# Optimal Capacity Partitioning of Multi-Use Customer Premise Energy Storage Systems

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***Abstract*--As electrochemical technology matures and capital costs decrease, battery energy storage systems (BESS) are becoming a viable means for commercial and industrial (C&I) customers to independently realize reliability improvements, service charge reductions and new, utility-remunerated revenue streams. This paper investigates the operation and planning of customer-side-of-the-meter BESS for multiple simultaneous objectives. For schedule-based applications, a new economic dispatch algorithm that accounts for battery cycling constraints is proposed for customers with net metering and a Time of Use (TOU) rate structure. In addition, service point reliability and outage cost models are presented to determine the economic value of emergency back-up resources in terms of standby energy capacity. Simulations are performed on a test C&I system with local generation resources using seven candidate storage systems. Service charge and outage savings solutions are combined to determine pareto-efficient partitioning of BESS energy capacity and assess the economic competitiveness of various storage technologies.**

***Index Terms*--Energy Storage, Multi-Objective Optimization, Distributed Energy Resources, Emergency Backup, Battery Energy Storage Systems**

## INTRODUCTION

In contrast to uninterrupted power supplies (UPS), diesel generators, and other traditional power quality and emergency backup technologies, high energy-density battery energy storage systems (BESS) have the ability to provide additional benefits such as local renewable generation energy arbitrage, demand charge reduction and distribution system utility support services [1]. Furthermore, inverter-based storage systems with dynamic scheduling and control capabilities can be deployed in diverse environments to simultaneously achieve multiple control objectives [2].

This paper investigates BESS operation and planning in large commercial and industrial (C&I) customer-premise applications for reduced service charges, increased local generation sell-back revenue and improved reliability. First, optimization models and solution methodologies are developed for the following end-use application areas:

1. Peak-shaving for demand charge reduction
2. Energy arbitrage in a Time-of-Use rate scenario for energy charge reduction
3. Energy arbitrage for increased Distributed Generation (DG) sell-back revenue
4. Emergency backup for outage ride-through

The first three applications are non-linear optimal scheduling problems that have been solved in the literature using dynamic programming [3], [4], particle swarm optimization [5] and is similar to the classic hydro-thermal scheduling problem [6]. The solution technique can also be incorporated into a planning study to determine optimal life-time savings for a given battery capacity [7], [8]. Most BESS technologies, however, have a limited cycle life and require an additional constraint to prevent excessive cycling and premature end-of-life [9]. This paper introduces a cycling penalty factor in conjunction with an iterative search-dynamic programming algorithm to moderate cycling duty over a weeks to months operations horizon.

The fourth application is probabilistic in nature and treated separately from the economic dispatch problem. Traditional emergency power system sizing and specifications for C&I applications involve deterministic calculations of capacity required to serve critical loads for worst-case conditions [10]. For energy-sensitive customers, however, standby sizing is increasingly a business decision that is driven by economic risk assessment [11]. This paper utilizes customer-perspective reliability analysis techniques developed in [12] and detailed in [13] to create outage duration and frequency probability distributions for a given customer. Given outage statistics, the expected value of emergency backup capacity can be determined using a customer damage function [14]. This paper uses a sophisticated data-driven outage cost model developed by Lawrence Berkeley National Laboratories (LBNL) in [15] to quantify the reliability benefits of energy storage to a customer.

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The combination of operational and reliability planning objectives in energy storage system sizing is discussed in [16] for microgrids, but has yet to be explored for customer-specific applications. This paper formulates the planning problem in terms of optimal partitioning of battery capacity between reliability and scheduling-applications for maximum global value, as depicted in Fig. 1. By first iteratively solving the optimal dispatch problem over a given set of dedicated capacities, the results are combined with calculations for annual outage ride-through savings per dedicated $kWh$ to determine pareto-efficient capacity partitions.

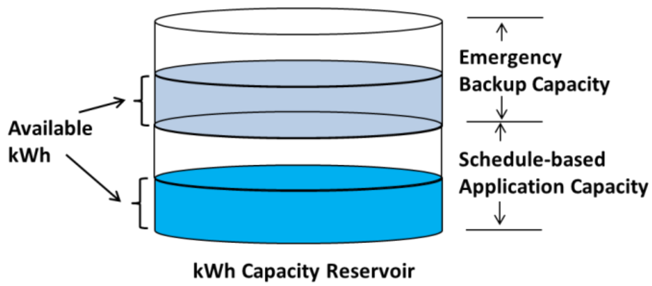


Fig. 1. BESS capacity partitioning.

Simulations are performed on seven candidate energy storage systems using historical data from the University of Minnesota-Morris, a renowned leader in sustainable development with significant onsite generation resources. Results include optimal dispatch schedules for different schedule applications, customer-based reliability analysis and outage ride-through valuation, optimal capacity partitioning pareto-efficiency curves, and comparative Return on Investment (ROI) analyses of different BESS technologies.

## CUSTOMER-PREMISE ENERGY STORAGE SYSTEMS

Customer-premise energy storage systems are located on the customer side of the utility meter and provide power services to the customer's facilities and potentially for the utility as well.

### *Storage System Modeling*

A single-variable linear system is used to model BESS. The energy stored, $W_{st}$, is determined by the power entering the system, $P_{ESS}$, times a constant one-way conversion efficiency, $\eta$ as shown in (1).

$$W_{st} = W_{st}(t_o) + \int_{t_o}^{t} \eta \times P_{ESS} d\tau \tag{1}$$

Total energy capacity is normalized to an operating region that is bounded by the available operating energy capacity, $W_{op}$, and the power rating of the unit, $P_{rated}$ as shown in (2) and (3) respectively.

$$0 < W_{st} < W_{op} \tag{2}$$

$$-P_{rated} < P_{ESS} < P_{rated} \tag{3}$$

This simplified model is generic to a wide range of technologies and the operating parameters are consistent with those utilized in recently developed wholesale ancillary service markets for short-term energy storage resources [17].

The magnitude of energy stored and released in one complete charge/discharge cycle is equal to twice the available capacity. Hence, the number of cycles for an incremental change in stored energy is given by (4).

$$N_{cycle} = \frac{\Delta W_{st}}{2W_{op}} = \frac{\eta P_{ESS}}{2W_{op}} \tag{4}$$

The lifespan of the battery is determined by either the rated operating life, in years, or the cycle life, in cycles, whichever occurs first. In cycle-intensive applications such as energy arbitrage, it is useful to define the average number of cycles per month that leads to the highest utilization over the operating life, $N_{cycle\_max}$, as shown in (5).

$$N_{cycle\_max} = \frac{Cycle\ Life}{Operating\ Life} \left[\frac{cycles}{month}\right] \tag{5}$$

For reliability applications, assuming the BESS is adequately rated to meet various loading requirements, the duration that standby power service is available, $t_{backup}$ is given by the ratio of available energy capacity and the sum of interval demands, $P_{load}$, during the outage (6).

$$t_{backup} = \frac{W_{op}}{\sum P_{load}} \tag{6}$$

### *Candidate Systems*

Energy storage system operating parameters and costs are provided for large C&I customer-premise applications in [12] and were used as the basis for the seven candidate energy storage systems presented in Table I.

TABLE I
CANDIDATE ENERGY STORAGE SYSTEMS

| Storage System | $W_{op}$ ($kWh$) | $P_{rated}$ ($kVA$) | $\eta$ (%) | Cycle Life ($cycles$) | Cost ($\$/kWh$) |
|---|---|---|---|---|---|
| **Advanced Lead Acid 1** | 5000 | 1000 | 92 | 4500 | 600 |
| **Advanced Lead Acid 2** | 1000 | 200 | 92 | 4500 | 720 |
| **Sodium Sulfur (NaS)** | 7200 | 1000 | 87 | 4500 | 500 |
| **Zinc Bromine (Zn-Br) Flow** | 625 | 125 | 79 | 12000 | 480 |
| **Vanadium Flow** | 1000 | 285 | 79 | 12000 | 1085 |
| **Lithium Ion** | 625 | 175 | 93 | 12000 | 1085 |

Storage systems are assumed to be modular, to include the necessary communications and control sub-systems to support real-time operations, and to have a fifteen-year operating life.

## SERVICE CHARGE MINIMIZATION

### Customer Power System Model

A large C&I customer system is modeled as a single bus with a net-metered tie to the distribution primary network as shown in Fig. 2. The customer's load, $P_{load}$, and distributed generation resources, $P_{DG}$, are aggregated into a single sink and source, respectively. The contribution from the customer-premise energy storage system, $P_{ESS}$, can be in both directions, with positive defined as charging.

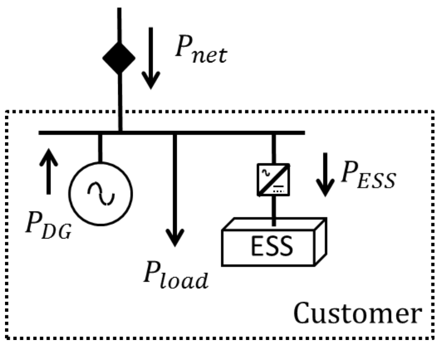


Fig. 2. Customer power system model.

The average metered tie flow for each demand period, $t$, is given as shown in (7).

$$P_{net,t} = P_{load,t} - P_{DG,t} + P_{ESS,t} \tag{7}$$

Two additional variables, $P_{net\_pos}$ and $P_{net\_neg}$, shown in (8) and (9) are defined to differentiate between positive and negative tie flow and aid in net metered optimization modeling.

$$if\ P_{net} > 0, \quad P_{net\_pos} = P_{net}; \quad P_{net\_neg} = 0 \tag{8}$$
$$if\ P_{net} < 0, \quad P_{net\_pos} = 0; \quad P_{net\_neg} = P_{net} \tag{9}$$

### Time of Use Rate Structure and Power Sellback Agreement

The rate schedule used in the optimization modeling and simulations is based on [18] and uses Time of Use (TOU) pricing over three price periods: Off-Peak, Shoulder and On-Peak. Primary service customers are billed monthly based on a flat-rate connection and facilities charge as well as variable energy and demand charges. Energy costs are given by the hourly $kWh$ consumption times the respective price-period energy charge, $C_e$ [$\$/kWh$], summed over the billing period. Three demand charges are incurred, and given as the peak hourly $kW$ demand over the billing cycle for the price period times the respective price-period demand charge, $C_d$ [$\$/kW$]. Reactive power demand charges were shown to be minimal in the simulations and are neglected for simplicity of exposition.

In addition to these service charges, the customer has a regulated agreement with the utility to sell excess generation at a fixed rate, $C_{gen}$ [$\$/kWh$], that is independent of the TOU price periods.

### Optimization Model

Given a load and distributed generation production forecast over the billing period, the customer's monthly service charges are minimized by determining the optimal charge/discharge schedule of the energy storage system as shown in (10).

$$\begin{gathered}\min_{W_{st,t}} \sum_{p=1}^{3} max\left\{P_{net_{pos},t,p}\right\} C_{d,p} + \sum_{p=1}^{3}\sum_{t=1}^{T} P_{net_{pos},t,p} C_{e,p} \\ - \sum_{t=1}^{T} P_{net_{neg},t} C_{gen} \\ s.t. \\ 0 < W_{st} < W_{op} \\ -P_{rated} < P < P_{rated}\end{gathered} \tag{10}$$

In (10), $p \in [1,3]$ is the price period index and $t \in [1,T]$ is the hour during the billing period. The three terms represent the three simultaneous objectives:

1. Minimize demand charges
2. Minimize energy charges
3. Maximize energy sell-back revenue

For operations and planning purposes, it is also desirable to limit excessive cycling and maximize the operating lifespan of the unit. This additional constraint is expressed in (11):

$$N_{cycles} < N_{cycle\_max} \tag{10}$$

### Solution Methodology

Dynamic programming is well suited to scheduling operations problems and is based on the principle that "an optimal policy must only contain optimal sub-policies" [19]. Using this numerical approach, the optimization variable, $W_{st}$, is subdivided in $N_W$ discrete segments and the dispatch schedule is determined by the path from one capacity value to another from hour $t = 1$ to $t = T$.

One disadvantage of dynamic programming as related to the current problem is the inability to handle the third constraint directly, which breaks the requirement for optimal sub-structure. To overcome this, the constraint is relaxed by introducing a virtual cycle cost term, defined as the total number of cycles during the billing period times a penalty factor, $PF$ [$\$/cycle$] as shown in (12).

$$Cost_{cycle} = -\sum_{t=1}^{T} \frac{\eta(P_{net\_pos,t} + P_{net\_neg,t})}{2W_{op}} PF \tag{12}$$

If the optimal cycling duty, $N_{cycles^*}$, exceeds the maximum allowed monthly cycles, $N_{cycle\_max}$, a simple heuristic search algorithm is used iteratively with dynamic programming to adjust the penalty factor to bring the total number of cycles within a desired threshold, $\varepsilon$, of $N_{cycle\_max}$ as shown in (13).

$$\left|N_{cycles} - N_{cycle\_max}\right| > \varepsilon \tag{13}$$

*Simulations*

The University of Minnesota–Morris (UMM) is a residential campus in rural Minnesota with approximately 1800 students. UMM owns and operates a biomass gasification plant fueled by crop residues from nearby farms, solar thermal panels, a solar photovoltaic system and two 1.65 $MW$ wind turbines [20]. An MV90 metering system collects real and reactive demand/production data for the wind turbines, net tie flow with the utility grid, and campus load, which peaks at 1.5 $MW$ and accounts for all other local generation sources. UMM has a primary service connection with Otter Tail Power Company (OTPC), the local distribution company, and it is assumed to subscribe to a TOU rate [18] with a monthly billing cycle.

The Advanced Lead Acid 2 BESS is used for optimal dispatch simulation for the UMM system. Battery capacity is divided into 100 discrete capacity steps, and hourly wind and load data from May 2011, as shown in Fig. 3, is used in the analysis.

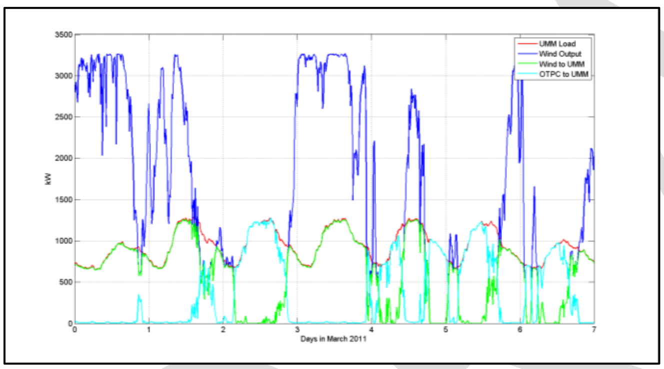


Fig. 3. UMM wind generation (blue) and load (red) for May 1-7, 2011.

For illustration, demand charge reduction, application 1), is analyzed first in a no-wind scenario. Fig. 4 shows the campus load, tie flow, and BESS discharge over the entire month. As opposed to typical daily peak-shaving schemes, one can see that, due to the nature of the demand charge, maximum apparent load is minimized over the entire month.

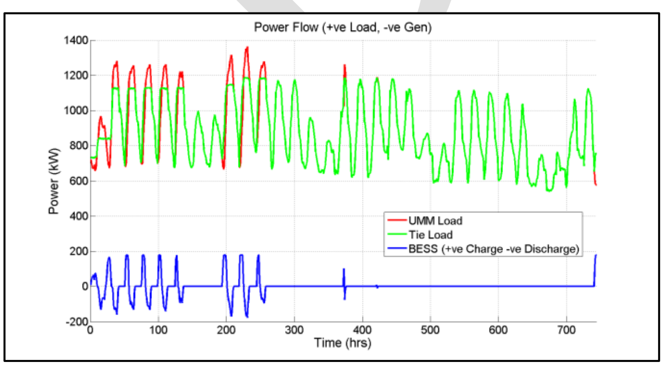


Fig. 4. Demand charge reduction - no wind.

Energy charge reduction, application 2), is also analyzed under the same conditions. Fig. 5 shows the charge/discharge schedule over the first 48 hours.

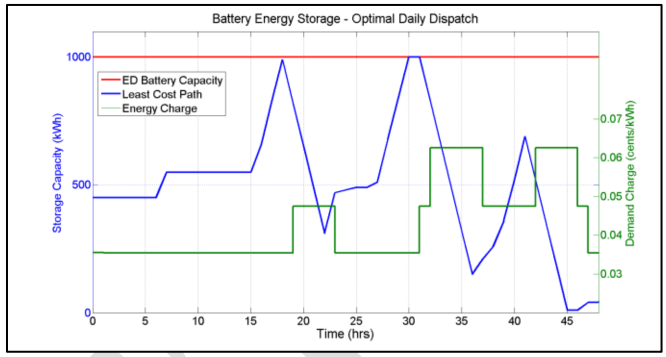


Fig. 5. Energy charge reduction - no wind.

With no cycling penalty, the system cycles 46.3 times over the course of a month. Averaged over the unit's lifetime, this cycling duty would reduce the operating life from 15 to 8 years.

For the next simulation, the effects of local wind generation and the cycling constraint are added. With no storage, UMM incurs \$7,957 of energy charges and \$7,075 of demand charges during the May 2011 billing cycle. Table II summarizes the charges, sell-back revenue and cycling penalty factors calculated with for optimal BESS dispatch schedules for various objectives with a cycling threshold $\varepsilon = 1$. The last column shows the combined objective formulated in (9).

TABLE II
UMM MONTHLY UTILITY BILL - OPTIMAL BESS DISPATCH

| | Base Case | Obj. 1 | Obj. 2 | Obj. 3 | Obj. 1,2,3 |
|---|---|---|---|---|---|
| **Energy Charge (\$)** | 7,957 | 7,953 | 7,598 | 9,135 | 7,861 |
| **Demand Charge (\$)** | 7,075 | 6,144 | 6,408 | 7,249 | 6,142 |
| **Sell-Back Revenue (\$)** | ---- | 29 | 2 | 1,094 | 285 |
| **Cycling Pen. Factor (\$)** | ---- | 0 | 0 | 44.15 | 7.64 |
| **Cycles** | ---- | 4.2 | 22.7 | 24.6 | 24.4 |
| **Total (\$)** | 15,032 | 14,067 | 14,012 | 15,290 | 13,718 |
| **Savings (\$)** | ---- | 965 | 1,028 | -258 | 1,313 |

For the energy sell-back and combined objective schedules, the penalty factor was required to limit monthly cycling to within +/- 1 cycle of the Lead Acid 2 BESS's 25 cycle monthly maximum. Despite this constraint, the combined objective was superior to each individual application treated individually, and the maximum savings were achieved by reducing demand charges.

## Outage Cost Minimization

In addition to reduced monthly utility bills, increased reliability is another potential benefit for customer-premise BESS. Given an measure of a customer's service point reliability, the economic value of an emergency back-up resource can be estimated in terms of the outage costs avoided [14], where outage costs for non-residential customers include lost revenue, labor and material costs, etc. [21]. To accomplish this valuation, it is necessary to estimate the number of outages of each length a customer would expect over a course of the year. These reliability statistics can then be combined with an outage cost model to determine the expected value of yearly outage-related savings per dedicated $kWh$ emergency back-up capacity.

*Customer-Perspective Reliability Modeling*

Analytical and probabilistic methods exist for analyzing distribution network reliability and determining load-point reliability statistics, but they require detailed knowledge of distribution system loading, circuit topology, protection schemes, and equipment reliability characteristics [22]. For customer-premise BESS applications that may not be utility-sponsored, such detailed analysis may be impractical. This paper employs an alternative method, detailed in [12], that utilizes system-wide reliability indices and assumptions based on empirical observations to develop a given customer's annual outage duration and frequency probability distributions. The method consists of the following steps:

1. Using a left-skewed distribution, estimate the probability that an outage will be of a given duration.
2. Estimate and apply a customer weighting, which is the proportion of customers that will experience outages for a given outage duration.
3. Next, adjust the outage probability and the customer weighting to yield a Customer Average Interruption Duration Index (CAIDI) similar to the system-wide CAIDI reported by the utility.
4. The customer perspective outage probability for a given outage duration is then the normalized product of the outage duration and customer weighting.
5. Multiply the result by the System Average Interruption Frequency Index (SAIFI) to determine the expected number of outages of a given duration that the customer will experience in a year.

The results will typically show a left-skewed distribution, with the highest probability outage lengths between 30 minutes and 2 hours [13].

*Outage Cost Model*

A customer damage function, CDF, is an analytical model of the expected cost of a given power interruption, $E(C)$, for a given customer. This paper utilizes customer damage functions developed in [15] that are based on the statistical analysis of a meta data set synthesized from over fifteen years of customer value service reliability studies conducted by ten major utilities. Outage costs are statistically modeled by a combined general linear model lognormal function and a normally distributed indicator function. With all other parameters fixed, the expected outage cost for a given customer type can be simplified to the following non-linear, non-convex CDF of outage duration $t_{out}$ as shown in (15).

$$CDF(t_{out}) = \alpha * \exp\{(\beta_1 - \gamma\beta_2)t_{out} + (-\beta_3 + \gamma\beta_4)t_{out}^2\} \tag{14}$$

In (13), $\alpha$ is lumped coefficient, $\gamma$ is the log of annual $MWh$ demand, and $\beta_1, \beta_2, \beta_3, \beta_4 > 0$ are attribute coefficients determined from regression analysis.

*Simulations*

Based on the definitions in [15], UMM is classified as a large C&I customer in the Public Administration industry. With all other outage characteristics assuming averaged values, UMM outage costs as a function of outage duration are shown in Fig. 6.

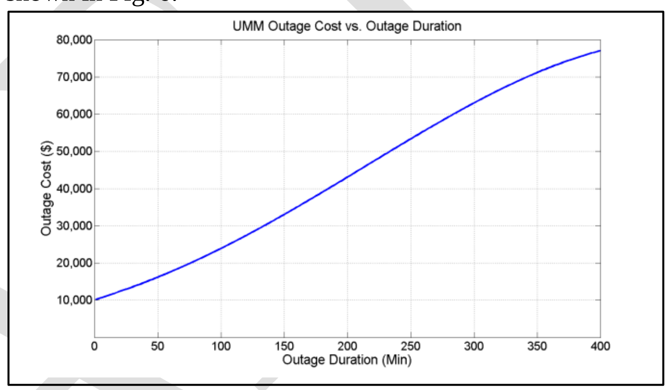


Fig. 6. University of Minnesota Morris - customer damage function (CDF).

In addition to outage cost modeling, Table III shows the steps involved in developing UMM's service connection reliability statistics. System-wide CAIDI and SAIFI reliability metrics are given as 57 and 1.3 respectively, which are two year-averages for 2009 and 2010 as reported by OTPC [23].

TABLE III
UMM RELIABILITY STATISTICS

| | 0-15m | 15-30m | 30m-1h | 1-2h | 2-4h | 4-8h |
|---|---|---|---|---|---|---|
| **Average Duration, $t_{out}(min)$** | 10 | 22.5 | 45 | 90 | 180 | 360 |
| **Duration Weighting** (%) | 8 | 20 | 35 | 23 | 8 | 2 |
| **Customer Weighting** (%) | 23 | 21 | 20 | 17 | 13 | 3 |
| **Outage Probability** (%) | 10 | 23 | 39 | 22 | 6 | 0 |
| **Outages per year, $E(N_{out})$** | 0.13 | 0.30 | 0.50 | 0.28 | 0.074 | 0.004 |

The $kWh$ value of a dedicated BESS for an outage duration bin can now be estimated as shown in (15), where $E(N_{out})$ is the expected number of outages per year. The argument of the CDF is the outage duration experienced, or the difference of the interruption duration and the BESS's maximum backup duration.

$$E(value_{BESS}) = E(N_{out}) \times CDF(t_{out} - t_{backup}) \qquad (15)$$

Eq. (15) illustrates the fact that BESS value is determined by its capacity to reduce apparent outage length. In assessing the entire distribution, as outage duration increases a BESS of a given capacity will serve an increasingly smaller fraction of the outage duration, hence the total value per $kWh$ is the sum of Eq. (15) over each outage bin. Fig. 7 shows the university's annual avoided outage costs as a function of emergency back-up capacity, assuming an average tie load, $P_{load}$, of 875 $kW$.

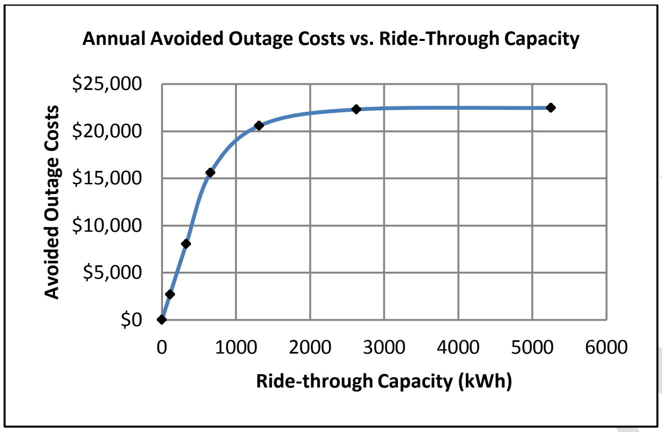

Fig. 7. Avoided outage costs vs. ride-through capacity.

As an example, a 500kWh emergency backup capacity could be used to ride through all 0-15 and 15-30 minute outages, in addition to partially riding through all longer duration outages. The exact value is determined using linear interpolation of the discrete data points.

## Optimal Capacity Partitioning

For a given BESS unit, economic dispatch will lead to a reduction in service charges. Likewise, an emergency backup resource has the potential to provide a significant reduction in outage-related costs. Treating all savings equally, dividing available BESS capacity between application areas in varying proportions creates pareto-efficiency.

### *Simulations*

The 1000kWh lead acid 2 BESS is chosen for simulations and capacity is partitioned in ten discrete proportions. As a first approximation, monthly service charge savings from May 2011 are extrapolated over the entire year. With battery capacity divided equally between applications, yearly service charges are reduced by $12,752 and avoided outage costs are reduced by $12,006. Figure 9 shows relative savings for pareto-efficient capacity partitioning, with a maximum combined savings of $25,344 occurring at a ratio of 40% to 60% for outage and service charge applications, respectively.

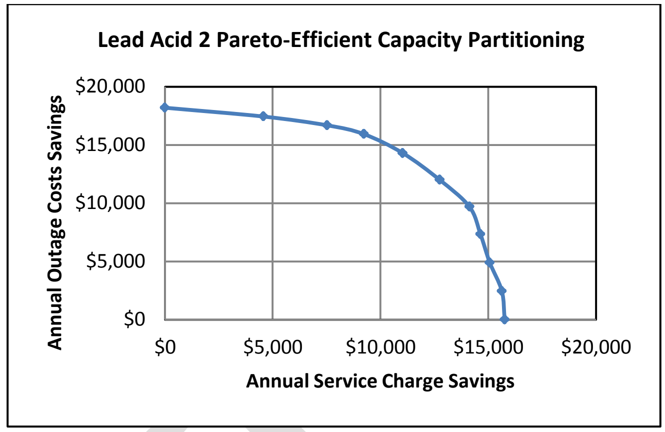

Fig. 8. Lead Acid 2 BESS pareto-efficient capacity partitioning.

Table IV summarizes results of similar analyses performed on all seven candidate systems. Results columns show optimal economic dispatch (ED) capacity, emergency back-up (EBU) capacity and yearly savings for each unit. In addition, the annual ROI is calculated as the ratio of yearly savings to capital cost.

TABLE IV
OPTIMAL PARTITIONING – TECHNOLOGY COMPARISON

| BESS | $W_{op}$ $(kWh)$ | ED Capacity | EBU Capacity | Yearly Savings* | ROI |
|---|---|---|---|---|---|
| ***LA1*** | 5000 | 80% | 20% | $ 83,348 | ***2.78%*** |
| ***LA2*** | 1000 | 40% | 60% | $ 25,344 | ***3.52%*** |
| ***NaS*** | 7200 | 70% | 30% | $ 78,171 | ***2.17%*** |
| ***Zn-Br1*** | 625 | 10% | 90% | $ 15,722 | ***5.24%*** |
| ***Zn-Br2*** | 2500 | 50% | 50% | $ 38,182 | ***3.47%*** |
| ***Van Flow*** | 1000 | 30% | 70% | $ 22,395 | ***2.06%*** |
| ***Li-Ion*** | 625 | 20% | 80% | $ 17,523 | ***2.58%*** |

Table IV indicates that the Zinc-Bromine 1 BESS is the most competitive technology, which is due primarily to its low capital cost. Another observation is that smaller units have more value for emergency backup applications due to the high marginal value of riding-through more commonly occurring short-duration outages and declining return. Likewise, larger capacity units can generate significant savings via energy and demand management applications, but these savings are diminished by either cycling constraints (LA1, NaS) or poor efficiency (Zn-Br, Van Flow).

## Conclusion

This paper presents techniques for planning application-specific BESS capacity partitions for customer-premise applications. In addition to providing added benefits over single-use systems, allotting reserve capacity for emergency backup has the added benefits of reducing cycling and maximum depth of discharge (DoD) that occurs with energy arbitrage applications. For technologies sensitive to DoD, such as Lead Acid, this can potentially extend unit lifespan. Finally, with the proper local control technology, the unused portion of the economic dispatch partition could be dynamically repurposed to supplement emergency backup, thereby providing an additional capacity margin for outage ride-through. Further work in this area would investigate BESS unit dynamic operation for achieving multiple simultaneous control objectives.

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