Battery Storage System Sizing Evaluation for Utility Distribution Asset Investment Deferral

By

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B.S. Mechanical Engineering
Stanford University, 2011

Submitted to the MIT Sloan School of Management and the Mechanical Engineering Department in Partial Fulfillment of the Requirements for the Degrees of

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Abstract

A need exists for systematic evaluation methods of battery storage sizing as an electric utility asset investment. Atlantic Electric, like many US utilities, has begun to consider battery energy storage systems for multiple applications, and will likely continue to evaluate potential investments in energy storage in the future.

This thesis developes and evaluates three sizing methodologies for battery energy storage systems for a reliability application at an electric distribution substation. The methods are applied to three substation locations using real historical load data to understand the required supplemental capacity provided by on-site battery storage energy systems in situations of peak demand coinciding with N-1 contingency. The study also includes analysis of business processes for asset planning and recommendations.

The results of the analysis indicate that deterministic conservative sizing methods, when compared to a probabilistic historical risk-based method, yield battery size that is significantly larger. The most conservative battery size, which would cover the most extreme capacity needs, is approximately twice the size of the risk-based battery size, which would cover approximately 80% of capacity need events.

Going forward, the methodologies from this thesis can be developed further for evaluating battery storage systems for reliability applications among diverse conditions and use cases. Furthermore, integrating multiple use cases and potential value streams for battery storage systems in utility operations will involve cross-functional and comprehensive processes for evaluation in the future.

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1 Introduction

1.1 Problem Statement

In collaboration with Atlantic Electric, this thesis develops processes and methods to size a battery storage system for transmission and distribution (T&D) deferral in an electric sub-station as an option to consider during the asset planning process. Specifically, the evaluation focused on capital cost of battery and a reliability application in N-1 contingency events during peak demand.

Existing studies in industry and academia focus on comprehensive systems analysis, often incorporating other potential revenue generating streams of battery storage. In this thesis, added value streams are excluded to better identify the advantages of a battery storage system in a cost and reliability driven decision-making process. Thus, cost is isolated as the driving metric of selection to compare to reliability and coverage in extreme situations. The site-specific analysis of real data in a sub-station provides insights into how, in a reliability-only focus, battery storage might become an attractive option for deferral of traditional transmission and distribution asset investment.

The thesis's scope focuses on existing processes, in order to provide realistic recommendations for Atlantic Electric, an organization that would consider incorporating battery storage system evaluation into current standard operating procedures related to capital investments. Organizational dynamics around existing structures, processing, and planning for the future are taken into account in parallel.

1.2 Company Background

Atlantic Electric USA is a gas and electric utility that serves over 30,000 customers in its service territory. Atlantic Electric and regulators set electric rates for customers periodically, based on in-depth analyses of capital costs, delivery costs, and required margin to continue operations. To ensure affordable and reasonable rates, the company must balance its need for cost recovery with critical infrastructure investments in the network. Regulators review investments and deem them prudent for operations, in order to protect consumers from unjust rate hikes.

Many of the capital costs associated with ongoing operations are determined during the network planning studies that occur periodically. These studies require multidisciplinary collaboration among engineers, regulators, strategy, and others to analyze each aspect of operations within a given network area. They then come up with required infrastructure investments and upgrades, and present multiple options with a recommendation that often favors the least cost option. Traditional types of investmens included purchase or upgrades of existing equipment such as transformers or lines.

1.3 Grid-Scale Energy Storage Today

Up until recent years, utilities have been slow to systematically expand battery storage installation, in large part due to relatively high unit costs. Interest in grid-scale battery storage has been motivated by several applications: peak load shaving, smoothing of renewable energy, capital deferral, system reliability, and other ancillary services.

According to the US Department of Energy, there will be continued growth in deployments of battery storage, projected to be over 2 GW of annual deployments per year by 2021[7]. Figure 1 shows the forecasted energy storage deployment in the United States, split by residential, non-residential (likely commercial), and utility customers. Utilities are forecasted to continue to be the largest deployers of energy storage.

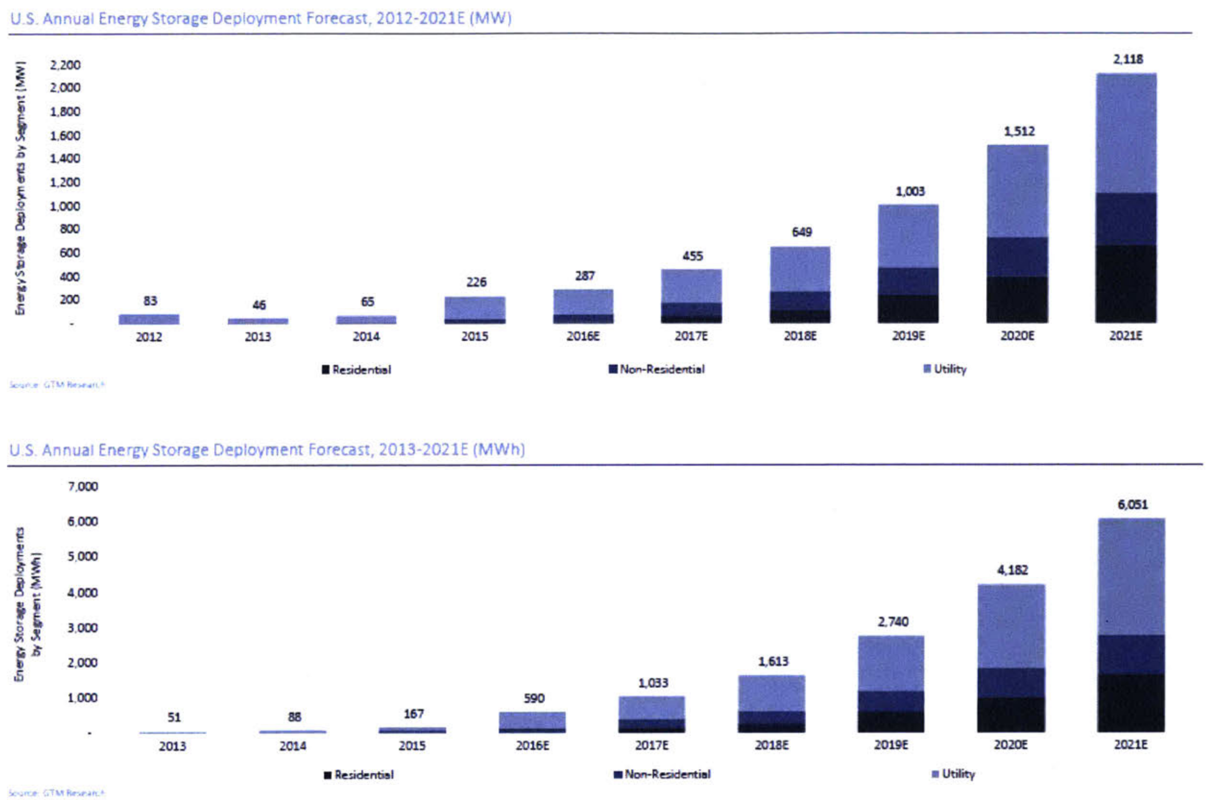
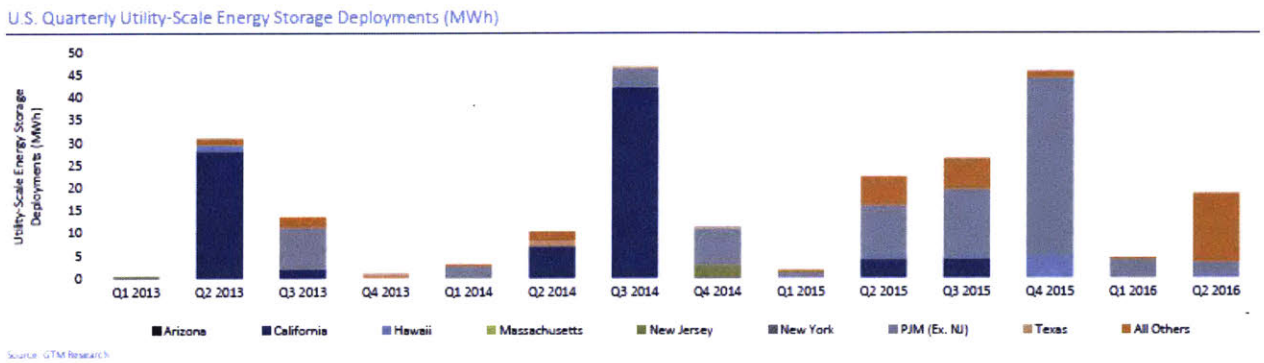


Figure 1: GTM Research US Annual Energy Storage Deployment Forecasts (MW and MWh; GTM Research U.S. Energy Storage Monitor Q3 2016)

In August 2016, Southern California Edison (SoCal Edison) and San Diego Gas & Electric's (SDG&E) filed a request for rapid approval of lithium-ion battery storage projects accounting for more than 50 megawatts of storage. This action demonstrated that it is possible for utilities to justify battery storage when there is a demonstrated and urgent need. In the case of SoCal Edison and SDG&E, the shutdown of the Aliso Valley natural-gas storage facility due to safety issues resulted in a decrease in overall system capacity[10]. The shutdown provided an added risk of service disruptions to a significant number of customers in the region. There are other examples of this as well, in large part due to the requirements set under the state of

California's broader storage mandate to require the state's utilities to procure a total of 1.3 GW of energy storage by 2020. California has led the way with grid-scale storage, and is poised to continue leading battery storage system installations. Texas will also play a large part in the market growth, and the Northeast US is predicted to also be a leading area in terms of utility-scale storage deployment in the future (see Figure 2).



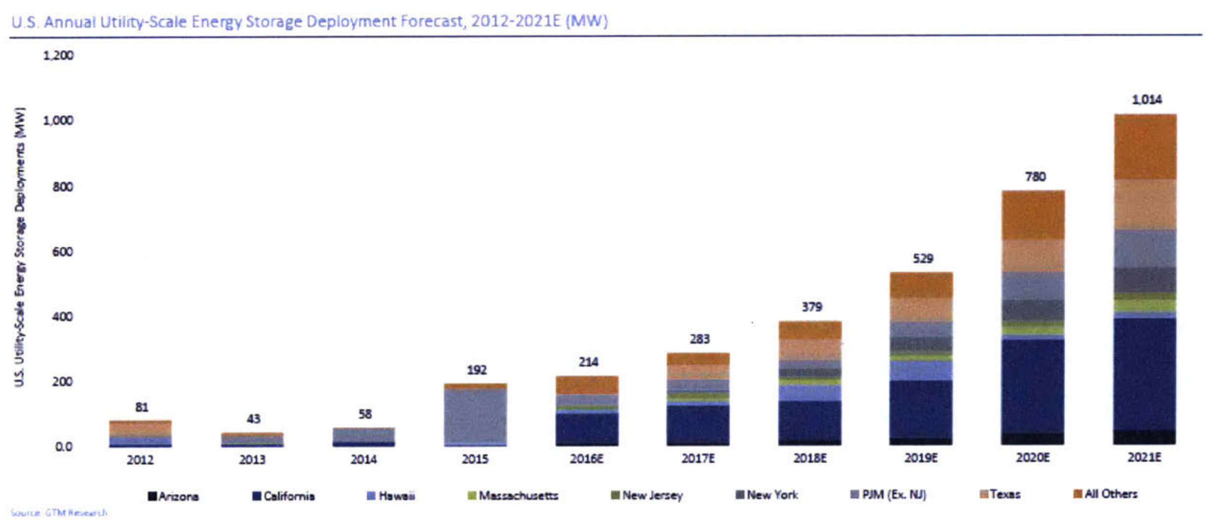


Figure 2: US Annual Utility Scale Energy Storage Deployment Forecasts (GTM Research U.S. Energy Storage Monitor Q3 2016)

Combining grid-scale energy storage with intermittent renewables can provide multiple capacity and reliability benefits to the network. For example, Green Mountain Power in Vermont has deployed storage technology in combination with solar energy (2.5-MW solar and 4-MW lithium ion battery) to shave peak demand load and therefore lower costs for their customers.

In addition to combining storage with renewables, there is interest in understanding the additional benefits of grid-scale battery storage. Pacific Gas & Electric (PG&E) performed a comprehensive pilot study to consider both participation in markets and reliability as a combined use case for battery systems in its network[19]. The findings of the multi-year study, published in 2016, were multifold. Among many, one interesting conclusion was a confirmation of past theoretical analysis: participation in wholesale markets is necessary for battery cost-effectiveness. Other benefits for storage include frequency regulation in the grid. There are more than 250 megawatts of energy storage installed for frequency regulation purposes in the Midwest and Mid-Atlantic on the PJM Interconnection Grid[2].

Many types of actors exist as generators and distributors of energy. Atlantic Electric owns transmission and distribution infrastructure in its network. Because the utility purchases and sells electricity using this infrastructure, its customers pay a rate-based fee for the actual electricity used as well as a transmission/distribution fee. Atlantic Electricity does not generate the power that customers use. Their ability to own 'generation' assets like solar or to participate in wholesale markets remains unconfirmed, thus motivating a cost-focused scope for this project analysis. Specifically, this analysis is aimed at understanding whether, given current operating norms of no participation in wholesale markets, battery storage could be a viable option when compared to conventional upgrade or investment options.

Recent industry cases have demonstrated that storage projects can be scoped, justified, and proposed in a reasonable timeline if the right processes and organizational sponsorship are in place. They have also demonstrated that a comprehensive process including both cost and revenues may increase the attractiveness of continued incorporation of battery storage.

1.4 Atlantic Electric Current Asset Planning Process

The Atlantic Electric distribution asset planning process is led by the Distribution Planning group. For each area of Atlantic Electric's territory, a designated distribution planner acts as both project manager and principal analyst in a collaborative effort among several groups. The planner works with others to gather required data of historical load data, irregularities in operations, concerns about local developments or customers, and any other relevant information.

Occurring every 10-15 years, these Area Studies can take anywhere from two months to over a year, depending on the complexity and needs of the network. In some cases, there is no additional action required; areas' electric load capacity and demand are analyzed and there is relatively stable demand with sufficient excess capacity and few operational issues. In other areas, there are aging infrastructure, concerns about future reliability, and other potential issues that the planner must address before significant problems develop and cause actual service interruption.

The planner uses capacity and load peak data from historical load data for a given electric substation or set of substations, applies forecasted demand for each asset (e.g., transformer, feeder), and determines whether there will be a need for system upgrades. He/she also evaluates any known issues or alerts that have been flagged by the engineering or operations teams, such as common outages or failures. If an upgrade or increase in capacity is needed, the planner begins in-depth analysis to explore the possible options, which may include purchasing new equipment like transformers or other alternatives. The planner will involve all relevant parties, coordinate analysis, present options, and recommend a course of action. The planner's recommendation is considered by directors in the organization who make the final decision for capital investments or other courses of action.

Asset planning requires cross-functional collaboration among groups throughout the company. Analytics teams use industry inputs and internal data to model forecasted load growth throughout Atlantic Electric's territory. Regulatory teams must make sure that the proposed asset investments will be approved by regulators in order for the capital investment cost to be considered recoverable in a later rate filing. Once specifications are set, the assets must meet a standard set of requirements for integration in a substation. Substation engineers design configurations to meet the specifications. Managers must balance capital costs across the business and prioritize their investments to maintain reasonable rates for its customers. As such, each area planning study's recommendation must be coordinated and balanced with other recommendations from asset planning.

There are a few different options for upgrades or expansions depending on need and specific conditions at the site. While conventional options are well-incorporated into the planning process, emerging technology has become increasingly attractive for utilities to invest in. When there are specific statements of interest, the planning study may request analysis from other groups at Atlantic Electric to develop a proposal incorporating other methods for demand reduction such as demand response and battery storage. However, standard processes for new technology evaluation are still at an early stage of development.

Regarding the emerging processes for non-traditional solutions, a group within the Customer department performs analysis as needed for non-wires alternatives, which has been sufficient for the use cases up until today. Non-wires alternatives include targeted demand response and energy efficiency initiatives as ways to decrease peak demand on feeders instead of or in addition to upgrades in equipment. This thesis contributes to advancing standardized processes for regularly evaluating energy storage as an option during asset planning.

1.5 Atlantic Electric Internal Site Evaluation

Battery storage has not historically been a standard consideration in the asset planning process largely due to the high unit costs. However, there has been growing interest across the organization in battery storage, especially given the possibility of an energy storage mandate that would follow a similar path as that of California. The September 2016 "State of Charge: Massachusetts Energy Storage Initiative Study" released by the state of Massachusetts recommended a "comprehensive suite of policy recommendations to generate 600 MW of advanced energy storage in the Commonwealth by 2025, thereby capturing $800 million in system benefits to Massachusetts ratepayers" through cost savings and improved reliability. These findings are likely to inform and drive procurement goals for storage, following on the example of California and Oregon.

In summer 2016, managers in electric asset planning requested a short list of potential battery storage sites, partially in preparation for a regulatory environment that could favor battery storage procurement. This was tasked to field engineers, who requested specific substation level information from area engineers. Requested information included: challenges with load growth or insufficient capacity, availability of historical load data in the data system, approximate land availability, a lack of established conventional solution. The informal effort over several weeks yielded a short list of nine locations and briefing documents sharing the requested information. The information collection process consisted of emails and requests for the planning engineers to volunteer their sites for evaluation.

Going forward for similar analyses, it could be beneficial to incorporate a formalized element for each area engineer to input ratings quarterly or yearly for the requested information mentioned previously. This could be automatically collated, and at any point managers in Strategy or Asset Planning could then use the regularly-updated database to filter and define the candidate sites for storage. In a situation in which there were a regulatory mandate for installed storage capacity, the planning studies would need to mobilize resources to quickly identify which sites to filter through and continue to analyze. Potentially missing opportunities or pursuing analysis of unqualified sites would waste time and resources. Information should be recorded periodically so that a dedicated storage analyst or evaluator would be able to easily identify the data indicating site attractiveness, without requiring immediate input of operations or field staff.

Aside from the potential for standardization for the future, the criteria are aligned with other research studies of T&D capacity deferral[18]. Moreover, the informal process provided output that was a useful starting point for site-specific storage analysis. Among the nine sites, three were evaluated in this project.

1.6 Battery Storage Modeling Literature Review

Available literature did not indicate a single agreed-upon methodology for sizing a battery for asset deferral and reliability purposes. A SANDIA 2009 study[5] focused on the transmission and distribution deferral benefits outlines an approach of focusing on a peak demand load profile and analyzing forecasted loads to size the required models. This was used as a basis for our initial method of sizing, which is a deterministic and conservative way to reduce the probability of a service disruption.

More broadly, for battery storage system sizing there are industry tools available such as StorageVET[3] from EPRI and GridLab-D[6], which provide comprehensive platforms for utilities and other entities to perform systems analyses incorporating battery storage. There are also commercial models for sale through private engagements[23]. Atlantic Electric was interested in developing internal capabilities before contracting the work to outside providers.

There is a wide range of available academic research and publications focusing on the applications, benefits, and approaches to modeling of battery energy storage systems for power and energy applications for utilities. The modeling methods in existing research had several different types of focuses, from comprehensive full stack of battery storage benefits to specific use cases or value streams. Studies of battery storage, system effects, lifecycle, and cost when combined with high-penetration distributed solar photovoltaic systems provide interesting results for peak load shavings and frequency regulation[24]. Simulations of battery storage system integration with wind and other renewables to compare with demand management suggest that centralized battery storage systems are more promising in reducing costs[21]. The approaches included vary in resolution at the physical modeling level to system level optimization over time for load curves at a given location[17]. Other studies focus on control and management systems to optimize peak load shaving and voltage control[1][14]. Wholesale markets, specifically PJM, are also an area where storage enables significant benefits through energy arbitrage and energy capacity bidding[22].

Existing research approaches informed the initial analysis in this thesis work. There exist fewer resources focused on sizing utility-scale battery storage for reliability-only purposes, and the relative variance in potential outputs for this analysis should be evaluated. The goal of this thesis's approach was to compare different methodologies to investigate the advantages and disadvantages of using each in the specific use case mentioned for a selected site. Three different methodologies were developed to analyze the potential battery size for Area A substation.

1.7 Contributions and Outline

The contributions of this thesis are:

1) Development of battery storage sizing methods applied to reliability applications in asset investment deferral evaluation
2) Quantified difference in reliability when varying battery storage system size in a substation reliability application
3) Use of real historical data to estimate likelihood of risk for N-1 contingency coinciding with peak demand in specific site
4) Provides foundation for realistic integration of new technology evaluation within existing businesses processes

Chapter 2 will address the current planning processes of Atlantic Electric, the case study selected for this thesis work, as well as the context for technology selection of battery storage. Chapter 3 discusses the results, advantages, and disadvantages of three battery storage sizing methods developed and applied to the use case for Area A substation. Chapter 4 concludes with recommendations for the sizing methodology and an evaluation of the associated business processes required for the future.

2 Battery Storage Analysis

2.1 Inputs

Specific situations at Atlantic Electric have arisen in the past in which a battery storage system could have provided advantages to an isolated or remote system. In one instance, an islanded system required substantial additional capacity for reliability purposes. A battery storage system was proposed as a potential alternative to conventional fossil-fuel back-up generation and as a way to defer the need for a costly new transmission cable. In this case, additional resources from engineering and the US Strategy group performed high-level analysis to put together a Request for Proposals from battery vendors.

The goal of their analysis was to provide a reasonable order-of-magnitude power and energy requirement for the battery (and approximate cost) to compare to other solutions and justify moving forward with the battery procurement process. Once in conversations with potential partners, the cost estimates were refined with more tailored specifications of a given technology and system set-up.

The inputs to the analysis were an example hourly load profile (a historical peak day was chosen), forecasted load growth over the lifetime of the battery, capacity and thresholds, alternate generation capacity, and assumptions about battery performance (e.g., charge rate, depth of discharge). The model mapped the load over the specified time period. Once the load exceeded the threshold, the alternate generation and battery began to discharge to meet the excess demand, and the model analyzed the extent to which the load was met by the battery storage. Inputs on battery energy and power could be changed to assess a suitable battery duty cycle for the given load cycle.

The results of the analysis provided the basis for a request for proposals from several battery technology vendors to further specify technical details, potential costs, and operational performance metrics for their systems. One of the primary areas for investigation in this work was the set of assumptions underlying the inputs of this existing battery storage estimation model.

2.2 Forecasting

Forecasting is currently performed taking into account several factors, including macroeconomic growth, local population growth, new large construction, and others. The Advanced Data and Analytics Group performs the macroeconomic forecasting for each region, and produces growth rates for the planning group. The planning group then takes the peak hour values of the past year for each element (e.g., transformer), applies the growth rates over multiple years, and checks whether there will be a projected demand load that will exceed emergency capacity of the system.

Analysis was performed to understand the drivers of forecasting, particularly whether there were significant drivers of peak day occurrences that may not have been considered in the current forecasting. Taking into consideration weather factors such as temperature, wind speed, local growth factors for a given site, the significant driver that emerged from a multivariate regression was temperature. Existing research shows consistent results; this can be explained in practical terms by the known electricity usage of air conditioners. Thus, it makes sense that on hotter days, during the hours that most people are home from work, there will be a heightened level of electricity usage.

The Area A substation was chosen as an example case dataset to use for analysis. The data used was the hourly electric load on two transformers that share a load, T10 and T20. Figure 3 shows that the hourly load of Area A predictably followed this pattern. During an average day, electricity usage increased as temperatures increased and during the afternoon and evening as people returned home from work.

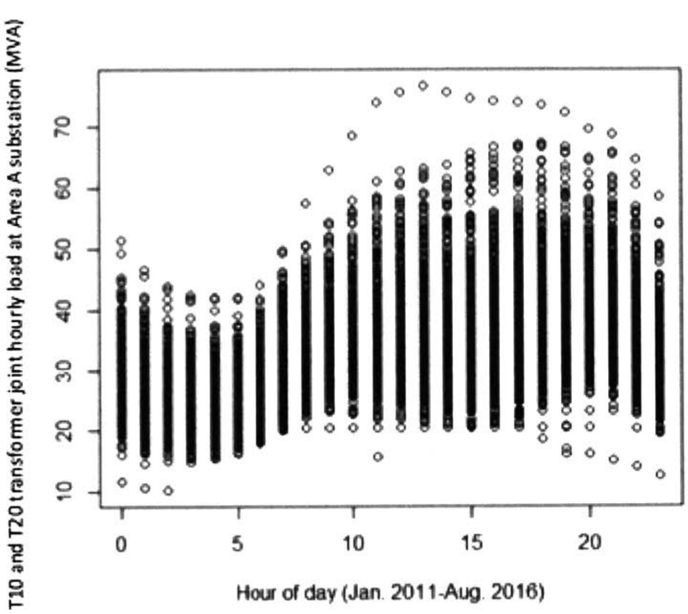


Figure 3 Area A Substation Load Profile by Hour of Day

On an example peak summer day, the load followed a roughly sinusoidal curve, peaking in the afternoon when air conditioners were commonly in use.

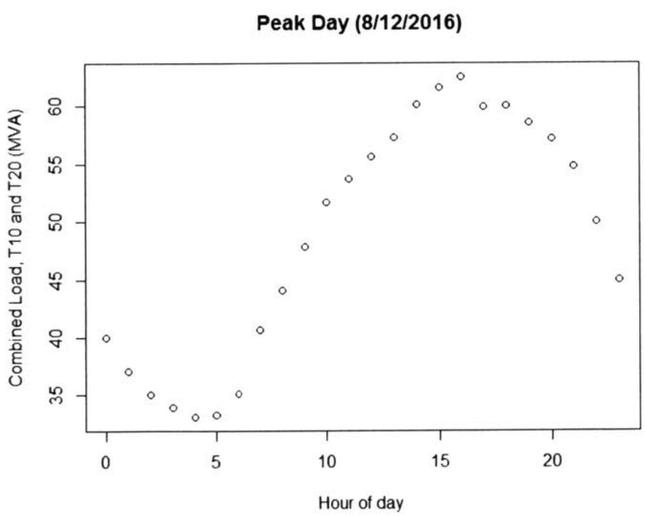


Figure 4: August Peak Day Load Shape for 2016

To understand the drivers of load, several regressions were run among the joint T10 and T20 load versus different factors.

First, a model was built to understand the relationship among various hourly factors (temperature, humidity, wind speed, wind direction, precipitation) and the hourly joint load from January 2011 through July 2016. Successive multi-linear regressions were performed, each time excluding non-statistically significant factors. In the end, temperature was the most statistically significant driver of the load, as we had expected. The model was generated based on temperature using a training data set of about two thirds of the data. Out of sampling testing was then performed. The out of sample test r-square value was lower than that of the model training set, indicating that the model predictive strength was low, or perhaps that the model had been over-fit. This could be developed further by other modifications, such as separating weekends or holidays to remove outlier load profiles and focus on the 'typical' workday profile. Because our findings were consistent with the consensus view that temperature is the most important factor driving electric load, we did not pursue further development or refinement of the model. Weather forecast methods themselves are an entire area of continuing research, so basing a battery sizing method on load forecasts also based on temperature forecasts could provide misleading results.

As an additional approach, single linear regressions were also run among the many possible driving factors and the electric load at Area A substation. For the results, see Figures 5-9.

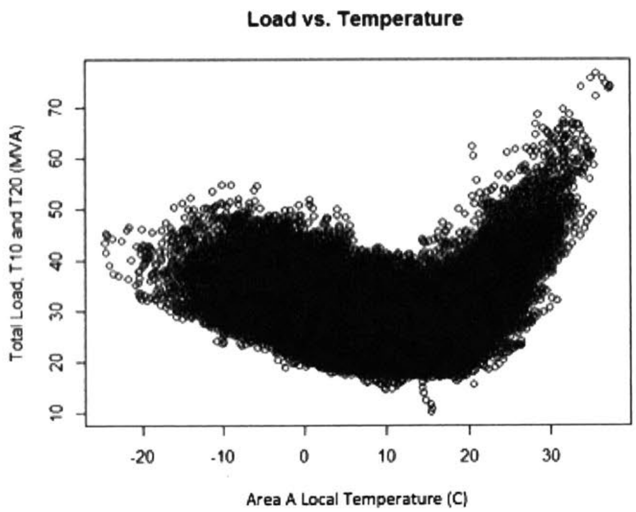


Figure 5: Joint Electric Load versus Average Daily Temperature

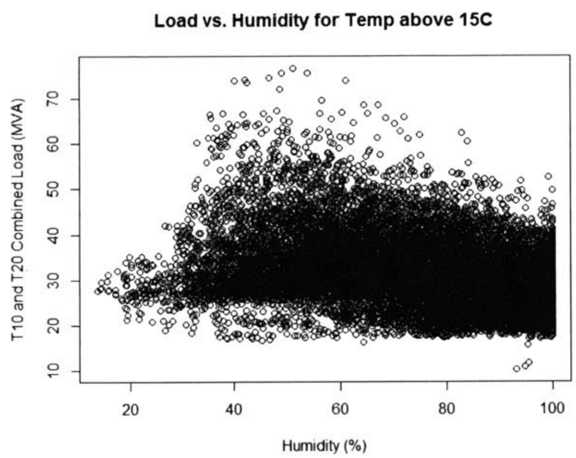


Figure 6: Joint Electric Load versus Percent Daily Humidity for Higher Temperature Days

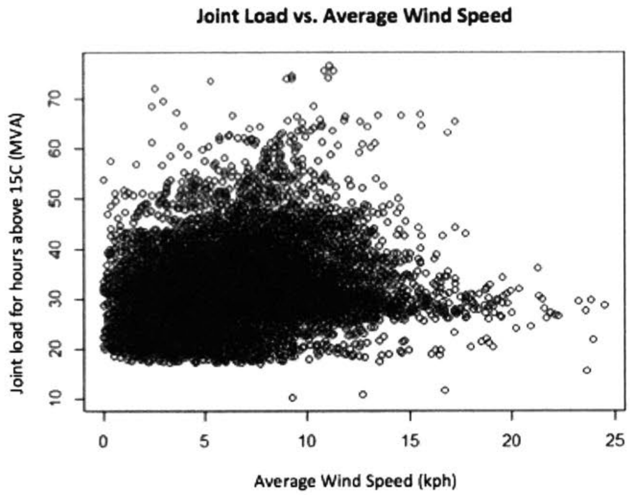


Figure 7: Joint Electric Load versus Average Daily Wind Speed

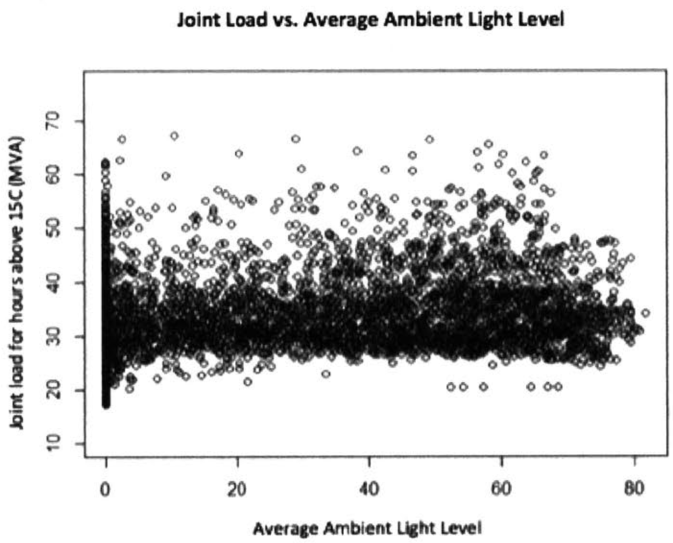


Figure 8: Joint Electric Load versus Average Daily Light

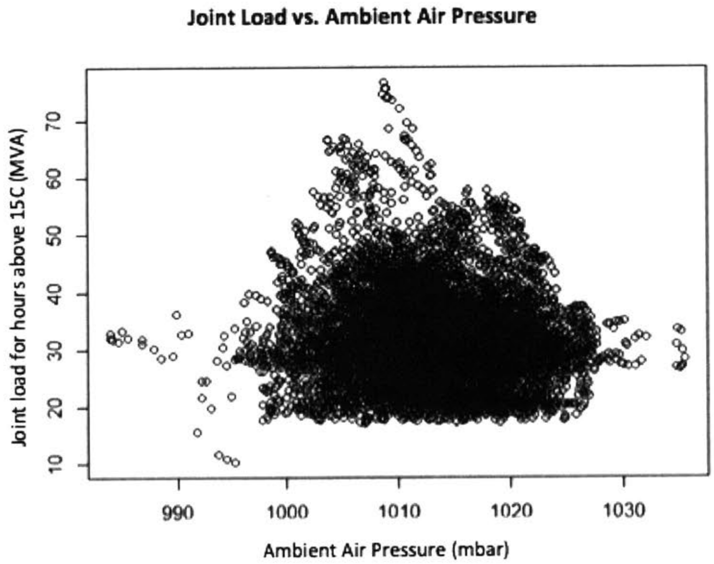


Figure 9: Joint Electric Load versus Average Ambient Pressure

Single Factor Linear Regressions with Factors Affecting Electric Load for T10 and T20 Cumulative Load

As can be seen from Figures 5-9, there was no significant relationship between load and factors such as wind speed, pressure, light, and humidity, whereas there appears to be a clear trend in the load vs. temperature plot. Temperature was once again the most statistically significant individual factor in correlation with joint load for a single-factor linear regression.

It is notable that there is a "hockey stick" shape to the load vs. temperature data plot. This can be interpreted to show that at very low temperatures, electricity usage would increase due to fewer daylight hours and potentially more time inside using appliances. At moderate temperatures, people might be relatively comfortable and daylight hours would likely not be especially few. At higher temperatures, people are more likely to use their air conditioners to stay comfortable while they are at home.

This plot may be showing two distributions of data; heat-related electricity use and cold-related electricity use. Because peak days and therefore risky situations at the Area A substation have all coincided in the summertime during hot days, we are interested in the temperatures above the inflection point of the data, which is at approximately 15C.

When we select for temperatures above 15C, our results are shown in Figure 10.

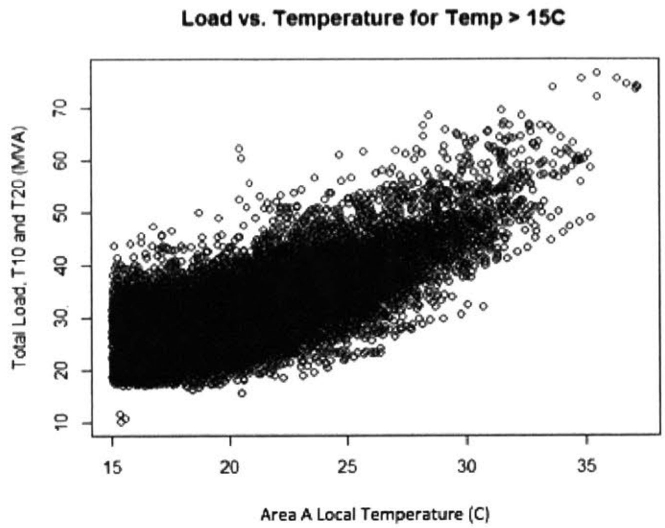


Figure 10: Area A Substation Temperature Above Threshold versus Load Ambient Average Temperature Above Degrees Celsius Versus T10 and T20 Cumulative Load

To disaggregate the data over time, we then plotted the data per year (see Figures 11 and 12). Interestingly, the plots from year to year did not appear significantly different, and some changes in the spread of joint load may have been due to general differences in weather. The linear relationship between joint load and temperature all remained similar over years.

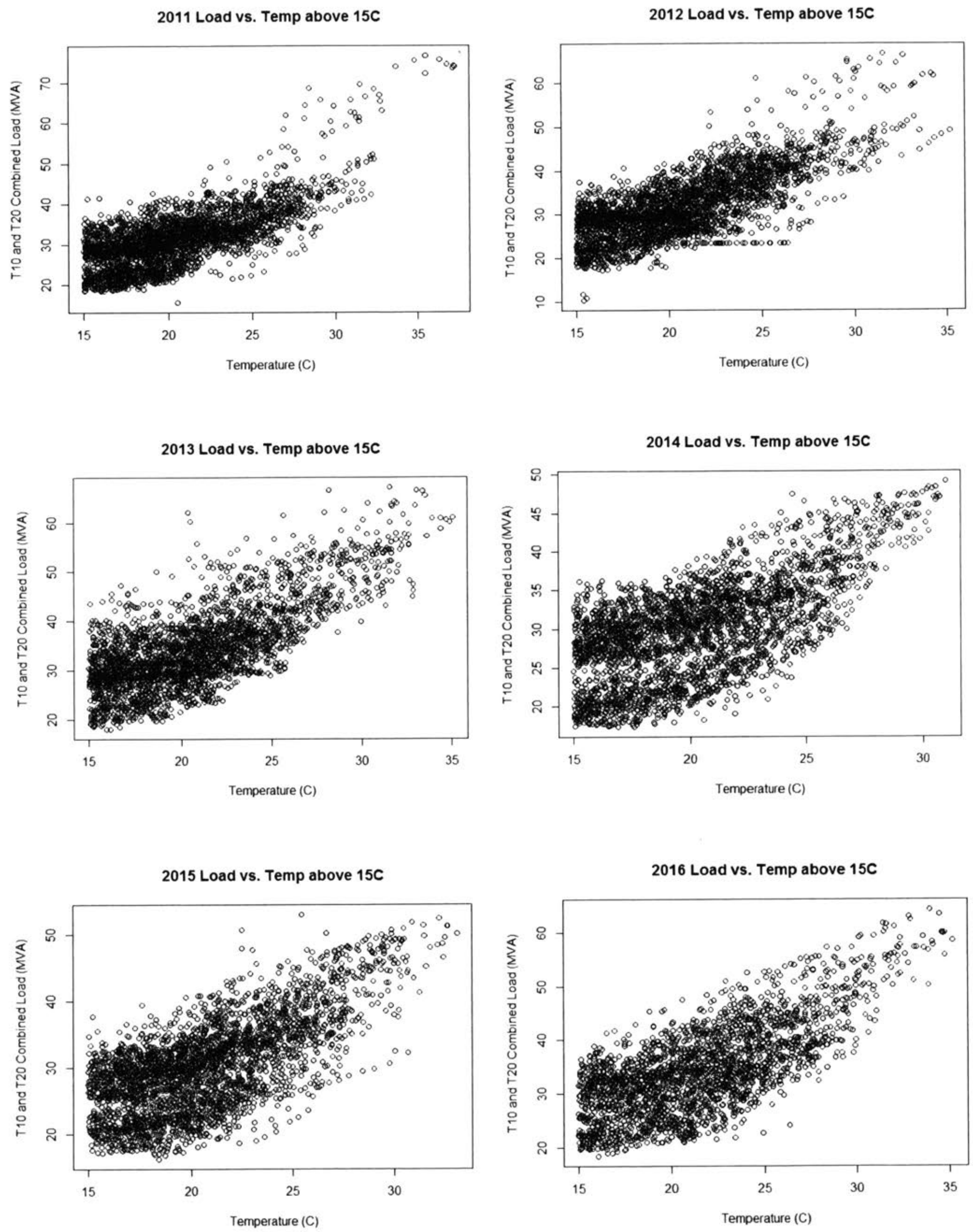


Figure 11: Temperature versus T10 and T20 Cumulative Load by Year

Year	Coefficient of temp vs. load	Adjusted R-sq	Max Sum Load (T10+T20)
2011	1.3635	0.5139	76.62939
2012	1.4296	0.5521	66.75748
2013	1.51329	0.5396	67.31439
2014	1.18694	0.4385	49.14844

2015	1.27784	0.4633	53.02356
2016	1.41001	0.5139	64.32047

Figure 12: Linear Regression Results Comparison, Temperatures versus Cumulative Load by Year

In conclusion, the analysis on weather factors and the joint transformer load demonstrated that temperature was the primary correlated factor associated with the load magnitude. However, because weather temperature predictive models have their own high level of uncertainty, this information does not provide concrete improvement recommendations for the load forecasting at Atlantic Electric. A further investigation into this could be an evaluation of the econometric models used to determine growth. Those models were not accessible for the purposes of this project.

2.3 Battery Storage Technology

Battery storage has applications in many industries, including technology, transportation and utilities. The feasibility of other grid-scale technologies such as flywheels, flow redox, and zinc-air, among many others is an area of research, with some experimental projects installed. While there is significant research in different types of batteries whose characteristics might be optimized for specific use cases, the prevailing technology that utilities have considered is lithium ion batteries. They offer the advantages of high energy density, high tolerance of discharge cycles, and high efficiency. Because there are commercial applications such as consumer electronics, there is more known about performance of lithium ion batteries, making the technology a more attractive initial technology to evaluate for utilities, as they consider safety in their system.

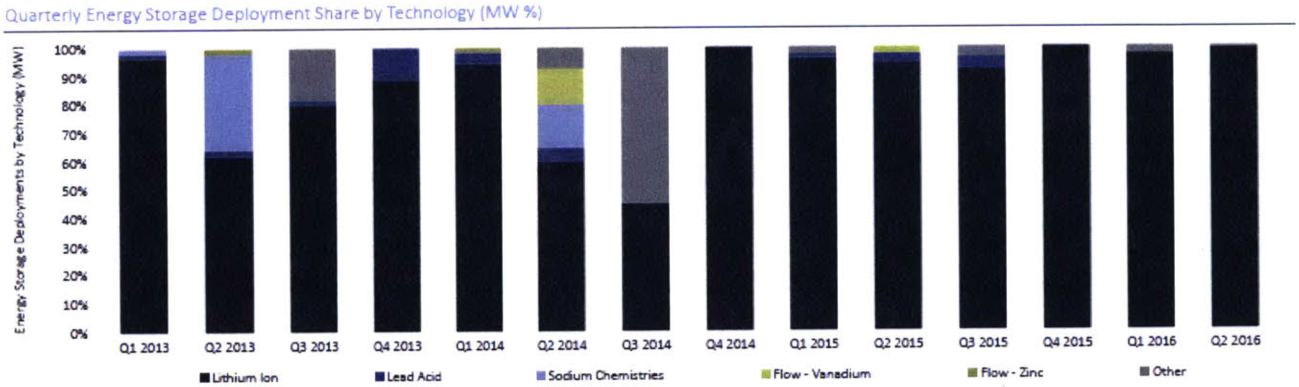


Figure 13: Quarterly Energy Storage Deployment Share by Technology (MW%; GTM Research U.S. Energy Storage Monitor Q3 2016)

As can be seen from the GTM Storage Deployment Share analysis in Figure 13, lithium ion has been the preferred technology for the majority of energy storage deployments in the United States, and is the preferred technology for larger-scale deployments.

Other battery technologies considered include compressed air storage, pumped hydro, flywheel, lead-acid, sodium, zinc, and flow batteries.

- While *compressed air* storage has the advantage of being relatively well-developed and flexible technology, it provides a low energy density and requires suitable geology. Furthermore, it is exposed to natural gas price changes.
- Similarly, *pumped hydro* requires suitable sites and provides low energy density.
- *Flywheels* could be considered, but they tend to provide relatively low energy capacity and high heat generation despite high power density and scalability.

- *Lead-acid* is a mature technology but is not well served for full depth discharge and partial charge operations; it also provides poor environment, healthy, and safety performance.
- *Sodium ion* is very high cost and high potential risk for flammability, making it a non-option for utilities.
- *Zinc* batteries and other newer technologies are not fully commercially proven, which makes these types of battery technologies unlikely candidates for near-term utility-scale applications.

In comparison, lithium-ion is a relatively mature technology with multiple chemistries available and efficient power and energy density. In addition, lack of memory effects, self-monitoring tendencies, and relative environmental safety make lithium ion batteries attractive candidates for bulk utility usage. When comparing lithium-ion to other types of batteries in terms of energy density, cycles of discharge available before degradation to 80% of capacity, and environmental considerations, lithium-ion and lithium-polymer perform most successfully. See Figure 14 for a summary comparison with select other technologies.

TABLE 2.6: Performance of Li-Ion versus Other Technologies.

Technology	Energy density (Wh/L)	Cycles (80% DOD)	Environment, Health and Safety
Lead acid	40–70	180–200	Poor
NiCd	150–200	800–1000	Poor
NiMH	150–300	500*	Good
Li-ion	80–200	1200	Good
Li-polymer	200–300	1500–7000†	Good

* NiMH provides no useful power after 50% DOD.
† GM is testing with A123 batteries.

Figure 14: Comparison of Battery Technologies (NRECA)

The disadvantages of lithium ion batteries of relatively high cost appear to be lowering over time. This thesis analysis seeks to understand the methods required to size a battery, assuming that lowering unit costs may improve the feasibility[11]. Thus, for this project's purposes, lithium ion batteries were used to model a more realistic use case with today's technologies.

3 Battery Storage System Sizing

3.1 Area A Substation Background

Atlantic Electric's electric service territory extends across several states. Their network moves power through high-voltage transmission lines from power generation sources through sub-stations that convert high-voltage to medium and low-voltage currents traveling through sub-transmission and distribution lines, eventually reaching the customers at low voltages. The extensive network carries redundancy through multiple paths from a given transmission line to an end customer, making it difficult to analyze any single substation's operations alone.

Area A substation serves over 30,000 customers who are mainly residential, with some small commercial and industrial customers. At the time of the research, Area A substation was already being evaluated in a routine area planning study and flagged for a potential asset upgrade requirement. A particular interesting characteristic of Area A substation is its isolation as a network element; the entirety of the area and the follow-on sub-stations and distribution lines are fed through this one station. In the case of an outage at Area A substation there would be a significant number of customers without electricity.

The first step in analysis was to understand the trends in demand and consider potential causes of a need for capacity expansion. Upon evaluation, the load profile of Area A appeared as expected, with the summer months being the highest in demand due to electric usage such as more prevalence of air conditioner usage.

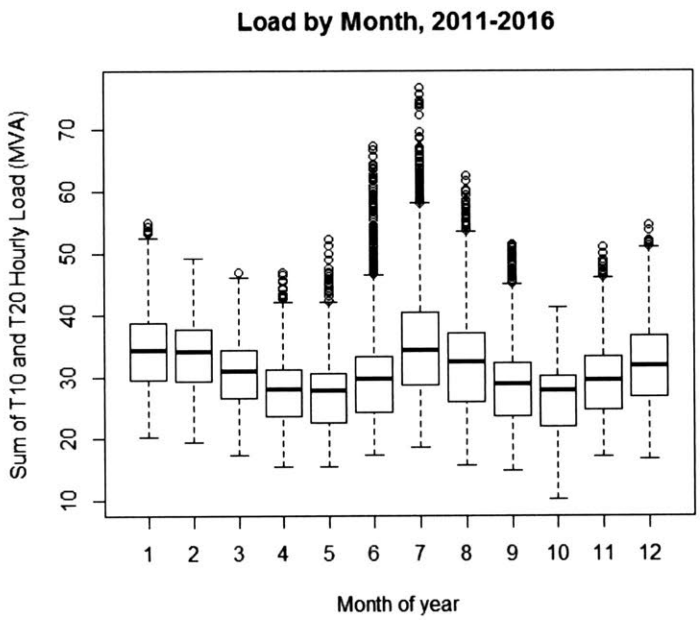


Figure 15: Electric Load Distribution by Month
(Area A T10 and T20 Joint Electric Load Distribution by Month, January 2011-July 2016)

Over time, the peak load of Area A has not increased substantially. Forecasted demand growth remains close to 0% year-over-year. However, there is a concern that at present peak levels, if one of the transformers were to go out of service while there was peak electric demand, the current capacity would be insufficient.

Area A substation converts 115 kV to lower voltage and then passes the power along to other stations. Incoming power must pass through one of four transformers: T10 and T20 are 115-34.5 kV, while T1 and T2 are 115-23 kV transformers. T10 and T20 are in parallel, sharing a total load ("sum load") that is then distributed through lines leaving the substation. There is a switch between T10 and T20 that allows for load sharing.

In a situation in which one of the transformers were to experience an outage, the remaining transformer could compensate and serve the combined demand, up to a rated capacity. During the summer, the relevant rated capacity, the "summer emergency capacity", is the upper limit for the capacity available for electric load. Above this load, the transformer would be overloaded and risk overheating, which could degrade the equipment. In a situation in which both T10 and T20 were to experience an outage, the load could theoretically be switched to other transformers manually, which would require a service visit. The associated outage duration would be directly linked to the amount of time it took for Atlantic Electric service crews to arrive and switch. The maximum number of hours it would take under normal circumstances is four hours, which was used as a parameter for battery sizing and general reliability analysis in this work.

Each transformer has seasonal normal capacity ratings and emergency capacity ratings. Normal ratings are continuous loading capability for the transformer at different ambient temperatures, whereas the emergency ratings are a higher threshold for higher temperatures. These ratings may change over time with equipment degradation, and are periodically re-evaluated. For Area A, transformers T10 and T20, while being equivalent technology, have slightly different summer emergency thresholds.

More specifically, if peak electric demand coincided with an outage in one of the transformers, what would be the threshold above which either T10 or T20 would be unable to temporarily serve the peak demand? To be conservative, the lower of these two thresholds, 49.2 MVA was used as the threshold for analysis. If electric load were to exceed 49.2 MVA and the transformer with higher summer emergency threshold were to experience a service interruption or go out of service, at current asset conditions, the remaining transformer would be unable to safely meet the demand. This could result in a service disruption, which could affect all downstream stations and customers.

The above situation would be an N-1 contingency situation at peak demand. Given N number of elements in a system, an N-1 contingency situation occurs when one of those elements is unable to serve the network. Utilities are subject to national reliability standards. These are enforced by financial penalties based on a threshold maximum MWh of unserved load. While the goal is to reduce likelihood of service disruptions, it is impossible to guarantee zero outages or service disruptions across the entire system. The first standard of a transmission system is an N-0 scenario, in which the system is analyzed under normal operation conditions, without any equipment or component failures. N-1 would be the next scenario assessed, in which a single element would fail or provide a disruption, as explained above. While these standards are for transmission with a specific focus on security, in distribution, the utility also strives to maximize reliablity. The system Customer Average Interruption Duration Index (CAIDI), which is the the average outage duration that a given customer would experience, and the System Average Interruption Duration Index (SAIDI) are tracked commonly among electric utilities to compare relative reliability. These system-wide metrics make it difficult to analyze specific areas of the network. Thus, the N-1 scenario in this substation provides a more realistic situation upon which to base specific reliability analysis for the Area A Substation distribution network.

A battery storage system could be advantageous in an N-1 contingency situation, because it could provide excess capacity in the case of lost transformer capacity. It would maintain service and improve reliability of the substation in an extreme situation. Thus, adding a battery could be attractive instead of replacing the transformers with new equipment.

To perform an adequate cost comparison, the costs for a battery storage system need to be estimated by establishing the appropriate size for this use case at Substation A. As discussed previously, the method to size battery storage is not standardized in the utility industry given the multiple possible use cases.

3.2 Method 1: Plan to Peak

The first method, "Plan to Peak", uses a chosen peak demand level to determine required capacity. In the prior battery sizing analysis for the backup islanded system, analysts had used a single capacity as the planning criteria to meet. A single load curve was plotted for the selected peak day. Plan to Peak is a similar method that selects a given day to plan for as a conservative estimate of the maximum required demand.

Using real hourly load data for the peak demand day in the prior year, the worst-case scenario would be one transformer experiencing a disruption during hour with the highest electric demand. In the specific location of Substation A, operations estimated that a maximum time of four hours would be required for repair crews to arrive and manually switch the load to other transformers after the outage occurred. Thus, if the transformer went out of service at 2 PM, in the worst case, the service could be restored through alternate channels by 6 PM. The scenario that would result in the highest lost load would be for a four-hour outage to be centered around the maximum demand hour. Graphically, this can be visualized by finding the four-hour period for which the area under the demand curve and above the capacity curve would be largest.

This situation would also necessitate the largest battery size compared to any other potential scenarios. Thus, if it is assumed that the battery could be discharged completely, the battery capacity required would be the integral of the demand curve for the four hour period. This is the most conservative estimate, as the battery is sized for a single peak demand event that would require the most excess capacity and a full discharge.

The deterministic formulation solves for the battery energy (kWh) that yields the minimum cost of a battery system that would supplement the existing system in an N-1 contingency situation to result in zero lost load. For each hour after an outage in one transformer, the excess capacity above the summer emergency capacity threshold would be assumed to be supplemented by a battery energy storage system. The sum of these hourly required excess capacity quantitites over the four hours of outage before a service crew could arrive would be equivalent to the battery size required. In this case, we actually set the variable V of lost load to zero. Constants are assumed for unit costs of lost load ($/kWh), battery unit costs ($/kW and $/kWh).

The formulation is as follows:

Let V = total excess capacity required above threshold of 49.2 MVA (equivalent to lost load (kWh))

D_i= electric demand for hour i

C = total current system capacity per hour

B = battery power (kW)

H = battery duration (h)

With constants

l = unit cost of lost load ($/kWh)

a = battery power unit cost ($/kW)

b = battery energy unit cost ($/kWh)

Minimize (BH)

Where for j=24 hours of a peak day,

V = $\sum_{i=1}^{j}[Maximum\ \{(Di - C),0\}]$

$$lV \geq B(a + bH)$$

such that

$$V=0$$

Using this method, the resulting size of the battery required is approximately 48 MWh. Figure 16 is the output plot of an hourly load profile.

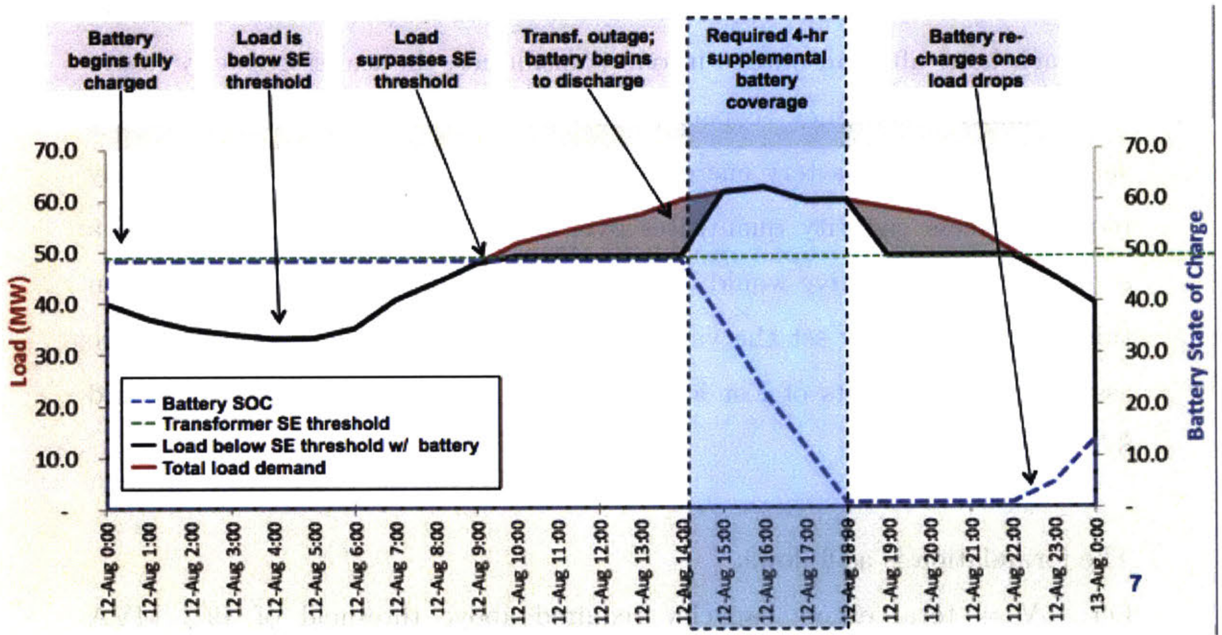


Figure 16: Method One: Plan to Peak Example Plot of Battery Discharge. (Note that the almost-instantaneous discharge of the battery is not captured due to granularity of data.)

To compare the investment cost required for a battery storage system of this size, it is necessary to make assumptions for battery unit costs. Cost was assumed to scale linearly, although in real life it would be more accurate to model a step-wise function given required additional land space or extra cooling for large systems. When comparing the cost of a battery of this size to the capital cost of a new transformer, there was a difference of an order of magnitude, which would make it non-competitive in the evaluation process.

An advantage of this method is that it is simple to calculate and to explain. In addition, it is the most conservative approach to planning, since the output assumes maximum capacity for peak conditions at all times. For regulatory purposes, the utility is then more secure in its ability to meet customer needs at all times.

The key disadvantage to the Plan to Peak method is that it risks over-sizing the battery storage system for the given use case, resulting in a more expensive option for the battery storage system. Another disadvantage is its use of a single peak day to plan; there is always risk for future outlier days that would yield different load curves or profiles. Even though it takes into account the forecasted growth rate applied to the peak value, the method does not take into account historical variability in demand behavior that could affect the required capacity of the subtation.

3.2.1 Battery Unit Cost Assumptions

The battery unit cost assumptions used in Method 1: Plan to Peak and Method 2: Cost Economics were based on benchmarks in industry and internal experience.

Current unit costs range depending on the vendor, application, and specific type of lithium ion technology. As of Q3 2016, Greentech Media estimates the median cost for a 2-hour utility-scale lithium ion battery to be ~850/kWh and $900/kW[7]. Another study by Lux estimates that installed stationary systems for residential and grid-scale use will hover around $655/kWh and $498/kWh in 2025, respectively.

Other sources indicate Li-ion system costs currently range between $350 and $700/kWh ($1,000 and $2,000/kW) and costs should continue to fall on the back of growing supply from mega battery factories from the likes of Tesla, Alevo, Sharp, LG Chem and Panasonic, and promising growth in electric vehicle sales[12].

Looking to the future, there is some consensus that lithium ion battery unit costs will continue to decrease significantly. According to Lazard's 2015 cost estimate study, the compound annual growth rate of capital cost of lithium ion batteries will be -12% year-over-year, meaning a 47% reduction over a 5-year period[11]. This reduction is cost will be likely due to an increase in capacity (e.g., Gigafactory), reduction in raw materials costs, and improvement in chemistry/design. Other sources predict that costs are expected to fall 30-50% within five years. Figure 17 shows a few predicted price trend ranges from GTM Research.

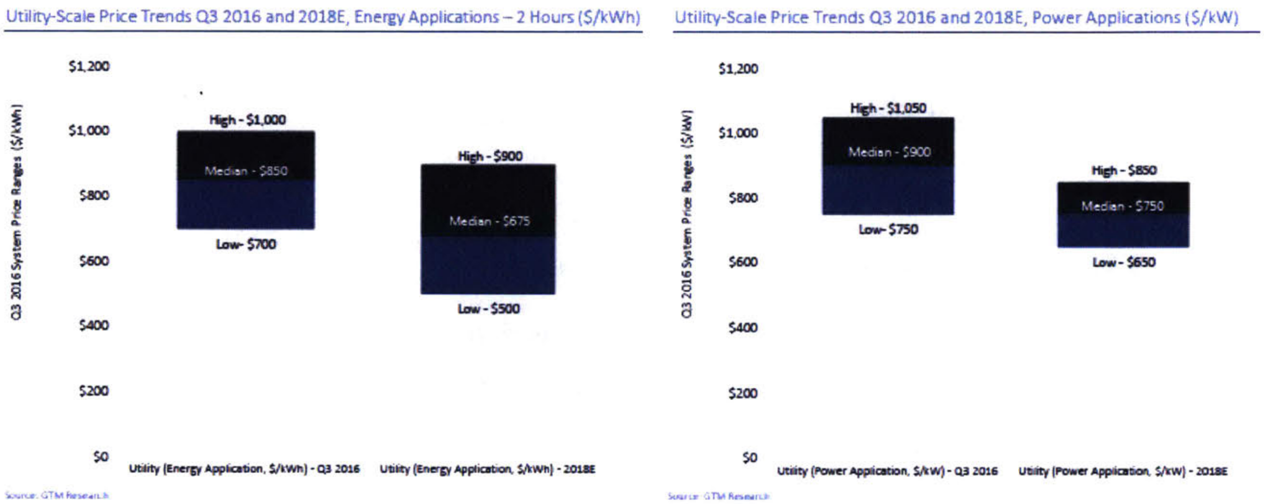


Figure 17: Utility-Scale Storage Price Trends
(GTM Research U.S. Energy Storage Monitor Q3 2016)

In addition to external benchmarks based on industry research, Atlantic Electric retained internal lithium ion battery unit cost estimates from past vendor proposals for battery storage system applications and requests for proposal. Compared to external benchmarks, internal cost estimates are at the low end of the range of industry cost estimates. This could be attributable to vendors attempting to compete on price, or bidding in at a lower price than average using future predicted unit costs as guidance. It could also be based on the value of additional future business, as storage becomes a more significant ongoing investment area for the utility.

To be consistent with the work being done in other groups within the company, the internal Atlantic Electric estimates were used in this work's analysis. It should be noted, however, that these costs would likely be fairly low, given the higher industry benchmark costs available. Furthermore, as mentioned, in this analysis it is assumed that battery costs would scale linearly. In reality, there might be step-wise changes in cost due to factors such as land usage and cooling systems, which would be case-specific. The same unit cost scaling assumptions are used among all three battery sizing methodologies to ensure that the outputs are comparable. The estimates were based on a \$/kW cost of the inverter, transformer, and other integration, in addition to a \$/kWh cost of the battery, and other materials. It should be noted that these initial capital costs do not include the operating cost that would contribute to the continuing costs of a battery storage system. These would include the cost to keep the battery charged, the charge effect on battery degradation, and the time of charge (and corresponding electricity rates). Thus, different charging strategies and optimization methods could be an area of further investigation when analyzing operating costs in the future.

3.3 Method 2: Cost Economics

The second battery sizing approach, "Cost Economics", used an optimization that balanced estimated cost of lost load and incremental costs of battery size. If Atlantic Electric were to take a strictly cost-based view of the given investment, they would need to balance the cost of the battery to cover an N-1 contingency event during peak demand with the quantified cost of losing the ability to provide service to customers at that time. The same peak day load profile from the Plan to Peak methodology was used.

An optimization method is used that solves for the minimum total cost of the system in an event of N-1 contingency during peak demand. The total cost is defined as the sum of the cost of load lost and the capital cost of the battery storage system. The decision variables are the battery energy (kW) and the duration of battery usage (h), which can be used to generate the battery system size (kWh). For a given peak day that we assume would occur once per year, the total excess capacity required (V) would be the sum of the difference between demand and capacity where demand is greater than capacity (from real data). We minimized the total cost, while solving for a battery size that adequately provided capacity meeting the total excess capacity required for that day.

The following formulation was used:

Decision Variables:

B = battery power (kW)

H = battery duration (h)

Data and calculations:

D_i= electric demand for hour i

C = total current system capacity per hour

With constants

l = unit cost of lost load ($/kWh)

a = battery power unit cost ($/kW)

b = battery energy unit cost ($/kWh)

Minimize (lV+B(a + bH))

Where

for j=24 hours of a peak day

$V = \sum_{i=1}^{j}[\text{Maximum}\{(D_i - C), 0\}]$

$BH \geq V \geq 0$

The resulting analysis returned a battery size of zero MWh.

This can be interpreted to mean that at the VOLL of $10,000 per MWh used in the analysis, it would be economically favorable for Atlantic Electric to allow for service disruption and subsequent lost load of four hours in the contingency event analyzed. It is interesting to note that despite this external benchmark cost, Atlantic Electric seeks to prevent any amount of lost load in its system, even though it could be considered less costly than the cost of the required battery.

It should also be noted that the value of lost load (VOLL) and the battery unit costs were used based on external and internal benchmarks mentioned. We also assume that the day only happens once a year, and that the value of lost load and the cost of batteries are compared on a single year basis.

To understand the required VOLL that would make a battery storage system economically equal or attractive, a sensitivity analysis was performed.

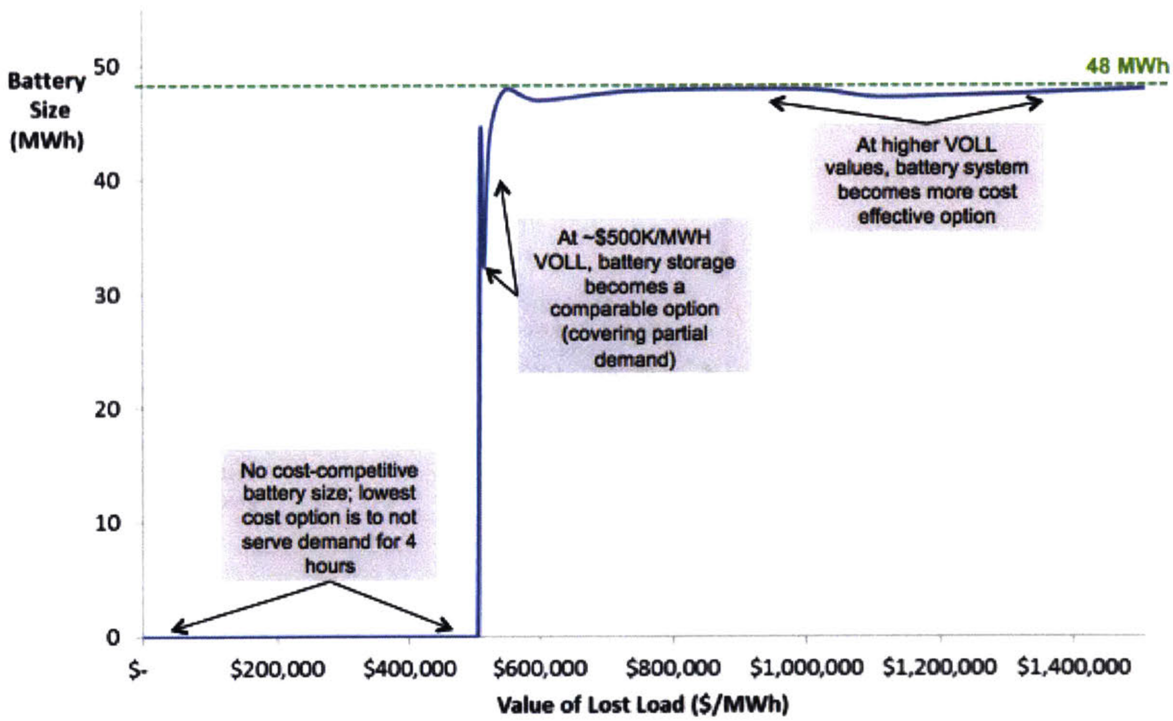


Figure 18: Cost Economics Method Sensitivity Analysis
(Battery Size vs. Value of Lost Load)

As can be seen from the tradeoffs in Figure 18, there is a specific turning point which the value of lost load would need to reach in order for a battery storage system to be comparatively attractive on a strictly cost economics basis. It can be seen that up to a value of approximately \$500,000/MWh VOLL, a battery storage system would not be cost-competitive compared to the cost of four hours of lost load. In these situations, the utility would likely choose to install a spare transformer as the lower cost option. Around that inflection point, there is a flip to a battery size close to the Plan to Peak value. In other words, once VOLL is greater than the battery storage system cost, it is so costly to lose load that allowing any lost load is not desirable. The local minimums in the optimization result in a small range of battery size from about 32 MWh to 48 MWh.

To understand the overall "cost" incurred at varying VOLL inputs, the cost components of battery storage system capital cost and lost load cost were plotted.

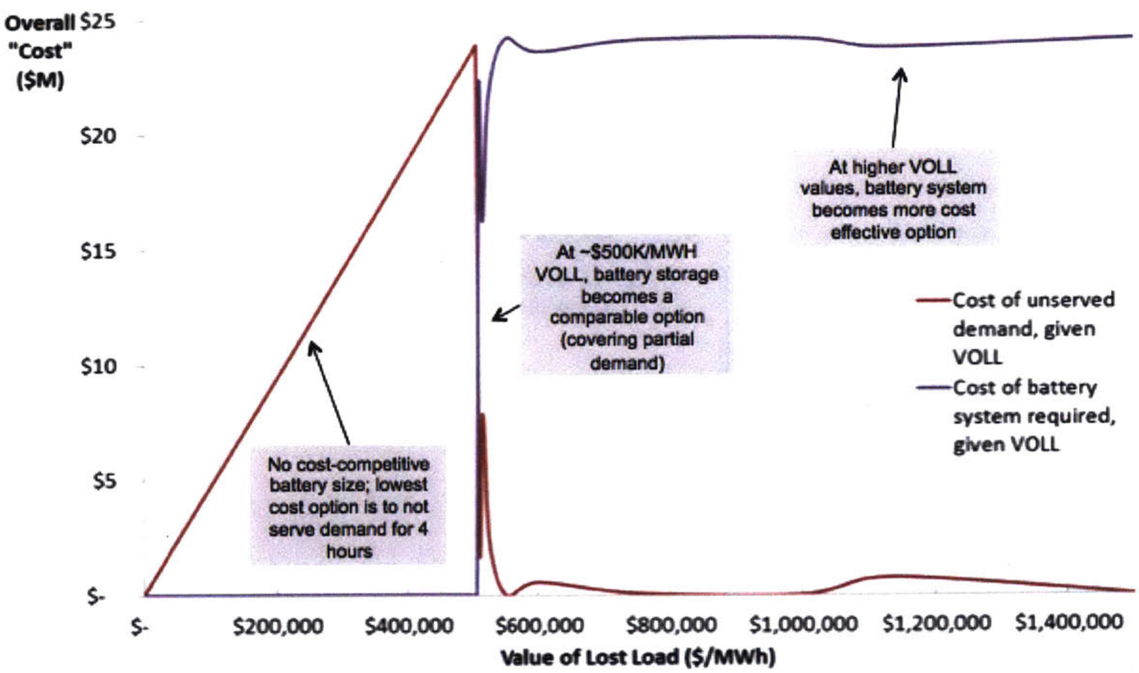


Figure 19: Cost Economics Method Overall Cost versus Value of Lost Load ("Cost" incurred equals cost of battery storage + unserved load)

The total cost of the system, once past the inflection point of around \$500,000/MWh VOLL, is close to \$25M. This is, once again, a significant cost that is substantially higher than the conventional solution of purchasing or upgrading a new transformer.

These results can be interpreted to confirm the general approach used in planning at Atlantic Electric. In reality, Atlantic Electric essentially places a considerably high premium on the cost of lost load, essentially planning to be as protected from risk as possible. In this case, the resulting battery size from Cost Economics is very similar to the Plan to Peak analysis approach.

The advantage of this method is that it evaluates the possibility of an outage with a more value-based lense instead of an assumed high premium placed on VOLL. It is therefore more flexible depending on an organization's or industry's preferences for VOLL.

The disadvantage of this method is that the assignment of a static VOLL may overlook specific situations or scenarios. It is also very difficult to accurately quantify or even fully define VOLL for a given organization or system, and there could be disagreement about which value of VOLL to use. The disadvantages of Method 1 Plan to Peak apply here as well: it risks over-sizing the battery storage system for the given use case, resulting in a more expensive option for the battery storage system. The use of a single peak day to plan also is a significant assumption to make, given the distribution of possible different peak day demand profiles.

3.3.1 Value of Lost Load

Research to understand what a reasonable cost assumption for valuing lost load revealed a wide range of methodologies to understanding how in a given area, a utility or economist can determine the value of lost load. It should be clarified that the issue of how to define VOLL is non-trivial. This thesis does not present a single best way to measure VOLL; it only considers how an assigned value of lost load could impact battery storage sizing. One definition of VOLL might be the value lost by the company supplying electricity; i.e., Atlantic Electric's economic and reputational loss as a result of disruption in its supply to customers. Another could be the value lost to society due to impact of lost electricity for customers in their businesses or for the personal impact of lost electricity in people's daily lives. Lost potential to produce economic value can be particularly significant for manufacturing and industrial customers whose production facilities may rely on electricity to produce revenue-generating product. Other societal costs could be incurred by vulnerable populations, such as patients in healthcare facilities where even mometary interruptions could be fatal, which may also be quantified as societal 'costs' of lost load.

Atlantic Electric does not formally define an internal value of lost load; instead its teams work to maintain service consistent with regulatory requirements for safety and reliability. Above a certain threshold of lost load for customers, Atlantic Electric is fined by regulators, which would factor into the real cost of losing service. There is also the reputational cost of service interruptions resulting in customer dissatisfaction. In essence, the company places a premium on the value of lost load, as they are ready to expend the costs necessary to avoid lost load.

If, however, Atlantic Electric were to more precisely assign the value of lost load for customers in a given area, it would be necessary to analyze the area's demographics and usage data at a granular level. The sum of value would consist of the economic value-per-time of revenue-generating production disruption calculated across all customers; the value-per-time of human quality of life for people whose health or functionality were dependent on electrically powered technology; the follow-on damages caused by the loss of said power; any other disruptions caused by electrical disruptions in urban systems, et cetera. The data and tools to sufficiently pursue an in-depth analysis with this approach were not available within Atlantic Electric's collected data.

Industry tools are available to estimate cost of outages, such as the US Department of Energy Interruption Cost Estimate Calculator (ICE Calculator)[8]. The ICE Calculator uses state-level aggregated data, reliability metric inputs, and an estimate of non-residential and residential customers to generate an estimate of the value of service disruptions. This calculation is best used for aggregate value over longer periods of time in which there could be several disruptions across service territory that would result in partial loss in service.

Existing literature studying a past actual outage Northeast event and the associated value estimated that the VOLL was between $9,284 and $13,925 per MWh (in 2012 USD). Translated to today's value, a rounded value of $10,000 2016 USD / MWh was used as an input for the analysis. This value would vary strongly with the type of load, such as life safety applications versus leisure uses. The importance of the input was for the order of magnitude, and not necessarily the actual value within a reasonable range.

3.4 Method 3: Historical Analysis

The third method, "Historical Analysis", used historical hourly load data over a six-year period to determine the distribution of potential peak contingency situations, and therefore generate a distribution of reliability vs. battery size. The motivation to develop this approach was the desire to quantify how conservative the Plan to Peak and Cost Economics methods were compared to the reality of historical peak load and potential N-1 contingency events.

The six-year period was chosen to ensure a variety of peak seasons during the summers. For the hourly load data over six years, analysis was conducted to isolate 'potential risk events', defined as instances in which the sum load (joint load of T10+T20) exceeded 49.2 MVA. In those instances, if there had been a concurrent outage of T10, the sum load would have overloaded the remaining transformer, which would potentially have resulted in either equipment degradation or a more serious outage. In reality, actual outages did not occur at these times.

The goal was to understand how many 'potential events' occurred in order to quantify the risk of N-1 contingency events resulting in an outage. These 'events' were identified, and the 4-hour window was applied such that the required supplemental capacity in the case of an outage was the sum of the load across four hours and above the summer emergency threshold.

Figure 20 shows the distribution of these events by size. In total, there were 77 'events', with 58 of them falling below 26.5 MWh capacity required across the four hours.

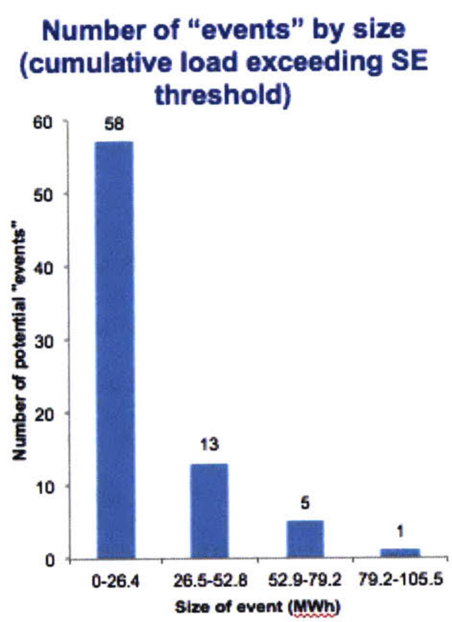


Figure 20: Distribution of Potential Event Cumulative Capacity

(Frequency of battery size required to cover each 'event' for four hours, by quartile of size)

To understand how well a given battery installation could serve the range of potential events that occurred, a cumulative plot was developed. If a 4-hour outage of one of the transformers centered around the peak load in each of these instances, we would want to understand how many of these events would have been sufficiently served by a given battery size. In other words, how 'reliable' would a battery of differing sizes have been, in an extreme scenario in which all potential 'events' actually had happened over time?

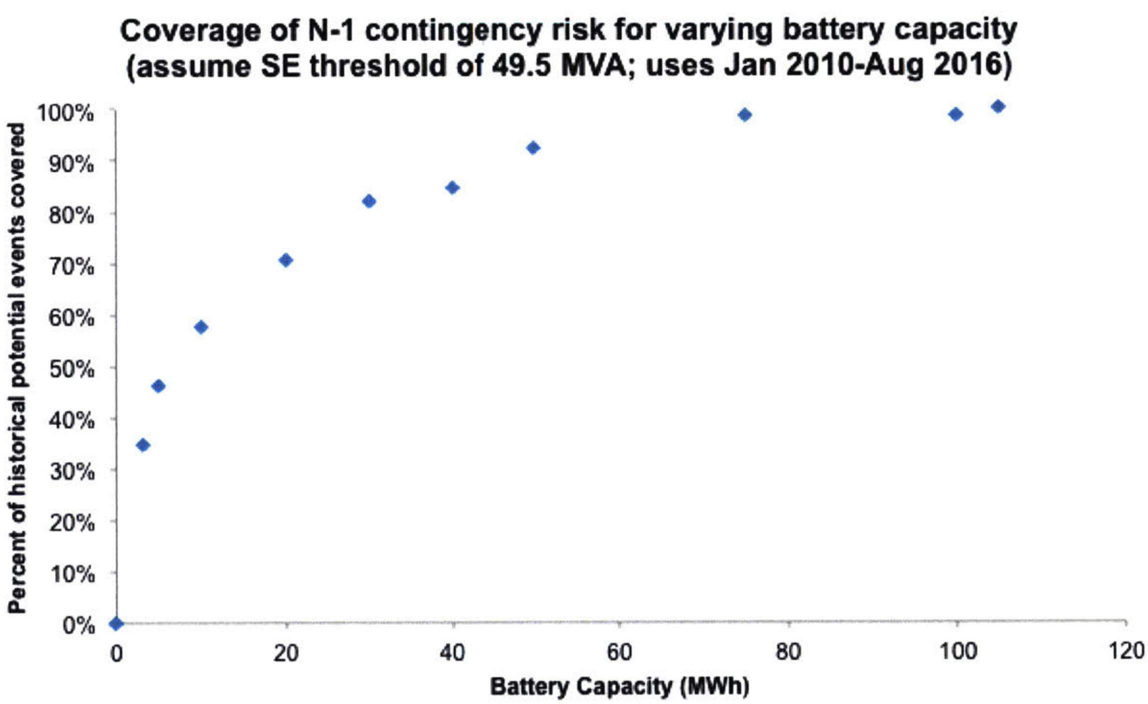


Figure 21: Reliability versus Required Battery Capacity
(Reliability coverage of peak N-1 contingency events vs. size of battery storage system relative to most conservative estimate)

Interestingly, in Figure 21 there appear to be diminishing 'returns' on each incremental increase in battery capacity. Because our models assumed that battery costs scale linearly with size (a significant assumption), there is a point after which every additional dollar spent (or for every additional Wh of capacity) there is a decreasing incremental gain in coverage percentage of these potential events. The results shown are notable because of the decreasing incremental improvement in reliability resulting from incremental battery capacity. Because such extreme peak events are so unlikely, the average expected cost of such events, even if they are large in magnitude, are low. This type of calculation has not been incorporated into Atlantic Electric's planning in the past, due to the desire to avoid lost service by planning to the peak load worst case scenario. The potential for cost savings from using this method of analysis could be sizable.

Method 3: Historical Analysis is advantageous as a battery sizing methodology, because of its approach to planning using a distribution of past events instead of a single deterministic analysis. Using more data from the past accounts for variations in electric usage during different years and over time, which could be overlooked if a single peak day is used for analysis. We could thus have a better understanding of the needs over time for a battery energy storage system. Therefore, it is more comprehensive and takes into account more probable peak magnitudes that may occur over time, instead of a single most extreme example. Arguably, it could be the most important to understand the load profiles on the more common peak days that occur for planning purposes.

However, the Historical Analysis method could cause analysis to inaccurately weight historical data that is less relevant for future projections, given changes in demand behavior or load over time. In addition, if there is an outlier year of extremely high peaks, this method could leave a substation vulnerable to multiple service disruptions, and therefore cause potential fines or other negative outcomes for the utility and its customers. The discussion regarding how a utility and the pulic utility commission balance risk of service disruption with the high economic costs of over-sizing systems should be one that is important when reevaluating planning methods for future needs.

3.4.1 Monte Carlo Simulation

After using historical load data for analysis, there was a need to use those results to develop a perspective on future load. To understand the implications for the future, a Monte Carlo simulation was performed to account for randomness in load and therefore randomness in the demand peak magnitudes in future predicted events.

The goal of the Monte Carlo simulation was to use the historical distribution of load magnitudes at Area A subtation to generate a possible distribution of future peak events. These potential events would be ones in which a battery storage system could be necessary to supplement the capacity given current infrastructure. The battery sizes that were required and the frequency of these required sizes were then used to understand what battery size would be necessary.

The formulation used all magnitudes for peak days in which there was load demand that exceeded the single transformer's summer emergency capacity rating. The magnitude and frequency distribution of 77 'events' identified in earlier analysis formed the basis for the distribution. Given that there were 77 events over 5.5 years, and given that planning took place over a 10 year time frame, we generated approximately 150 future events. For each event generated, a randomized magnitude was chosen based on the distribution of magnitudes from historical events. This generation was repeated each time for the events, refreshing randomization with each additional repetition, until 150 of them had been generated. These events, as proxies for the required battery sizes, would help give us another way to approach planning for future added capacity needs.

The results shown in Figure 22 reflected a distribution of battery capacity sizes that were clustered around fairly low required excess capacity instances. Most notably, a significant portion fell below half of the "Plan to Peak" result capacity.

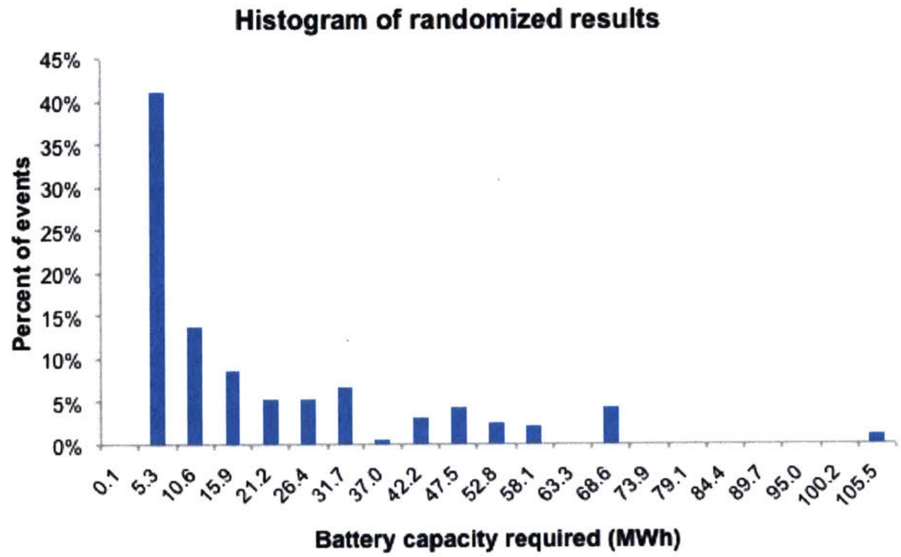


Figure 22: Monte Carlo Simulation Distribution Result
Monte Carlo simulation results of battery capacity required for potential 'events'.

The advantage of incorporating the Monte Carlo method into the Historical Analysis method is the incorporation of randomness in predicting future needs. This allows for flexibility in adjusting predictions. A disadvantage is that predictions are almost never correct, so this method does not accurately account for future potential changes in demand or load profiles. Furthermore, it is assumed that the future load curves will be similar to the past loads. In this case, for Area A substation, this assumption appears to be reasonable given knowledge of local demographics, economic conditions, and development. However, in order to apply this to other cases, it would be important to also incorporate factors that would adjust the method based on forcasted growth or changing demographics of the customer base.

3.5 Application to Other Sites

It is important to understand whether the insights resulting from the analysis of Area A substation could be expanded for evaluation of other sites with similar characteristics. Two other locations, Area B and Area C, were selected because the areas were also undergoing planning studies, there were concerns about overloading transformers, and the planners were interested in comparing battery storage as a potential alternative to conventional solutions. In these two specific cases, the conventional solution would be investment in a new transformer. In addition, Area B and Area C were both in a nearby geographical area with similar mixes of customer types, and were systems that were relatively isolated in the network; i.e. there were few viable alternative options for distribution through an alternate network, if these substations were to experience service disruption. The network also included important parallel transformers of similar technology that could share load in the event of a single service disruption. Most importantly, the fairly high data availability and quality made these sites feasible as additional subjects for analysis.

While Area B and Area C experienced different magnitudes of peak demand, the trends in load growth were similar. The Plan to Peak, Cost Economics, and Historical Analysis methods were all applied to these two sites in the same way as they were applied to the Area A substation. Once the analysis was complete, a comparison of the method results was performed relative to 'reliability', where reliability is defined as the percent of potential historical events covered by the capacity at a given battery size.

Reliability was plotted versus the relative battery size (percentage of that site's "Plan to Peak" battery size output). This approach to plotting allowed for a normalized comparison of the relative increase in battery size compared to the incremental benefits provided for reliability in case of extreme events of high peak demand coinciding with a service disruption in one of the parallel elements.

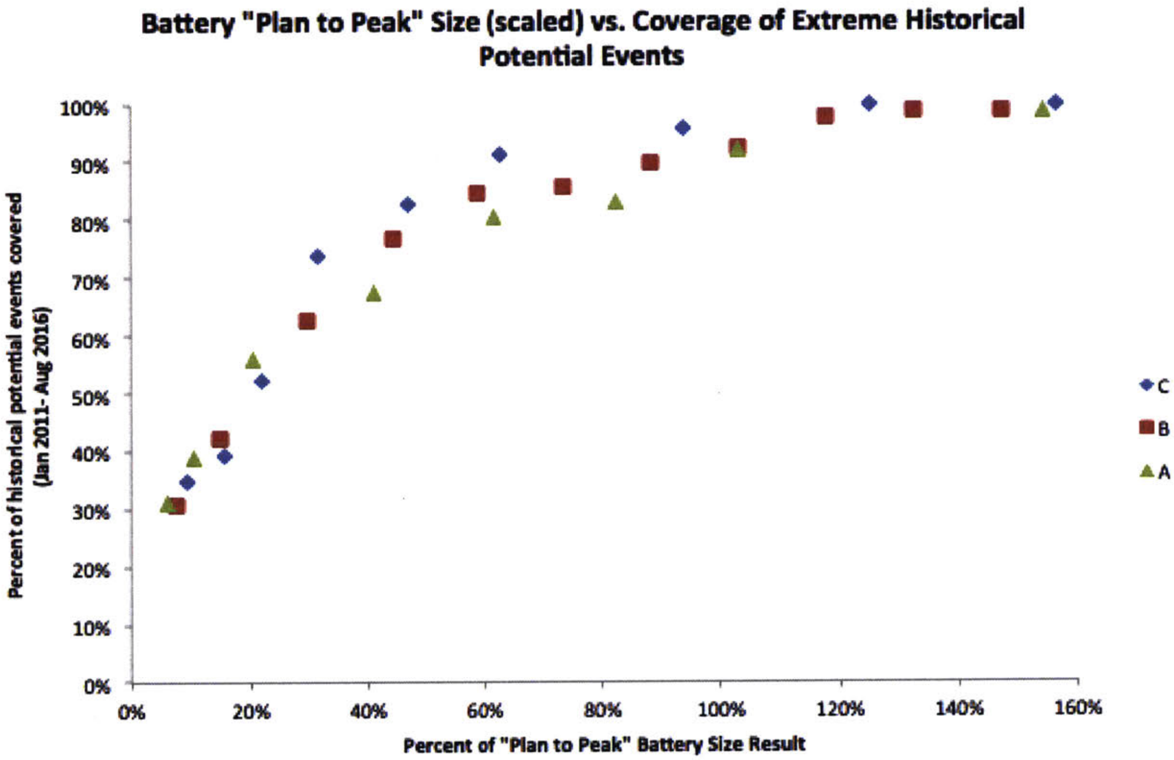


Figure 23: Normalized Reliability Proxy versus Battery Capacity Size (Percent coverage of peak N-1 contingency events vs. size of battery storage system relative to most conservative estimate. Normalized for each case's total number of events and most conservative battery size estimate calculated through Method One: Plan to Peak analysis)

The normalized results in Figure 23 suggest:

Given that the most conservative sizing method of "Plan to Peak" yields a battery energy storage system size B, a battery energy storage system size of 0.5B will be able to cover 75-85% of theoretical N-1 contingency extreme events. This also implies that by covering the anticipated 100% of theoretical N-1 contingency events instead of 75-85% of events, Atlantic Electric would need to increase the battery energy storage system's size and up-front costs by approximately 100%.

3.6 Business Process Analysis

As described previously, the planning process in which the battery storage evaluation currently occurs is a periodic area-specific planning process, led by electric asset planners (see Figure 24). Once a planning study is initiated, the planner centralizes information required to analyze the system's capabilities. This information comes from multiple departments, including substation engineering, advanced data and analytics teams, and regulatory. Individual cases may require the involvement of other groups based on the specific situation. This step in the process requires significant coordination among various stakeholders.

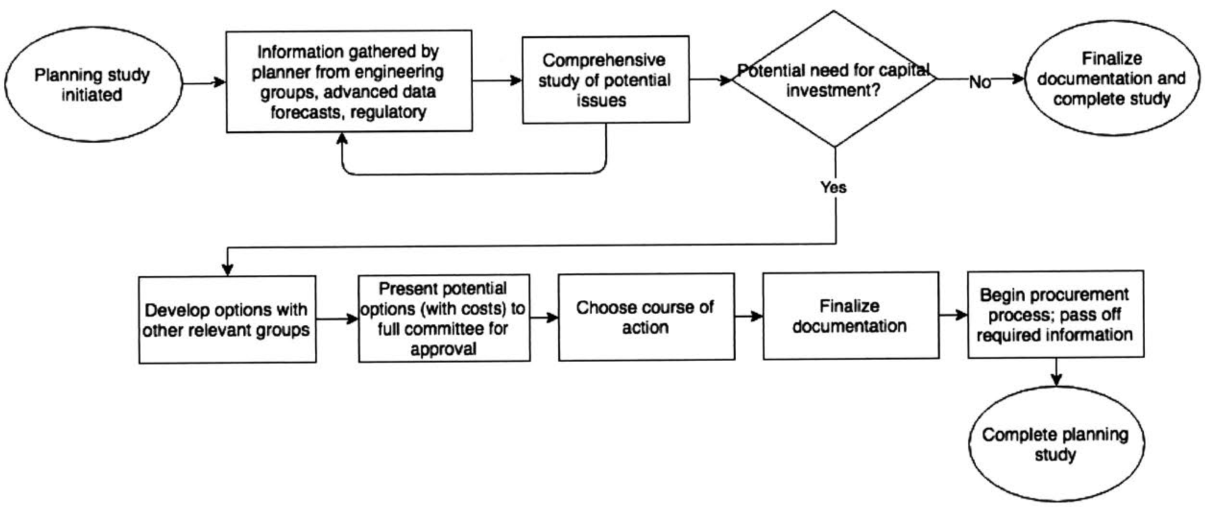


Figure 24: Current Asset Planning Business Process
High-level overview of current area planning study (and asset investment evaluation) process.

When there is a potential need for capital investment, the final decision is often made for the least cost option that meets sufficient requirements. One of the motivating factors is that external regulators consider all capital investments together when considering whether to include them in a new rate case approval. The sum of all capital investments that

Atlantic Electric is trying to recover is significant. Therefore, any individual investment is viewed in context of the total investments done across the whole organization. Atlantic Electric must maintain its network to provide safe and reliable service for customers, so there is no single dollar limit to total investment per time period. However, the managers who must give final approval to any capital costs incurred are in some capacity balancing a theoretical budget of what will be considered reasonable for total cost recovery.

Thus, the goals of the planners when developing options for an asset investment are first to meet the minimum requirements for safety and reliability for the following period, and second to minimize costs. In situations in which a higher up-front cost might yield ancillary benefits later on, such as with a battery storage system, unfortunately those longer-term benefits are not currently quantified and incorporated. Return on investment and net cost-benefits are not key metrics emphasized during the planning process. Instead, single one-time costs are used. This could appear to be a discordant method of evaluating decisions in a system that has a long time horizon of operations. If a longer-term and more comprehensive financial view were taken, the organization might actually reduce overall costs over time. Cost reductions for the utility could translate to reduced costs that are passed on to users, thus benefitting both the company and customers.

4 Recommendations and Conclusions

4.1 Battery Storage Evaluation Methodology Implications

The comparison among sites raises questions about how electric utilities can or should plan for reliability purposes. The similar shape of the plotted reliability metrics suggests that there may be a phenomenon in diminishing reliability relative to additional battery storage size capacity that applies in multiple situations.

If the decision-making framework in asset planning continues to be one-time cost-driven, then the Plan to Peak methodolosgy could be sufficient for planning for the extremely unlikely N-1 contingency scenarios that were outlined in these scenarios. In these cases, the required size of the battery storage system would make the option nonviable with present technology and lithium ion unit costs. The unit costs of lithium-ion would need to decrease significantly (estimated 60-70%) in order for the Plan to Peak battery system to be a viable option. Furthermore, that would not address the potential regulatory environment that may encourage battery storage through mandated capacity targets.

However, Atlantic Electric and other utilities could seek to use a methodology that would balance long-term cost with reliability, allowing for consistent evaluation of battery storage systems as viable options. In this case, the Historical Risk analysis would be a more appropriate methodology across sites. Examining real data over time to understand the actual expected value of the required battery storage capacity would allow planners or analysts to appropriately specify a system. They would also be able to better reduce capital expenditure while maintaining reliability in the system.

Similar to the concept of service level in inventory or operations management, Atlantic Electric could consider planning to a 75-85% "service level" for extreme events such as N-1 contingency events that coincide with peak demand. From the results and cost calculation used, it suggests that the 75-85% service level could cost roughly 50% of the cost to cover 100% of these events. Combined with additional value streams, further unit cost reductions, and regulatory requirements, battery storage systems could become much more attractive options. The analysis results also provide implications for the potential of standalone battery storage systems. In addition to multiple uses for a single battery, options such as mobile storage solutions and shared battery storage capacity might spread costs across a larger area, improving the overall value proposition.

4.2 Battery Storage Evaluation Business Process Recommendations

The results of the three sizing methodologies and the analysis of the internal business processes demonstrate that for a longer-term battery storage evaluation and implementation process, the current evaluation process may require augmentation of the metrics for which it is currently optimizing. Without a more comprehensive evaluation of the potential benefits that a battery storage system could provide, such as frequency regulation or peak shaving, the economics of battery storage are unattractive when compared to conventional asset investments.

Utilites could consider developing a standalone process and/or dedicated group with relevant expertise to systematically evaluate innovative solutions such as battery storage systems, taking into account up-front costs, technical requirements, optimized benefit use cases, and site-specific work (see Figure 25). This technical group could collaborate with planners in area planning studies to provide detailed proposals that also take into account other resources available in the system, such as battery storage systems in nearby substations or behind the meter.

Atlantic Electric could use the methods developed in this thesis and build upon them to incorporate additional value streams to develop a comprehensive evaluation process for battery storage solutions, as depicted in Figure 25. This process change and organizational addition would not require significant changes in the area planning study. Instead, it would provide more support from separate content matter experts working in parallel that would be dedicated to analyzing and developing potential battery storage solutions.

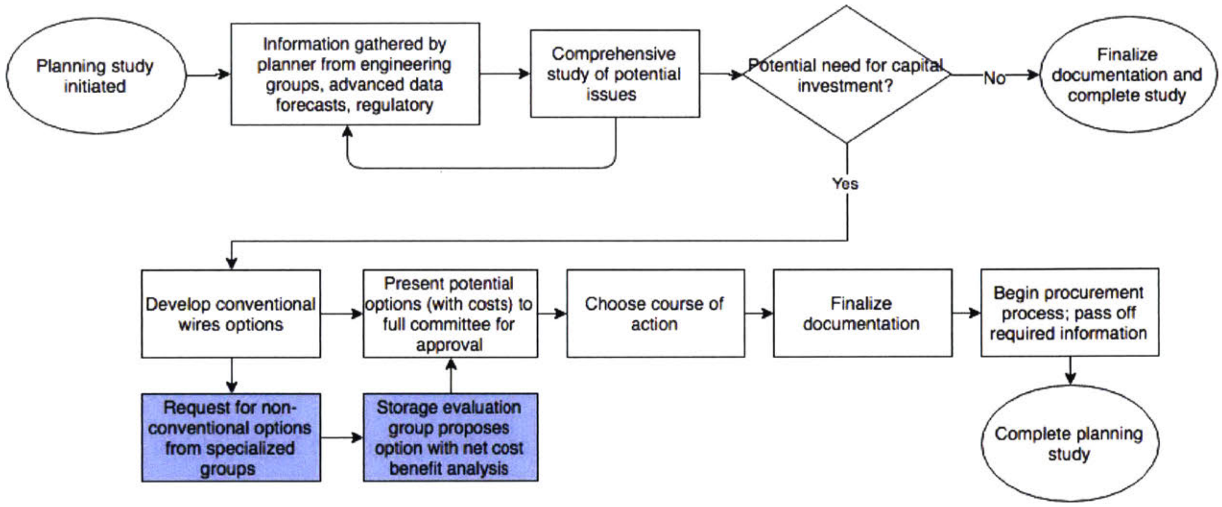


Figure 25: Modified Asset Planning Business Process
(Additional group would provide specialized input in blue.)

This process would have the added benefit of creating a group that would be able to oversee all battery storage system installation across the network. The group would be able to develop and iterate on a robust battery storage system evaluation method, centralize best practices, and also act as a resource for other groups in the organization. For example, if there were a request from regulatory agencies for information regarding total installed storage capacity mandates, this group would be able to provide the needed information. The formation of such a group would certainly require additional resources in recruiting, training, and developing new processes. Outside expertise would likely need to be found, and there could be internal resistance to change in the planning process. In the long-term, this structure could make the planning process more robust and allow for more innovation in the organization.

4.3 Conclusions

The site-specific battery sizing analysis from the case studies discussed in this thesis indicate that 75-85% of N-1 contingency reliability coverage could be achieved with approximately 50% of the most conservative battery energy storage system size, and therefore with approximately 50% of the cost of the most conservative method. While the most conservative Plan to Peak method is sufficient for the current processes, a more comprehensive Historical Analysis method may provide more reasonable battery storage system sizes at lower costs, while still maintaining sufficient reliability of the transmission and distribution systems.

This thesis focused on site-specific evaluation for battery storage systems intended to provide supplemental reliability in the case of an N-1 contingency event coinciding with peak demand in an electric distribution sub-station with parallel transformers. Due to the cost-focused lens of capital planning processes, a cost-only method was employed to understand several ways to determine the appropriate size of the battery. The three methods developed and recommended process changes provide insights for continued work to evaluate and incorporate battery storage systems in electric distribution. Existing assumptions can be further refined to form more comprehensive and realistic sizing methods for the future. These approaches may also have applications in reliability analyses of other industries for low probability, high magnitude events.

Going forward, Atlantic Electric should consider ways to incorporate both reliability applications and other value streams of battery storage that can provide benefits for its network. The analytical approach and organizational processes will require further development and reinforcement to form a comprehensive and sustainable utility-scale battery storage deployment strategy.

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