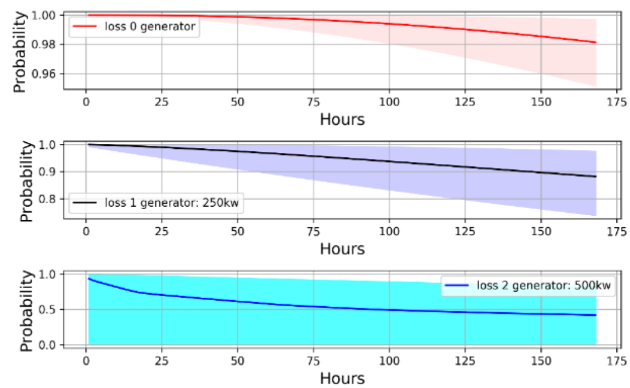


Figure 58. Reliability Decay Due to the Loss of 1 or 2 Generators at March ARB (no Battery)

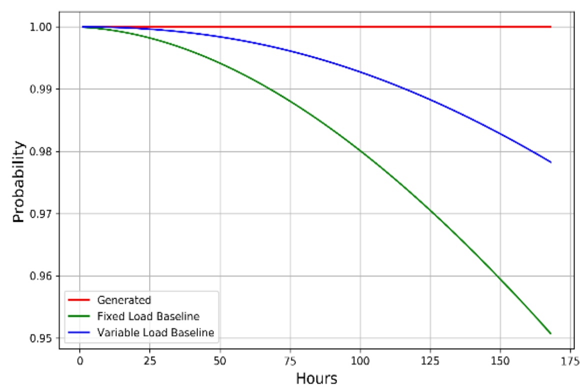


Figure 59. Reliability Curve for March ARB with Loss of One Generator and with Battery

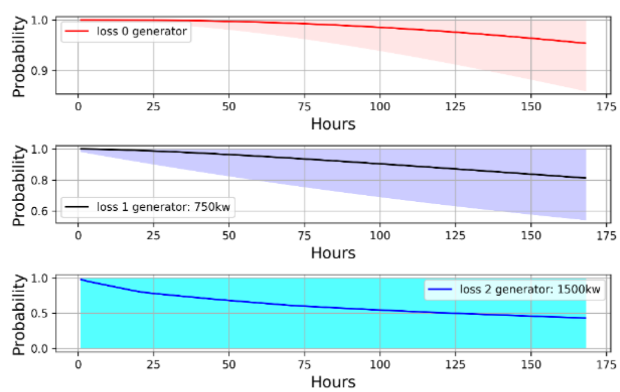


Figure 60. Reliability Decay Due to the Loss of 1 or 2 Generators at NAS Corpus Christi (no Battery)

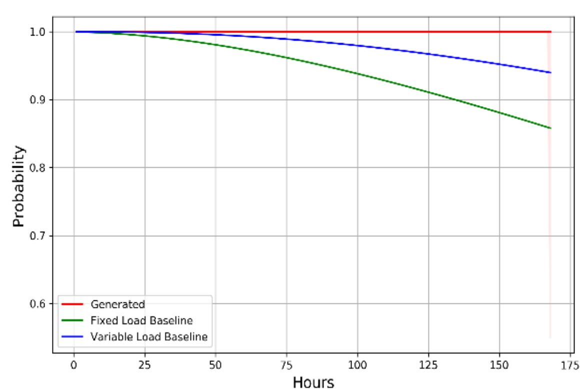


Figure 61. Reliability Curve for NAS Corpus Christi with Loss of One Generator and with Battery

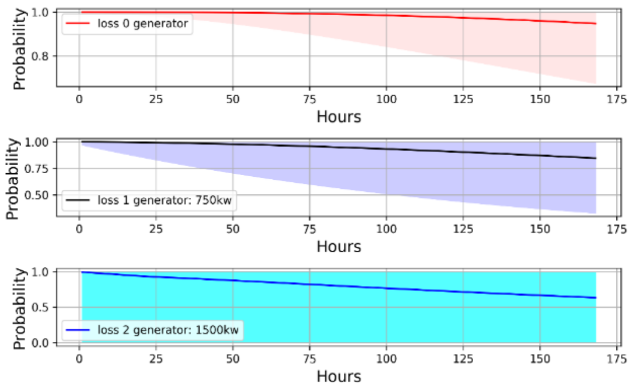


Figure 62. Reliability Decay Due to the Loss of 1 or 2 Generators at NAS Patuxent River (no Battery)

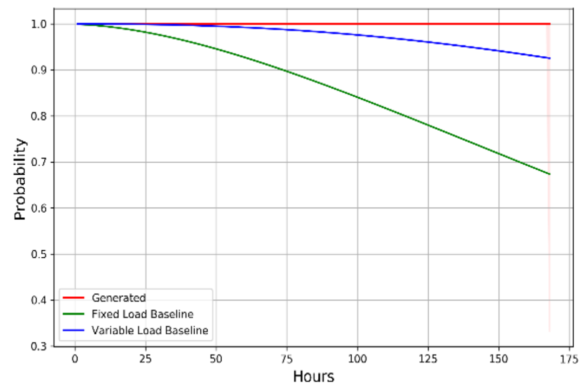


Figure 63. Reliability Curve for NAS Patuxent River with Loss of One Generator and with Battery

6.6 RELIABILITY VS LIFE-CYCLE-COST

We have further examined how different sizes of battery would impact the reliability curve at each site. The results are summarized in Figures 64-68 below. We varied the battery size from 100% to 60% and 30% of the size recommended. The lifecycle cost is assumed to scale proportionally with battery sizing. A 100% size installation will boost the survival rate to 100%. It is clear from the figures below that by reducing the size of the installation (i.e., 60% or 30%), 100% reliability goals can no longer be met.

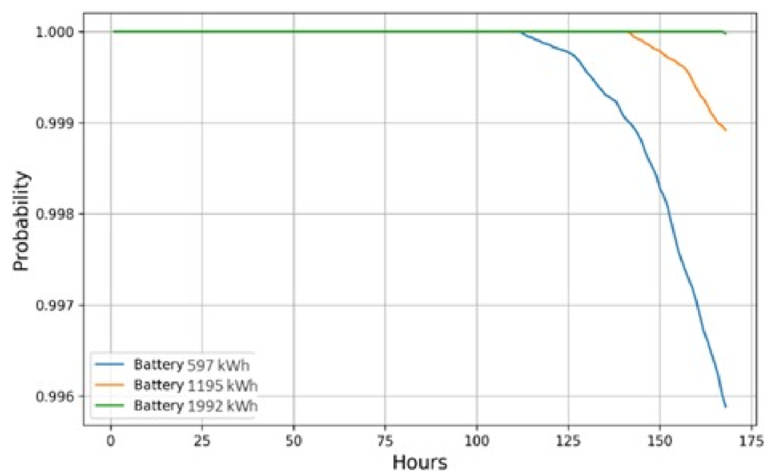


Figure 64. Reliability vs LCC for Fort Bliss

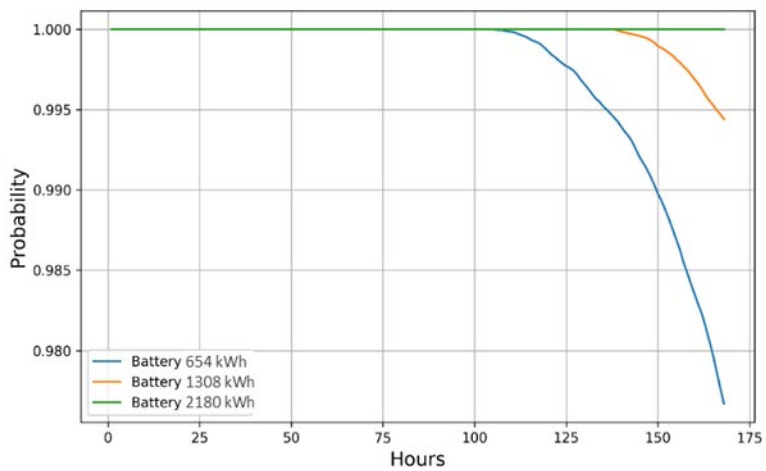


Figure 65. Reliability vs LCC for Holloman AFB

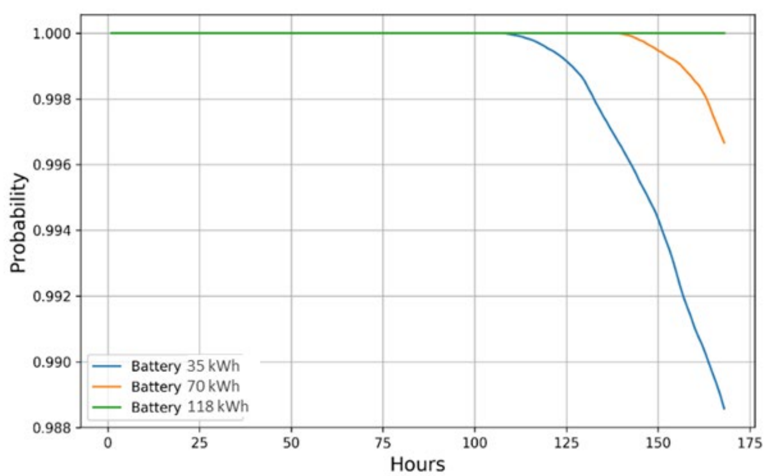


Figure 66. Reliability vs LCC for March ARB

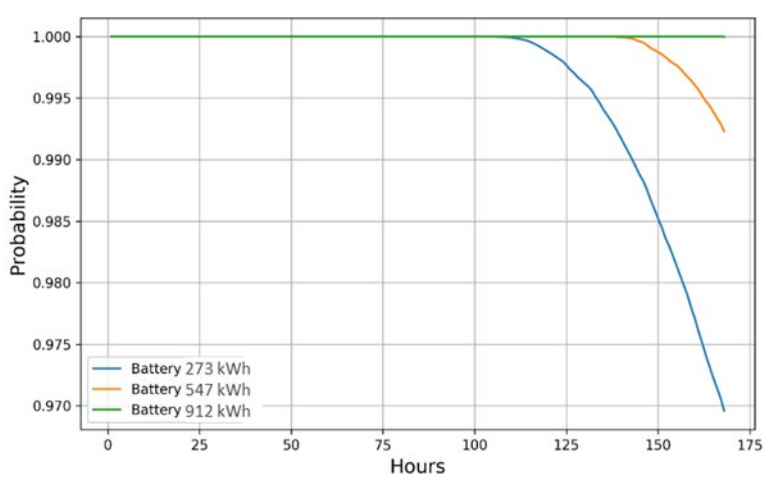


Figure 67. Reliability vs LCC for NAS Corpus Christi

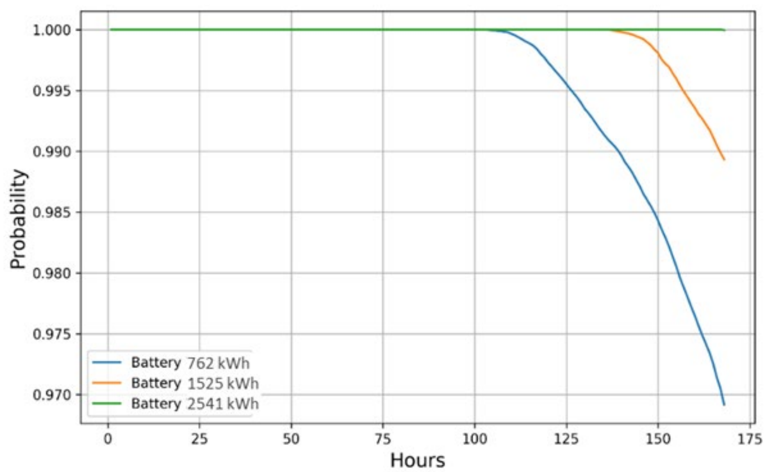


Figure 68. Reliability vs LCC for NAS Patuxent River

7.0 COST ASSESSMENT

7.1 COST DETAILS

Currently, all five sites meet their energy requirements through diesel generators. Thus, the annual cost of operation involves only the electricity bill. After incorporating batteries into the system, the electricity costs change and other costs like battery degradation also come into play. In the following sections, details of cost savings and revenue earned through market participation are given.

a) Peak shaving

Savings are primarily obtained through the reduction of the peak demand electricity bill when the battery is in operation. The cost breakdown for each site obtained through the optimization is shown in Table 8.

Table 8. Estimated Annual Costs and LCC Analysis for 20-year Lifetime

	NAS Corpus Christi	**NAS Patuxent River**	**Holloman AFB**	**March ARB**	**Fort Bliss**
Annual electricity bill before optimization	$7,127,185	$17,749,463	$ 6,066,698	$ 4,353,485	$ 20,749,629
Battery size after optimization (kWh)	1600	4500	4000	1000	3500
Battery power/Inverter size after optimization (kW)	600	600	600	300	1000
Battery & inverter installation cost	$140,000	$285,000	$260,000	$80,000	$275,000
Annual battery degradation cost	$3,575	$7,967	$11,491	$4,669	$5,247
Est. Annual electricity bill after optimization	$7,051,996	$17,682,167	$5,952,039	$4,328,007	$20,731,143
Est. Annual savings with accounting for battery degradation	$71,614	$59,329	$103,167	$20,807	$13,239
Internal Rate of Return	44%	20%	39%	26%	0%
NPV of savings over 20 years	**$843,204**	**$529,540**	**$1,156,403**	**$205,663**	**-$93,234**
Years to recover investment	3	6	2	13	> 20 years

In Table 8, for each site, the optimal battery and inverter sizes and the resulting savings are shown. The battery cost is 50 $/kWh and the inverter cost is 100 $/kW, which is used to calculate the installation cost of the entire storage system consisting of the battery and the inverter.

The annual battery degradation cost is a measure of the remaining battery life as a function of the original cost and the amount of discharging being done. When the cumulative degradation cost over multiple years of operation gets close to the original installation cost, then the battery would need to be replaced.

Table 8 also gives the Internal Rate of Return (IRR) and the Net Present Value (NPV) over 20 years. The annual inflation and discount rates are 2.2% and 6% respectively for all five sites. Since the load profile is assumed to be the same over the investment horizon of 20 years, the annual savings for the first year is used to calculate the NPV. The initial investment is the battery and inverter installation cost.

An example of how the battery saves cost though peak shaving is shown below in Figure 69 for NAS Corpus Christi. The energy supplied by the grid is marked in orange and the load profile is marked in blue over a single day. The red dotted line represents the State of Charge (SoC) of the battery. When the battery is fully charged the SoC takes a value of 1. It decreases when the battery is discharging and vice versa. During the afternoon, a load peak occurs, and the demand is almost 24 MW. It is also the highest demand in the entire month, and thus the site incurs peak demand costs along with the normal generation charges. The generation and distribution energy charges are \$0.035660 and \$0.000512 per kWh respectively. Monthly peak demand transmission and distribution charges are \$5.476816 and \$6.580761 per kW respectively, much higher than the energy charges.

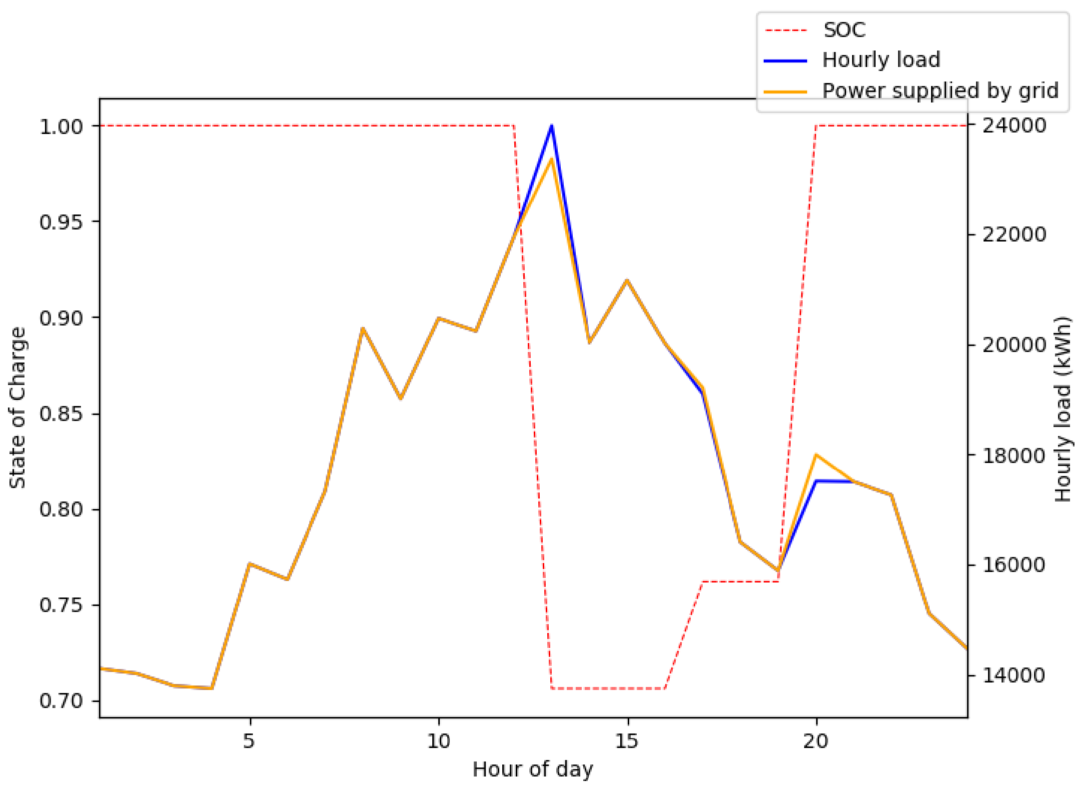


Figure 69. Load Profile for One Day at NAS Corpus Christi

As a result of the optimization, the battery, being fully charged at this point, starts discharging when the demand gets close to the peak. Thus, the grid supplies less load than it would have without the battery. In other words, from the perspective of the grid, the peak load is partially lowered or 'shaved' by the battery. This results in savings on the peak demand charges, which is much higher than the battery degradation cost during the discharging period. The battery is charged back again when the demand drops. The cost distribution in Table 9 further illustrates this point.

Table 9. Cost Distribution During 1-day Battery Operation at NAS Corpus Christi

Peak load cost incurred without battery	$ 288984
Peak load cost incurred with battery	$ 281785
Peak load savings	$ 7199
Battery degradation cost during peak shaving	$ 507
Energy cost to recharge battery to full capacity	$ 22
Overall savings	**$ 6670**

For the first three sites, NAS Corpus Christi, NAS Patuxent River, and Holloman AFB, the number of years to recover the investment ranges from 2 to 6 years. For March ARB, the recovery period is higher at around 13 years. For Fort Bliss even though there are annual savings, they are too low compared to the initial investment. The reasons for the poor savings in March ARB are as follows:

- March ARB is assumed to use 47,507 kWh each day of WAPA supply even if the actual demand is lower.
- If daily demand exceeds 47,507 kWh, the extra load is supplied by SCE.
- The SCE cost is the only component the optimization can use for cost reduction.
- Due to the high percentage of fixed costs in the total tariff, savings is very low compared to the investment.

The poor returns for Fort Bliss are due to the following reasons:

- Fort Bliss is charged for a 'firm' demand of 44,000 kW, both for energy and monthly peak demand.
- The 'interruptible' energy charges are the only component that can be optimized.
- Thus, a significant portion of the total cost is made up of fixed costs and results in the battery being ineffective.

Figure 70 shows the hourly demand for January 2018 in blue. The firm demand of 44,000 kW is shown in red. Hourly demand exceeds firm demand in only two instances towards the end of the month. Thus, for this month, a major portion of the electricity cost is due to the firm energy charges. The only room for optimization is the interruptible demand. But it occurs very few times in a month and the interruptible energy charges are also much lower than the firm charges. This results in miniscule savings which are not enough to justify the initial investment in the battery system.

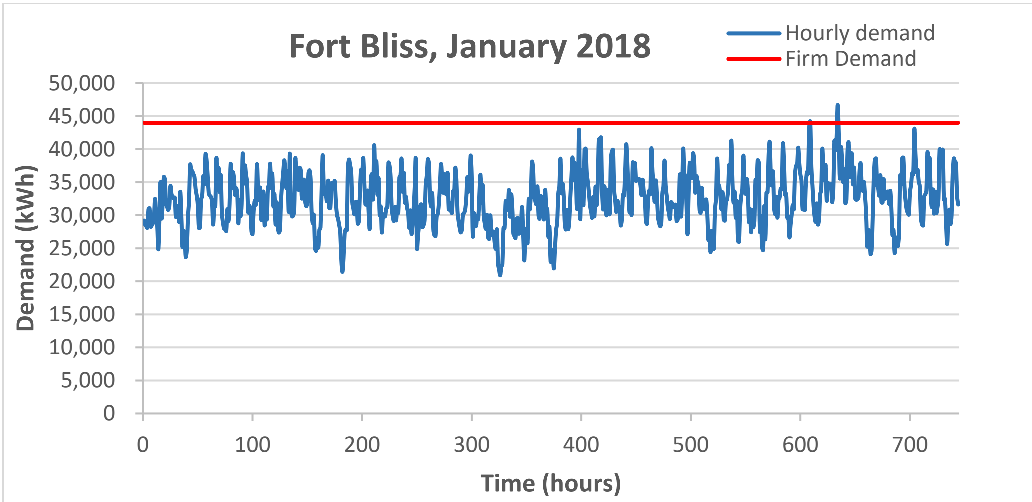


Figure 70. Fort Bliss Hourly Load in January 2018 Compared to the Firm Demand

b) Market participation

Figure 71 shows the market structure in the United States. Market participation by deploying energy storage in both energy and ancillary markets is studied for current and future volatile market scenarios. The energy market and ancillary service market are only available for three sites out of five sites in the present study. Based on the data given for price in current/volatile scenarios, there is no revenue opportunity by participating in the energy market for Corpus Christi and NAS Patuxent River with the current scenario. For the energy market, storage will maintain a constant output power over each hour. For the energy market, a resource offers a capacity and usually the scheduled and actual quantities are equal. We examined demand response program, and our finding was that many a time the return was negative due to the degradation of batteries. Therefore, we excluded demand response programs in our market study.

To maintain frequency of at 60 Hz in the United States, ancillary services are designed. In the ancillary market, it is assumed that the battery storage can track the regulation signal which comes regularly from the ISO. For CAISO, the regulation need can have a non-zero mean for up to several hours which could be different for other markets. For instance, the PJM regulation need is zero mean over most 1-hour intervals. Regulation up and regulation down (sometimes they are combined into a single regulation quantity, Patuxent facility) are ancillary services designed to maintain frequency stability. Regulation up is the ability to provide additional generation on command signal and regulation down is the ability to reduce generation, or store power, on demand. Based on FERC order 755, the industry is evolving towards "pay for performance" where the participants should be compensated based on the amount of regulation provided. For the regulation market, a resource usually offers a capacity and there is no guarantee that all the offer will be accepted. The accepted offer is proportional to the participant's load quantity in the market.

An alternative approach to maintain the grid frequency, is demand response, which refers to modulating the load to meet generation.

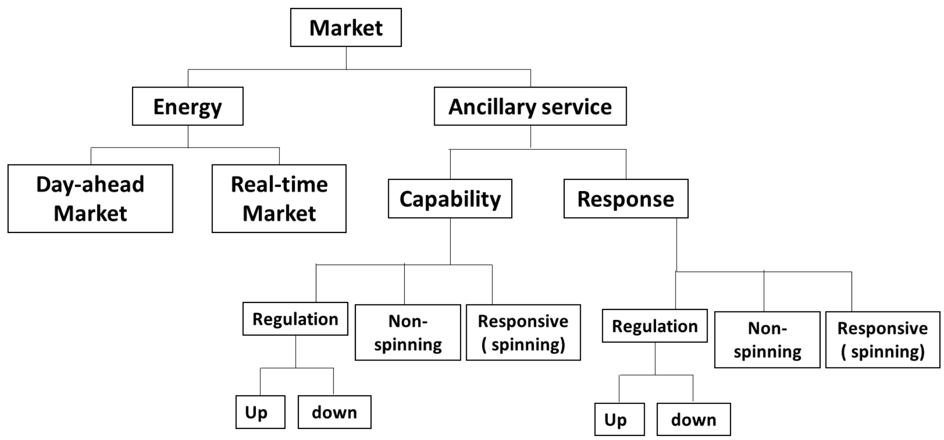


Figure 71. Market Structures

Whenever modeling the market for emerging battery storage, some constraints based on the type of storage device should be taken into consideration. The constraints include limits on the state of charge, the degradation cost and the storage inverter which manages the rate of stored or discharged energy. In this study, we neglect the effects of energy storage ramp rate, since the ramping time is negligible compared to the time period (one hour).

For the market analysis (current and future volatile market scenario), energy storage cost terms are considered. These costs are associated with the cost to discharge/recharge the battery. Since the battery storage has a limited life cycle, the cost of discharging is considered a degradation cost. In addition, we assumed that the battery should charge back each day in order to be ready for another signal for market participation. We assumed that the state of charge cannot be less than 0.6 every hour which limits the amount of energy available for market participation. For charging the battery, there are two options for the cost: charging with the same rate in the yearly contract with utilities or charging with the market prices whenever the price is low.

The market analysis is broken into two different sections. The first section presents the results for the Day-ahead energy market for three different sites and the second section explains participation in the ancillary market. The energy storage unit cell characteristics are listed in Table 10. Hourly market prices are given and used for the market analysis.

Table 10. Battery Unit Cell Characteristics

Nominal V	1.30 V
Max capacity	250 Ah
Max energy	325 Wh
Max power	100 W
Max P/E	0.31
Max Charge power	81 W
Dimension	4" x 4" x 9"

This analysis focuses on the maximum potential revenue by considering battery storage charging and degradation costs. The energy storage is also assumed to be operational up to 60 percent of its total capacity at each hour. Net revenue could be achieved when the price for day ahead market (DAM) and ancillary service recoup the battery storage related costs.

The maximum net revenue is a critical calculation because it shows the performance of energy storage in the market for both current and future volatile scenarios.

c) Day ahead market analysis

This section presents the maximum possible revenue from participation in the energy market. The energy storage system characteristics are the same for all three different sites. The price of electricity was assumed to be the Locational Marginal Price (LMP) in the day ahead market. For the degradation cost, we need the state of charge of the battery. Various scenarios (different kWh at each hour) are considered for the market participation of the battery energy storage.

The unit cell battery is not always guaranteed to be charged and discharged between fixed limits. The battery cycle is measured by the maximum number of charging and discharging cycles. The maximum number of cycles is mainly determined by how deeply the battery is used (11). In this study, to model the degradation of the battery, loss is defined as the reciprocal of the maximum number of cycles. Figure 72 shows the battery cell loss versus SOC (with curve fitting through the experimental data). By applying curve fitting curve via eq.1, we can find the battery degradation model. The loss can be converted into a monetary value with respect to the total cost of a unit cell. For modeling the battery degradation as a cost function, the initial cost of the battery should be considered (Eq.2). We follow this definition, and assuming there is no degradation during charging mode of the battery (1).

Hence, the degradation cost of the discharging battery is calculated. We consider the cost of battery ($/kWh) and the maximum capacity of the battery (kWh) to calculate the degradation cost.

Degradation cost function

Eq. 1 $$Deg_{bat} = -0.0064 \times SOC + 0.0066$$

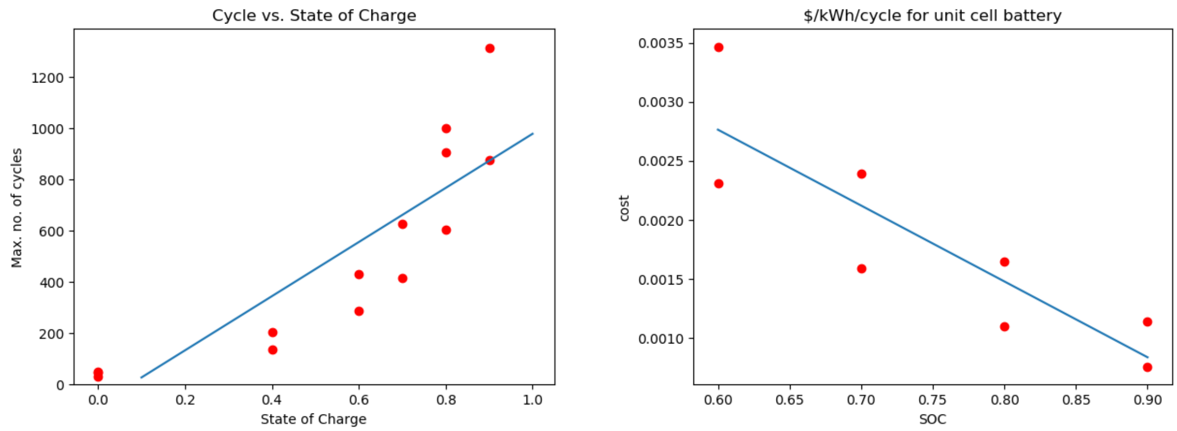
The degradation cost function can be expressed in monetary terms as follows

Eq. 2 $$C_{Deg_{bat}} = (-0.0064 \times SOC + 0.0066) \times C_b \times E_{max-bat}$$

For a battery discharging from time *t* to *t+1*, the cost can be expressed as,

Eq. 3 $$C_{Deg_{bat}}(t, t+1) = C_{Deg_{bat}}(SOC(t)) - C_{Deg_{bat}}(SOC(t+1))$$

Where C_b is the unit cost of the battery, and $E_{max-bat}$ is the battery size.



(a) (b)

Figure 72. a) Original Number of Cycles Curve from Manufacturer's Data Sheet with Curve Fitting. b) Battery Degradation Cost Curve Fitting for Each SOC

Table 11 summarizes the DAM participation by considering associated costs. The degradation cost is considered for the ancillary service market. For each site, the annual degradation cost is calculated using – a) based on the size of battery energy storage; b) assuming that each day the battery should charge back and be available for the next day. By considering costs of the energy storage, net revenue happens when the hourly price recoups the associated costs. For the three sites considered, studies show that for the current scenarios, there are few hours that net revenue happens by participating in the DAM. For future volatile scenario, based on the given price, revenue happens in some monthly windows with limited hourly participation. Hourly rates or charges minimum cost from the utility and from the market are also shown in Table 10. It is assumed that the battery can charge during the low-price hours and discharge when the price is high.

Table 11. Day ahead energy market participation summary

	Corpus Christi		**March ARB**		**NAS Patuxent River**	
Optimum battery size (kWh)	3300		1700		5000	
Battery participation size (kWh)	1300		680		2000	
Inverter Size (Kw)	600		300		600	
Degradation Cost ($)	$ 385.44		$ 320.96		$ 640	
Monthly Window (available for Energy Market)	**Current**	**Future Volatile**	**Current**	**Future Volatile**	**Current**	**Future Volatile**
	-	Feb, Mar, Dec	Jun, Aug, Sep, Oct	Jun, Aug, Sep, Oct	-	Feb
#hours Energy market price greater than degradation cost (hr)	0	75	31	75	0	20
Min daily charge ($)	$ 47.023 (Utility) $ 26.15 (Market)		$ 70.67 (Utility) $ 23.18 (Market)		$ 118.82 (Utility) $ 80.30 (Market)	

The maximum price for the current DAM in Corpus Christi, March ARB and NAS Patuxent River are 276.36, 753.67 and 201.93 ($/MWh) respectively. Based on the calculation, the market participation for the optimal storage size in kWh is small in comparison to the cost of charging the battery and its degradation cost. Revenue from battery participation in the market happens when the price of energy is higher than the price of charging plus the battery degradation cost.

Based on the battery characteristics provided by UEP (Figure 73), daily usage of the battery would require replacement of the battery in one year.

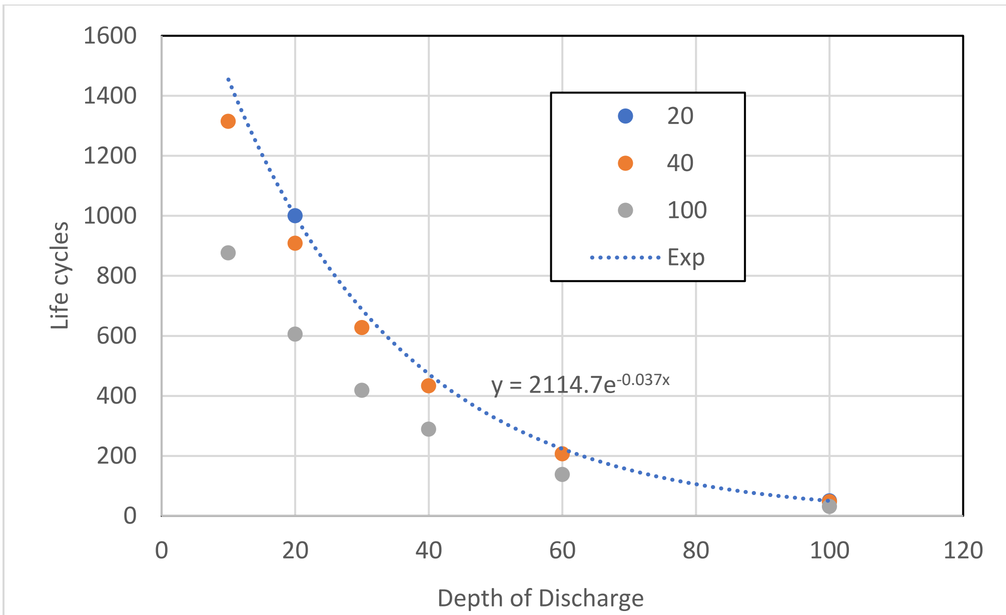


Figure 73. Battery Characteristics, DOD v/s Number of Cycles

d) Ancillary service market

This section presents the maximum possible revenue from participation in the ancillary market. The energy storage system parameters are the same as in the DAM analysis. To calculate the revenue from participation in the ancillary market, we must consider both capability and response. Since, we do not have any data related to the frequency of the signal coming from ISO, the calculation is done just with capability. Ancillary services certification is required for participating generators and participating load in order for them to bid for ancillary services.

For PJM market, the regulation requirements are fixed based on the previous percentage of peak load requirements. For ERCOT, regulation requirements are calculated hourly by using 5 minutes net load variability and short-term load forecast error. In CAISO, they are calculated as percentage of day-ahead and hour-ahead demand and they are basically based on the maximum ramping needs projected for each operating hour (12). It is important to note that in CAISO's market, resources are generally not penalized for excess or deficient energy, and as such these resources can chase prices in real-time when prices are above their dispatch signal, which could exacerbate an over-generation condition (13). There are some differences in the characteristics of ancillary market in the U.S. between ISOs/RTOs. Minimum capacity constraint for ERCOT and PJM market for regulation reserve are 1 MW and 0.1 MW respectively (14).

Maximum time to deliver nominated capacity for CAISO, ERCOT and PJM are 10 to 30 minutes, 10 minutes and 5 minutes. Minimum duration to maintain the capacity for participants in spinning reserve and non-spinning reserve for CAISO is 10 minutes and should be maintainable for two hours while there is no restriction for other markets (14).

In order to quantify the change in state of charge from participation in the ancillary market, the regulation up is defined as the fraction of the energy storage capacity. Similarly, the regulation down, responsive reserve and none-spinning reserve are defined in percentages. Table 11 summarizes each ancillary service percentage for each site. These fractions are assumed values that were used for the purpose of demonstrating how battery can participate in ancillary market and can be changed based on real condition at the site in Phase 2 of the project. In this study, these fractions of energy storage capacity are considered based on the price of each ancillary service. Higher fraction is given to the higher summation of price over a year and the net revenue is calculated based on these percentages. The amount of charging and degradation costs are considered similar to Table 4 for each site.

The percentages in Table 12 are used to calculate the revenue of battery energy storage participation in the ancillary services. For each site, some ancillary services are available in the market and some of them are not. Based on the price of each service ($/MWh), the maximum percentage of each battery storage capacity goes to the highest price available for the ancillary service. The signals for regulation up/down are more frequent than the responsive reserve or non-spinning. But, for Corpus Christi site, the price for the responsive reserve is much higher than the others and that is the reason for a higher percentage in that service.

Table 12. Ancillary Market Fractions for Each Service

	Responsive Reserve	Non-Spinning reserve	Regulation Up	Regulation Down
Corpus Christi (1200 kWh)	% 55	% 15	% 25	% 15
NAS Patuxent River (2000 kWh)	% 25	-	% 70	
March ARB (680 kWh)	% 25	-	% 35	% 35

Table 13 summarizes the ancillary market revenue just for the capability and not for response. There is no data available for calculating response revenue. Considering the response for ancillary service, increase the revenue from ancillary market. For each service, the capability of participant with various fraction are considered. The revenue happens when the number of energy storage life cycles as degradation cost is considered. For ancillary services, the revenue for Corpus Christi, Patuxent and March ARB are calculated as summarized in Table 12 and could be achievable when the number of signals for the actual response is less than the number of energy storage cycles calculated for each site. The last column in Table 13 shows the maximum annual cycle numbers if the signals come from the system /market operator for battery energy storage participation in ancillary market.

The market analysis focuses on the maximum potential revenue when considering battery storage charging and degradation costs. The energy storage is also assumed to be operational up to 60 percent of its total capacity at each hour. Net revenue could be achieved when the price for day ahead market (DAM) or ancillary service, recoup the battery storage related costs (Table 11 and Table 13) for three different sites Patuxent, March ARB and Corpus Christi. Table 11 shows that for the current scenarios, there are few hours that net revenue happens by participating in the DAM. For DAM future volatile scenario, based on the given price, revenue happens in some monthly windows with limited hourly participation. For Ancillary market, Table 13 shows that revenue may achieve from the market if the frequency of signals come from the ISO are less than the energy storage life cycles numbers. Degradation of the energy storage is the important factor which limits the participations for both DAM and ancillary service market.

Table 13. Ancillary Market Maximum Annual Revenue for Each Service

Facility	Responsive Reserve	Non-Spinning reserve	Regulation Up	Regulation Down	#Energy storage cycles
Corpus Christi (1200 kWh)	$ 98,248.93	$ 15,405.45	$ 38,211.16	$ 12,427.23	394
Patuxent (2000 kWh)	$ 8,032.79	-	$155,153.96		255
March ARB (680 kWh)	$ 1,482.85	-	$ 3,369.58	$ 3,400.3	15

7.2 COST DRIVERS

The UEP batteries will be available at a cost of $50/kWh by 2022 based on a 100% DOD. The cost is lower than the current and projected costs of Lead-Acid and Li-ion batteries. When assembling an energy storage system, however, battery cost is not the only component to consider. System integration and installation costs can sometime amount to >30% of the total project cost. System costs include power converters, racking system, battery monitoring and management system, DC cabling, and AC interconnect. The cost of power converters and AC interconnect is the same for all the battery systems. The cost of racking and DC cabling scales as the inverse of the energy density. Therefore, the high energy density of the UEP batteries (400Wh/L) helps control those costs. The UEP batteries do not require a battery management system and use a low-cost battery monitoring system. The permitting of energy storage systems has not yet been standardized. In general term, UL 1973 and UL 9540 certifications are required for the UEP and Lead-Acid batteries. UL 9540 A (an onerous external fire test) is required for Li-ion systems given their flammability. Outdoor installations have proven to be easier to permit than indoor installations. As a final note, it is important, as discussed in Section 3, to decide whether to use a grid-tied or UEP inverter. The decision can impact the ability of the energy storage system to operate and the load that can be served by it. In many cases, a modular approach is used with different energy storage units placed on different parts of an electric circuit.

8.0 SUMMARY

Siemens and Urban Electric Power (UEP) worked on a comprehensive microgrid energy storage solution (CMES) that addresses both reliability and cost performance of a microgrid. The CMES solution consists of an offline and an online optimizer module. During Phase 1 of the project, the Offline Optimizer module was developed to compute optimal size of storage that can meet reliability goals and minimize lifecycle cost. The module was implemented on five sites. The studies conducted across the five sites show extremely promising results for proposed CMES solution, including UEP batteries. The key findings and conclusions are listed below:

- CMES solution enable us to size and design a storage system that guarantees 100% of installation critical and ride-through load requirement for all the sites.
- We were able to demonstrate that with the addition of the sized CMES solution we were able to meet 130% of installation critical and ride-through load requirement for all the sites.
- We were able to demonstrate that with the addition of the sized CMES solution we were able to meet 10% and 30% of installation critical and ride-through load when no diesel fuel is available.
- The CMES solution is able to generate storage solution for four sites - NAS Corpus Christi, March ARB, Holloman AFB and NAS Patuxent River, such that not only all the reliability requirements are met but the technology investment cost can be recovered in less than 20 years.
- The CMES solution shows that for all the five sites one of the generators can be replaced with the storage system without significant impact on the site's reliability performance.

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9.0. REFERENCES

1. Wang, Y., Song, Z., De Angelis, V., Srivastava, S. Battery Life-cycle optimization and runtime control for commercial buildings demand side management: A New York City case study. 2018, Energy, Vol. 168, pp. 782-791.
2. Sarewitz, D., Thernstrom, S., Alic, J., Doom, T. *Energy Innovation at the Department of Defense. Assessing the opportunities.* Consortium for Science, Policy and Outcomes at Arizona State University, March 2012.
3. Greenley, H. *Department of Defense Energy Management: Background and Issues for Congress.* s.l. : Congretional Research Service, July 25, 2019.
4. Office of the Assistant Secretary of Defense for Energy, Installations, and Environment. *U.S. Department of Defense Annual Energy Management and Resilience (AEMRR) Report, Fiscal Year 2016.* July 2017.
5. Sustainment, Office of the Assistant Secretray of Defense for. *U.S. Department of Defense Annual Energy Management and Resilience (AEMRR) Report, Fiscal Year 2018.* July 2019.
6. Institute, Environmental and Energy Study. *Fact Sheet: DoD's Energy Efficiency and Renewable Energy Initiatives.* July 2011.
7. Energy Information Administration. [Online] www.eia.gov.
8. Zablocki, A. *Fact Sheet: Energy Storage (2019)* Environmental and Energy Study Institute, February 2019.
9. United States of America, Federal Energy Regulatory Commission, 18CFR Part 35 [Docket Nos. RM16-23-001, AD16-20-001 and 841-A], Order No. Electric Storage Participation in Markets Operated by Regional Transmission. May 16, 2019.
10. [Online] http://www.gurobi.com/.
11. Choi, Y., Hongseok, K. *Optimal scheduling of energy storage system for self-sustainable base station operation considering battery wear-out cost.* Computer Science - Eighth International Conference on Ubiquitous and Future Networks (ICUFN), 2016.
12. Bhatnagar, D., Currier, A., Hernandez, J., Ma, O., Kirby, B. *Market and policy barriers to energy storage deployment. A study for the energy strorage systems program.* Sandia National Laboratories, 2013.
13. Byrne, R.H., Silva-Monroy, C. A. *Estimating the maximum potential revenue for grid connected electricity storage: Arbitrage and regulation.* Sandia National Laboratories, 2012.
14. Ellison, J.F., Tesfatsion, L.S., Loose, V.W., Byrne, R.H. *A survey of operating reserve markets in U.S. ISO/RTO-managed electric energy regions.* Sandia National Laboratories, 2012.

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APPENDIX A BATTERY PLACEMENT OPTIMIZATION USING PSS®SINCAL

As one step further for the optimality studies performed in the report, we have studied optimal battery location placement using state-of-the-art analysis tool, i.e. Siemens PSS®SINCAL (SINCAL). In contrast to the "lumped" model used in the rest of this report, SINCAL is a "topology" based tool. It can consider the topology of the circuit, power flow analysis, and determine the optimal battery placement based on voltage improvements. Problems like voltage drop at feeder end cannot be observed with "lumped" model. The tool also gives a more practical planning that tells under which bus a battery should be placed. Thus, we perform an analysis using SINCAL.

Appendix A is organized as follows: we first have an introduction on the circuit that we use for optimization, followed by an explanation on how to distribute the lumped loads provided to the distribution system. Then, an optimal battery placement is carried out, with the predefined energy and power rating from the reliability and economic analysis. The workflow for using SINCAL for the battery optimization is detailed in Figure 74 below.

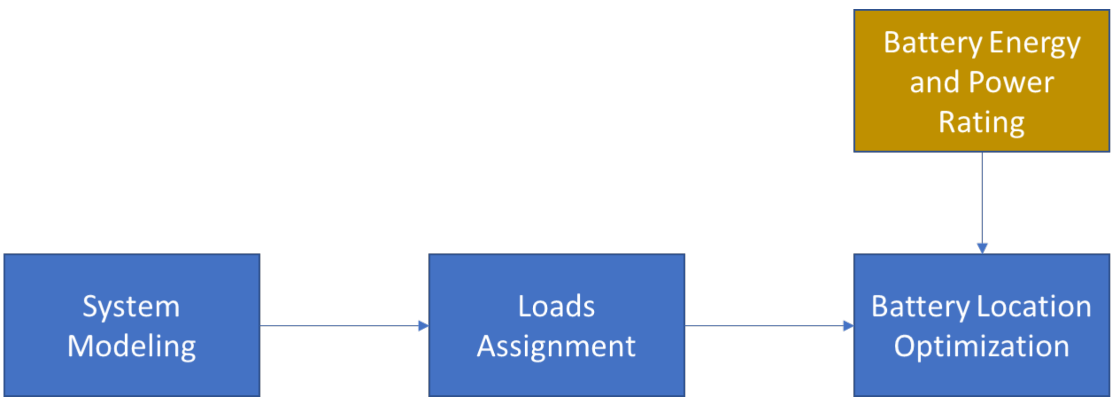

Figure 74. Workflow for PSS®SINCAL Based Battery Optimization

1. System Topology

We have used IEEE 123-bus test feeder as the model for this study. The consideration behind this choice is that IEEE 123-bus test feeder is a benchmark system that is three-phase unbalanced and distributed, all of which shares enough similarities with the military bases studied in this project. Figure 75 below shows the topology of IEEE 123-bus test feeder. It is a 4.16 kV distribution system. While this is not a popular voltage level it does address voltage drop problems that must be solved with the application of voltage regulators and shunt capacitors. This circuit is characterized by overhead and underground lines, unbalanced loading with constant current, impedance, and power, four voltage regulators, shunt capacitor banks, and multiple switches.

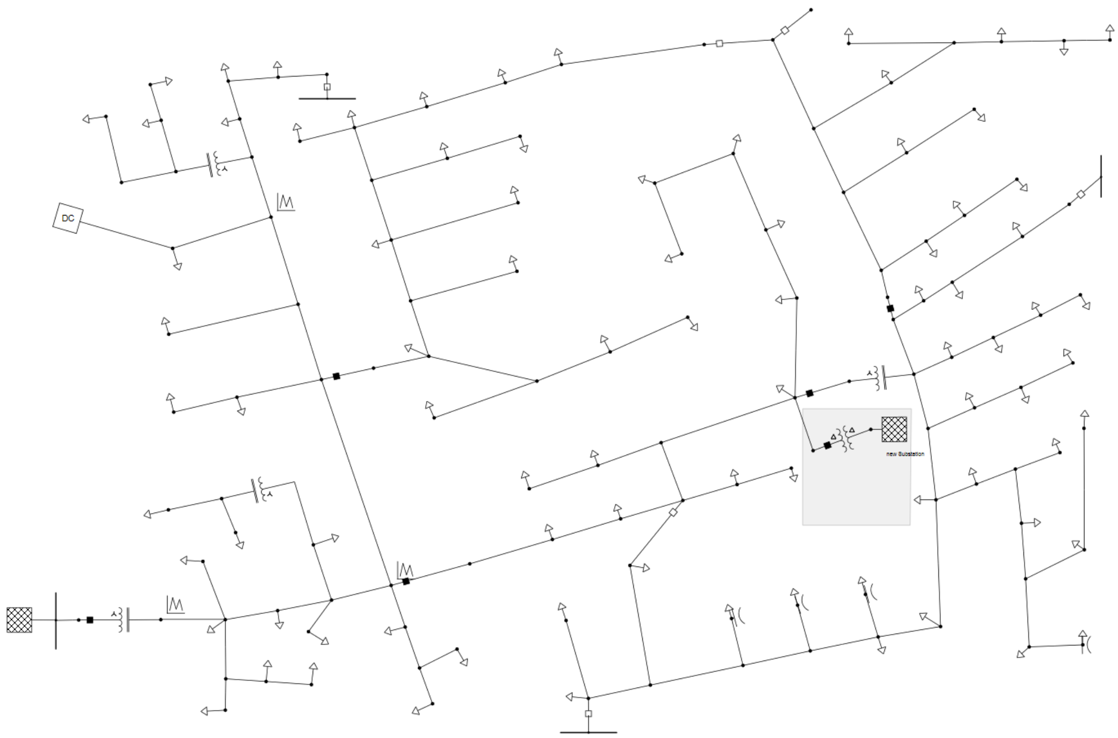

Figure 75. Topology of IEEE 123-bus Test Feeder

2. Load Assignments

Load assignment is used to calculate a load condition while taking measurements into consideration. Using Figure 76 as an example, measurement is taken at the substation (the red dot in the figure), while for the specific load under each bus, we only know the maximum or minimum values. This is the reality in distribution systems, where substations are closely monitored, while the system operator has limited knowledge of the specific loading under each bus. Therefore, we treat the data that ESTCP has provided as the measurements taken at the substation and perform a load assignment to each bus.

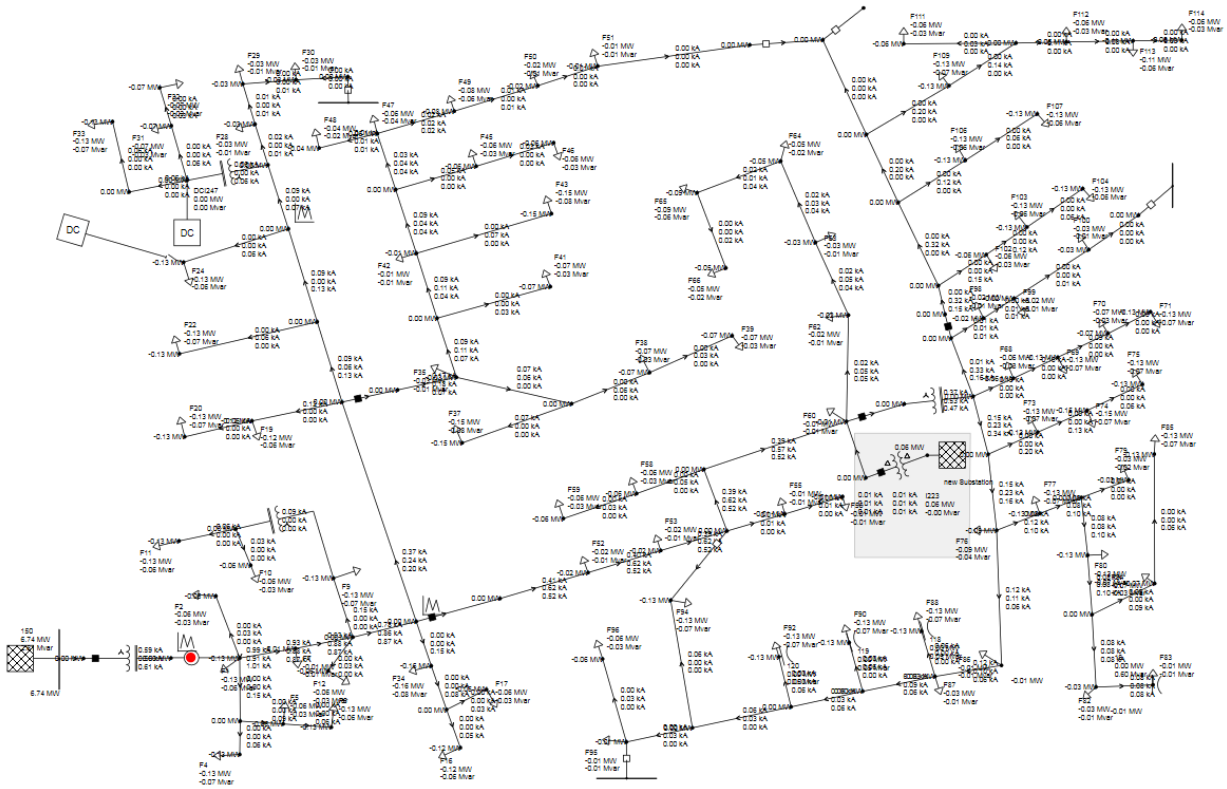

Figure 76. Load Assignment Results Showing the Power Flows Under Certain Loading Condition

Figure 77 shows the flowchart of a load assignment process. As shown in the figure, it does not guarantee a convergence of a load profile. Since the load profile that ESCTP program has provided is too large compared to the nominal loading of the IEEE 123-bus, we have scaled the load profile provided by the ESTCP program with a constant factor for each site. The detailed scaling factor is documented in Table 13 below. The scaling provides enough similarities to the load profile used in the ESTCP sites, thus becoming a good pilot for topology-based optimization.

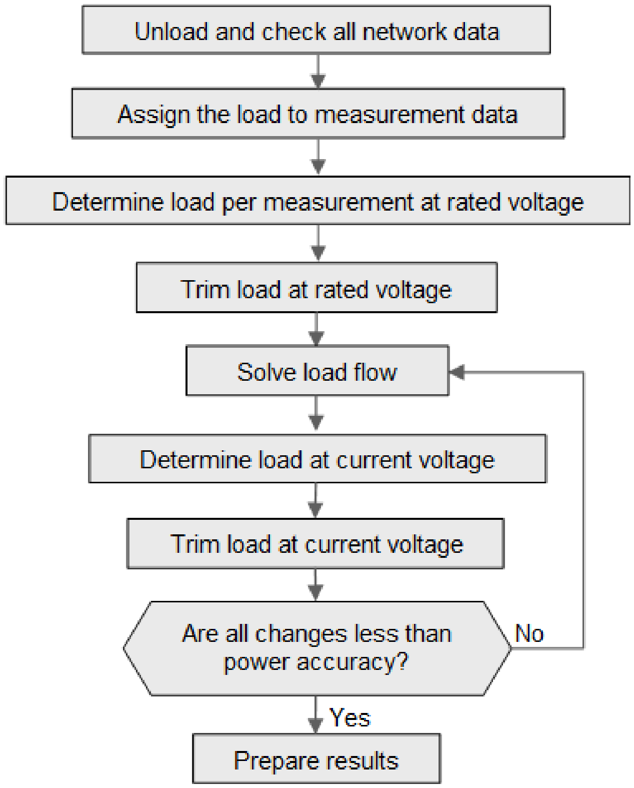

Figure 77. Flowchart of Load Assignment

Table 14. Scaling Factor for Different Sites.

Site	Scaling factor for load and battery sizing
NAS Patuxent River	0.1
NAS Corpus Christi	0.25
March ARB	0.3
Holloman AFB	0.2
Fort Bliss	0.06

3. Battery Placements

After load assignments, we utilized the battery sizing determined through the sizing provided in the economic and reliability analysis. Then we decide the optimal placement of the battery under different buses. As distributed networks face either overloading or overgeneration as a result of load consumption and solar generation, there exists undesired overvoltage and undervoltage in the feeder. This behavior is not constant but varies over time depending on the consumption situation, feed power of the parent supply network, the weather and other factors. The use of decentralized energy storage systems mitigates or largely prevents these problems. This requires placement of energy storage systems at suitable locations in the feeder, in order to take up the excess energy and store it for later requirements. Figure 78 shows the flowchart of the iterative optimization procedure.

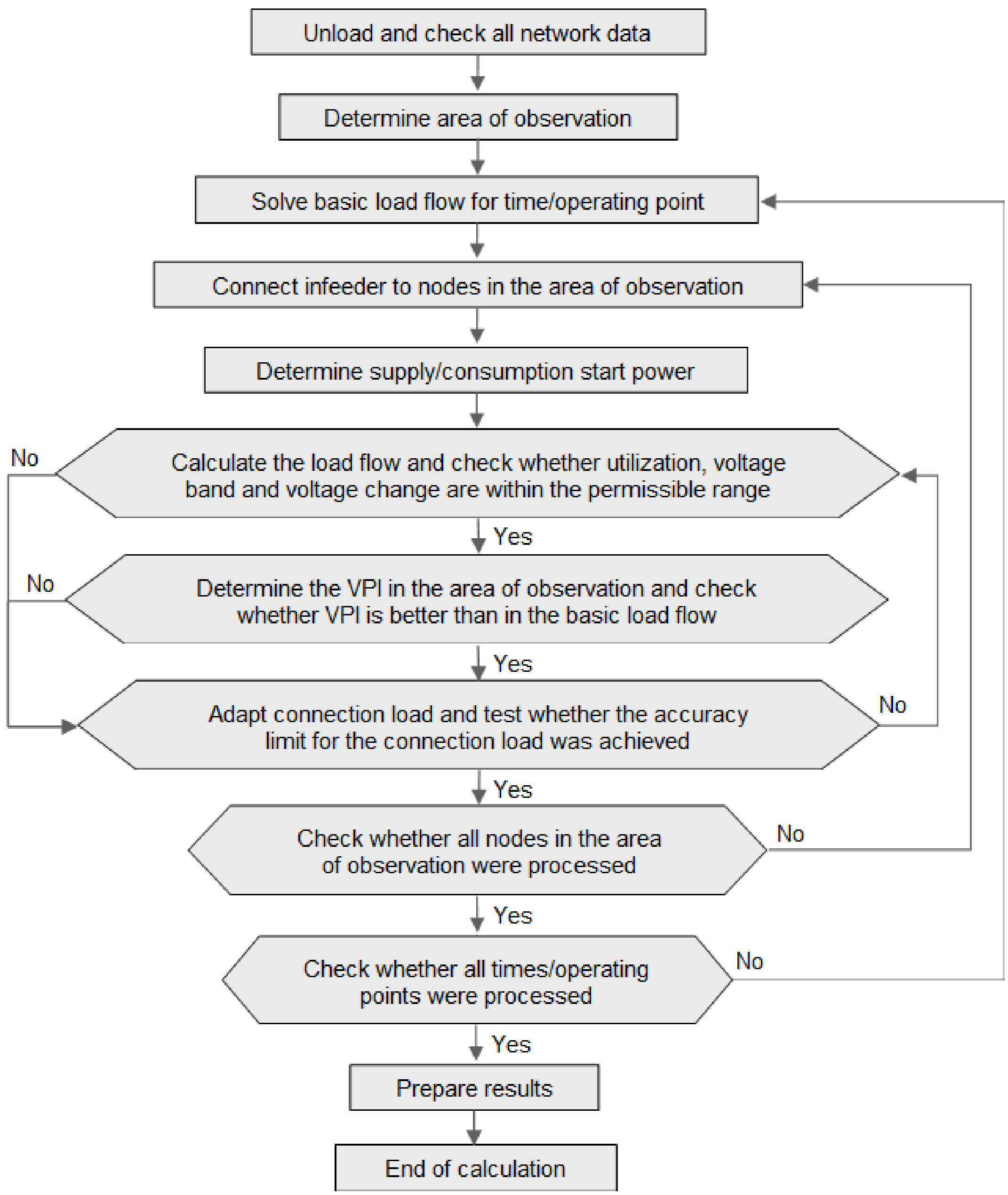

Figure 78. Flowchart of Load Assignment

Figure 79 below shows an example of the battery placement using the load profile provided by ESTCP program, following the load assignment procedure detailed earlier in this session. The highlighted area in Figure 79 shows where PV is placed in the system. We have chosen this position arbitrarily. With a more specific location on where PV should be placed in each military base, we could update the placement of the energy storage system. The figure also shows different optimal battery placements for each military site. We have searched optimal placement of battery through the 4.16kV feeder, and the SINCAL program has generated optimal placements. The placements are results of the controlling voltage profiles.

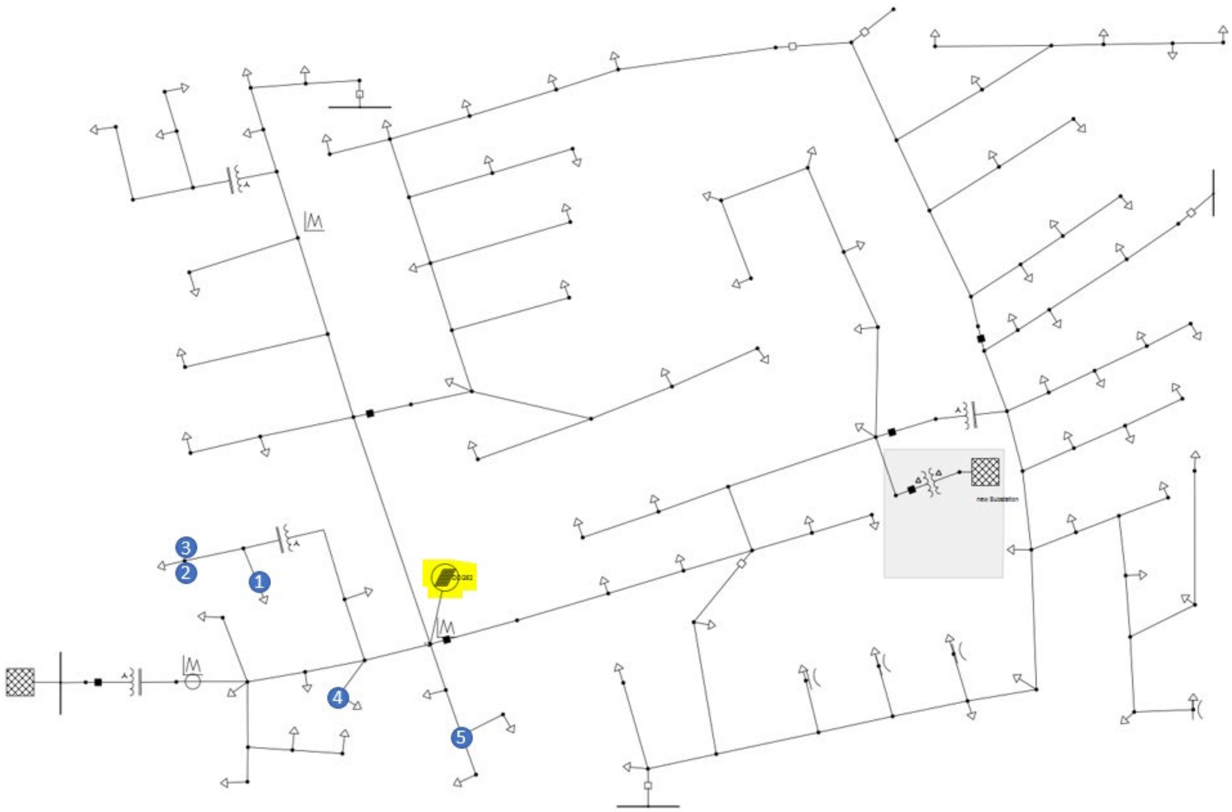

Figure 79. Optimal battery placement.

1. NAS Patuxent River 2. NAS Corpus Christi 3. March ARB 4. Holloman AFB 5. Fort Bliss

Figures 79-83 show the different voltage profiles at each site. The figures compare the voltage profile for the nodes with battery installations with their counterparts (i.e., without battery installation). For example, Figure 80, the voltage profile is more constrained with the battery installed (higher on low voltages, and lower on high voltages), which is exactly what the battery has been optimized for. The program has chosen the location because it sees the battery could bring up the voltage mostly at the place of installation. With a larger battery, it could further constrain the voltage profiles. The result show the effectiveness of the battery placement optimization.

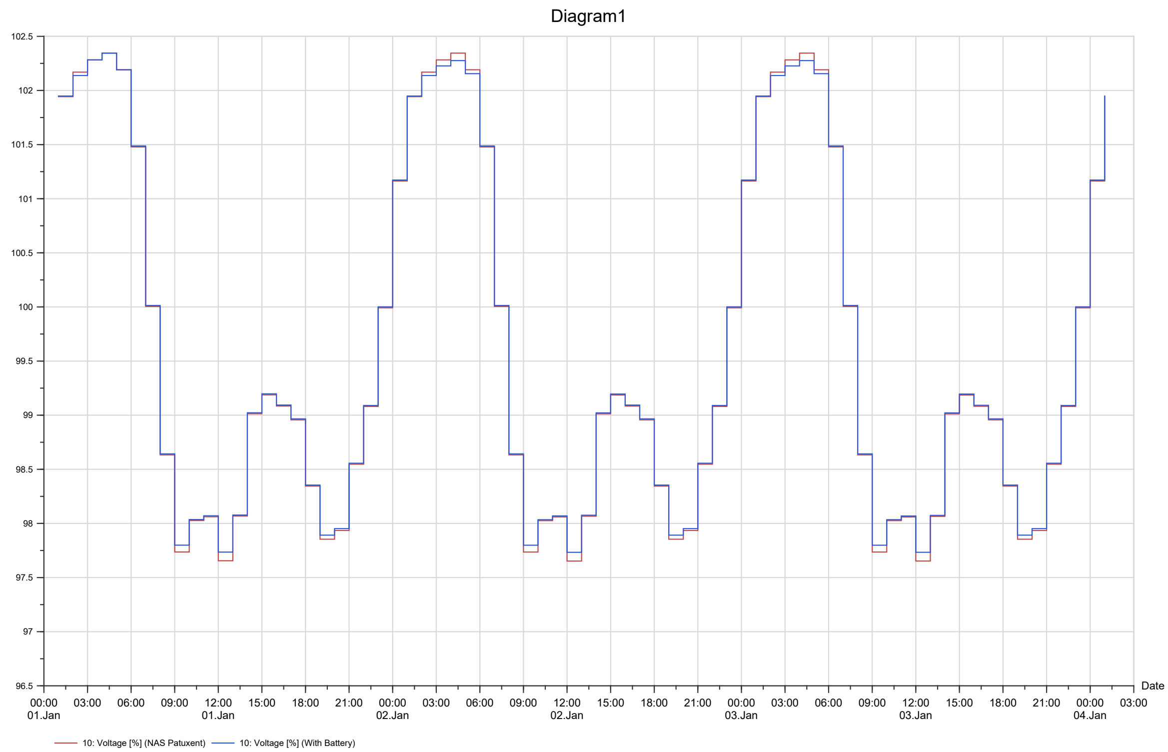

Figure 80. Voltage Profile of NAS Patuxent River

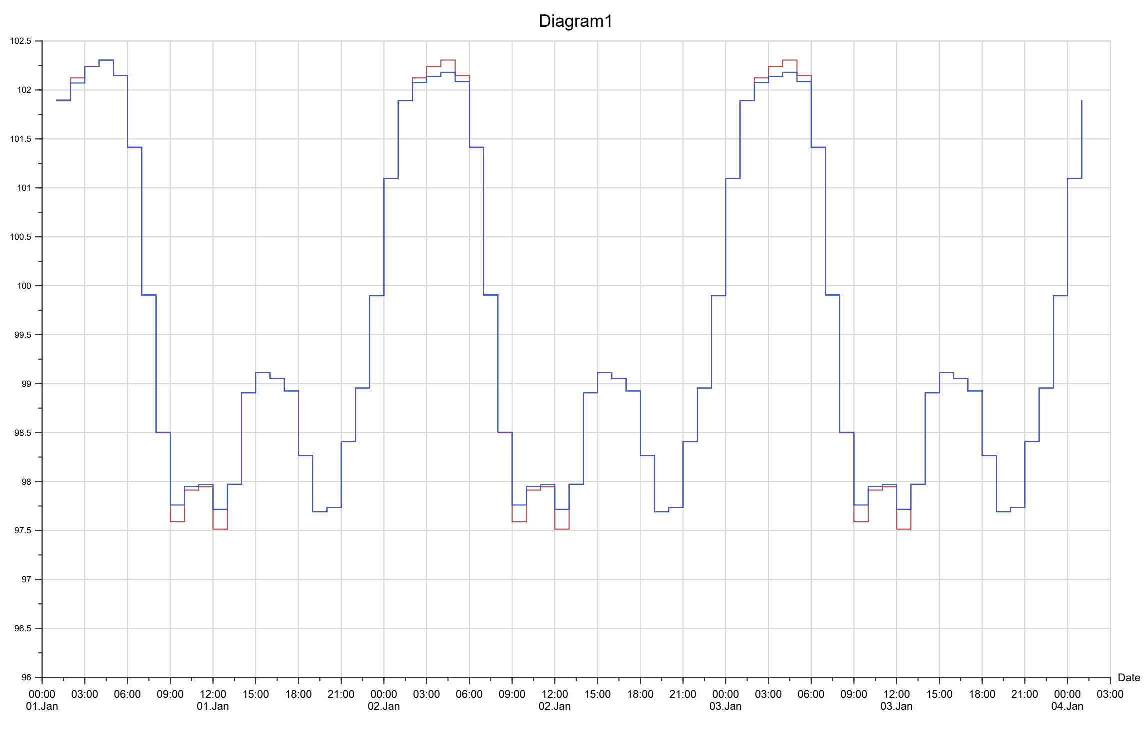

Figure 81. Voltage Profile of NAS Corpus Christi

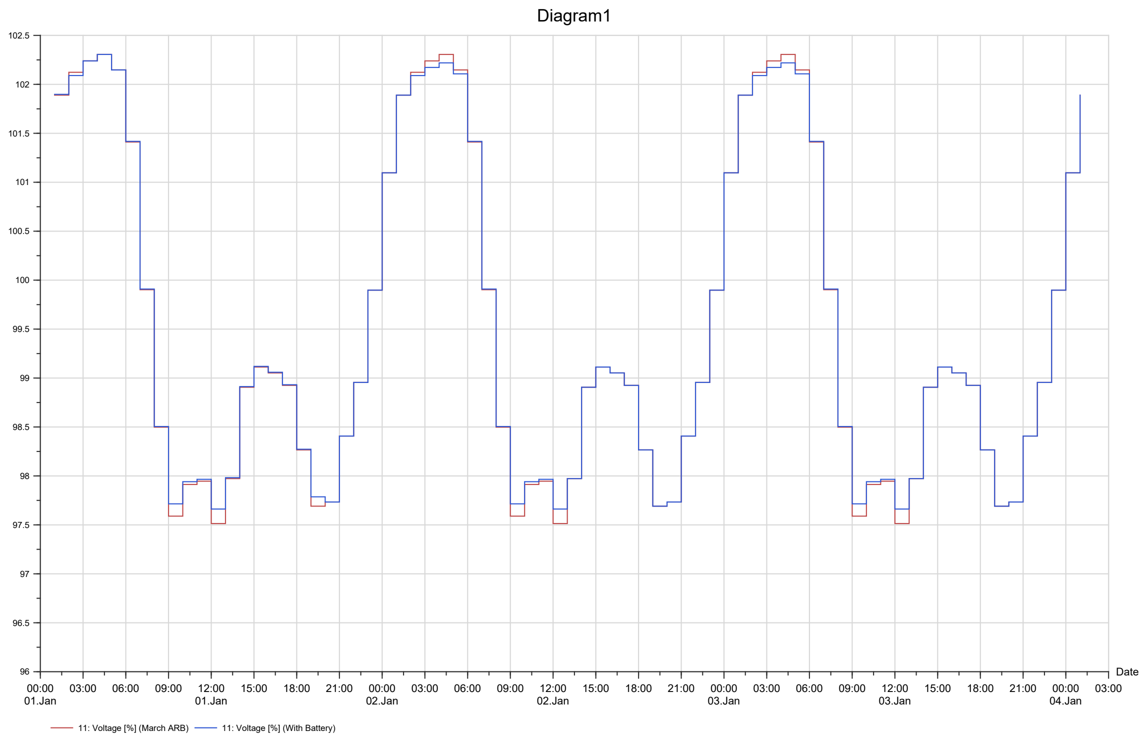

Figure 82. Voltage Profile of March ARB

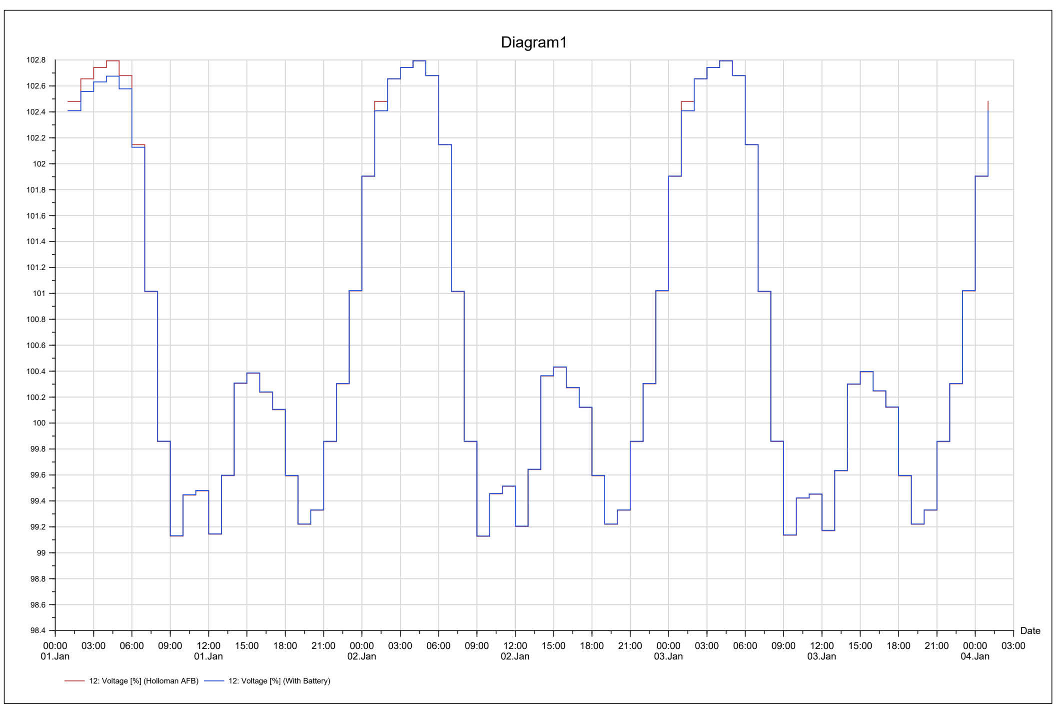

Figure 83. Voltage Profile of Holloman AFB

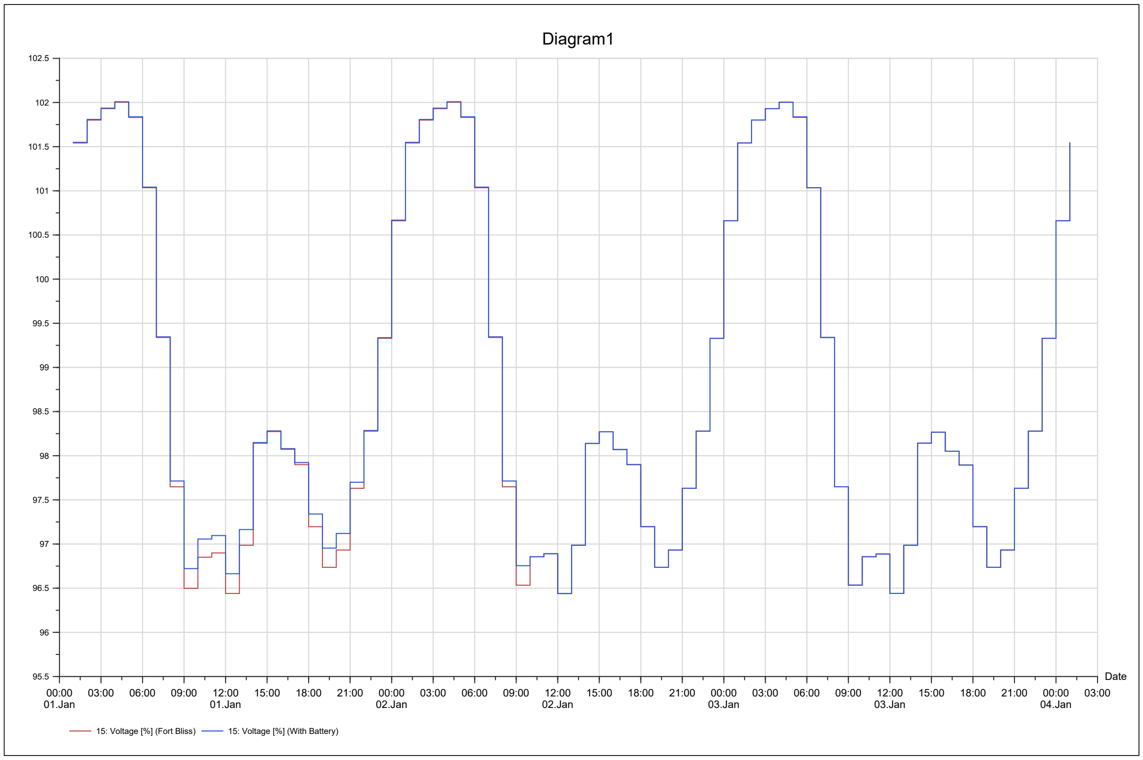

Figure 84. Voltage Profile of Fort Bliss

4. Summary

We have run the simulations using PSS®SINCAL. SINCAL can determine the optimal placement of the battery based on load profiles and circuit topology. Case studies are carried out to show the importance of using modeling and optimization of battery placements considering the circuit topology.

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APPENDIX B REFERENCES PERTAINING TO UEP BATTERY CHARACTERISTICS

Yadav, G.G., Turney, D., Huang, J., Xia, W., Banerjee, S. *Breaking the 2 V Barrier in Aqueous Zinc Chemistry: Creating 2.45 and 2.8 V MnO2–Zn Aqueous Batteries*. ACS Energy Lett. 2019, 4, 9, 2144-2146.

De Angelis, V., Yadav, G.G., Huang, J., Couzis, A., Banerjee, S. *Rechargeable Zn-MnO_2 batteries for utility load management and renewable integration*, 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)

Yadav, G.G., Gallaway, J.W., Turney, D.E., Nyce, M., Huang, J., Xia, W., Banerjee, S. *Regenerable Cu-intercalated MnO_2 layered cathode for highly cyclable energy dense batteries.* Nature Communications, 8, Article number: 14424 (2017).

Ingale, N.D, Gallaway, J.W., Nyce, M., Couzis, A., Banerjee, S. *Rechargeability and economic aspects of alkaline zinc–manganese dioxide cells for electrical storage and load leveling*. 2015, Journal of Power Sources, Vol. 276, pp 7-18.