Optimal Mix and Placement of Energy Storage Systems in Power Distribution Networks for Reduced Outage Costs

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***Abstract*--As energy infrastructure is upgraded to meet modern digital society's need for secure and high-quality electric power, grid-tied energy storage systems are becoming a viable means for improving system reliability and realizing the benefits of Smart Grid. This paper investigates the optimal implementation of distributed storage resources in a power distribution system or islanded microgrid in conjunction with an intelligent load shedding scheme to minimize the societal costs of blackouts. First, a non-linear combinatorial optimization problem for prioritizing outage ride-through service is formulated and a solution methodology is proposed that combines a local search heuristic with simulated annealing. Next, a resource allocation optimization problem is developed to determine the optimal mix and placement of energy storage resources in a power distribution network for intentional islanding of sectionalizable sub-networks. Simulations are performed on the IEEE 123 node test feeder model subject to realistic power system constraints.**

***Index Terms* -- Power Systems, Community Energy Storage, Power Distribution Systems, Microgrids, Emergency Backup, Distributed Energy Resources**

I. Introduction

Utilities are under increasing economic, regulatory and public pressure to meet the growing demand for high quality electric power without making new capital investments in generation and transmission infrastructure. Despite their best efforts, the Electric Power Research Institute (EPRI) estimates the annual cost outages in the United States to be on the order of magnitude of $100 billion USD [1] ,with 80% of interruptions occurring in the distribution system. In addition to the economic impact of outages, the U.S. Department of Defense has identified a lack of independence from the commercial power grid and reliance on traditional back-up power as a major vulnerability for military installations world-wide [2]. Distributed energy resources (DER), including distributed generation (DG), energy storage systems (ESS) and controllable loads, offer new possibilities for improving power distribution system reliability and power quality, but practical integration of DER requires careful consideration of existing protection schemes, voltage regulation, feeder switching operations and other power system constraints.

Much work on the optimal placement of DG and storage resources has been formulated in terms of minimizing network losses [3] or utility CAPEX/OPEX planning objectives [4], [5], and parallel work has been done in determining potential reliability improvements of integrating DER in legacy distribution systems [4], [6], or in self-controlled microgrids [7]. As discussed in [8], however, most DG reliability and power quality improvements will accrue to the owner, and customers or groups of customers will have the greatest economic incentive to implement DG or storage for backup power purposes. Some work has been done in determining the optimal selection and sizing of standby generation for large commercial and industrial facilities [9], and it was shown that DG is economically attractive for customers with high hourly costs-of-outages. However, the analysis was only performed for individual consumers and it assumed a linear relationship between cost and outage duration.

This paper analyzes the potential savings for groups of distribution customers that are served by emergency backup resources during outages and allowed to "ride through" interruptions. This value-based planning approach [10] uses a sophisticated cost model developed by Lawrence Berkeley National Labs in [11]. Since different customer types experience different interruption costs, this paper first analyzes the problem of prioritizing emergency backup resources for critical or high cost-of-outage loads. Physically, providing selective power can be realized at the level of the customer premise interconnection with the grid, i.e. the meter. Many smart meters currently being deployed have a remote connect-disconnect functionality that could potentially be leveraged to disconnect a subset of customers. Intelligent load shedding in distribution networks has been researched in the past [9], [10] and Quality of Service (QoS) load shedding is being investigated for naval shipboard applications by the Office of Naval Research [11], but has yet to be investigated with regards to minimizing the societal costs of outages. Results show that high cost-of-outage commercial and industrial (C&I) customers can benefit greatly from pooling storage resources.

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After developing a priority ride-through outage strategy and performing simulations, this paper next determines the optimal mix and placement of energy storage resources in a distribution network where sub-networks can be sectionalized and intentionally islanded during outages. A list of candidate storage systems is used in simulations to provide insight into the economic competitiveness of various storage technologies and highlight placement strategies.

II. Outage Cost Model

A customer damage function is an analytical model of the expected cost of a power interruption, *E(C)*, for a given customer. This paper utilizes customer damage functions developed by Lawrence Berkeley National Labs, which 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 [11]. Outage costs are statistically modeled by a combined lognormal function and normally distributed indicator function. With all other parameters fixed, customer outage cost is a non-linear, non-convex function of outage duration. Separate customer damage functions are available for three customer classes: Type I: residential, Type II: small C&I and Type III: medium and large C&I. The curves in Fig. 1 below depict outage costs for medium and large C&I customers in various industries.

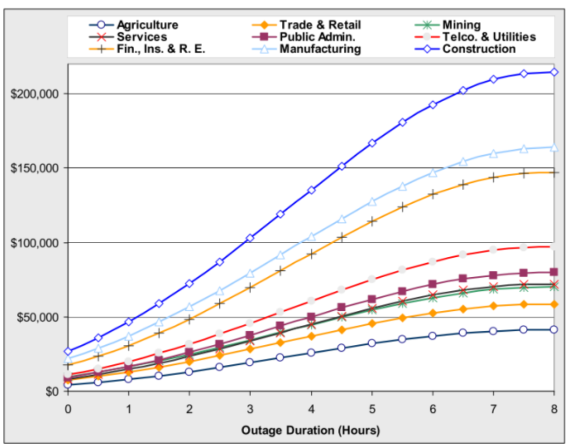


Fig. 1. Medium and Large C&I Customer Outage Cost vs. Outage Duration [11]

III. Energy Storage System Model

For planning emergency backup resources, energy storage systems are modeled as a simple reservoir. The storage system is characterized by energy stored, W_{st}, in kVAh and rate of discharge, S, in kVA. The system is operationally constrained by the total available energy capacity, W_{op}, and the rated discharge power, S_{rated}, as follows:

$$0 < W_{st} < W_{op} \tag{1}$$

$$S < S_{rated} \tag{2}$$

Subject to these constraints, if the energy storage system is at full capacity prior to use, the duration that storage system can supply emergency backup loads, $t_{storage}$, is given as as the ratio of available energy capacity to average discharge power, S_{ave}.

$$t_{storage} = \frac{W_{op}}{S_{ave}} \tag{3}$$

Conversion efficiency and non-linear effects are neglected as a first approximation for planning purposes.

IV. Priority Ride-Through Optimization Model and Solution Methodology

The optimal subset problem can be stated as follows: *Given an outage of a specific length and an energy storage system of specific capacity, power rating and location, determine the optimal subset of customers to "ride through" the outage to minimize the aggregate of all customers' outage costs.*

$$\underset{X\in\{X_1..X_N\}}{\text{minimize}} \sum_{n=1}^{N} C_n * CDF_n\left(t_{out} - X_n \frac{W_{op}}{\sum_i^N X_n S_n}\right) \quad s.t. \tag{4}$$

$$X_n \in \{0,1\}\ \forall\, n$$

$$\sum\nolimits_i^N X_n P_n < P_{rated}$$

Power System Operating Constraints

Where, n is the load index $n \in \{1 \dots . N\}$, C_n is the number of customers at load n, $CDF_n(\dots)$ is the Customer Damage Function for load n, t_{out} is the duration of system outage, X_n is an indicator variable for load n where $X=1$ is to serve and $X=0$ is to shed, and S_n is the average kVA demand of load n during the outage.

Each term in the summation in the objective function is the expected cost of an outage for a particular load point. The input to the load-specific customer damage function is the duration of the outage as experienced by the customer. This duration is the the system outage duration minus the duration that storage is serving the load, assuming it is active (i.e. $X_n = 1$). If storage is not active, the load experiences an outage of duration equal to that of the system outage. The duration that storage is available is the ratio of the available storage capacity (kVAh) and the aggregate kVA demand of all served loads.

The second constraint states that net demand on the storage system must not exceed rated power, a formulation that neglects network losses as a first approximation.

A. Power System Constraints

This paper treats non-linear power system constraints as a black box whereby all network and operating data are passed to a power flow program at each iteration to determine if any current or voltage limit violations occur. OpenDSS, an open source distribution system simulator developed by the Electric Power Research Institute (EPRI) [15], was integrated with Matlab to perform power flow analyses and report violations. On a modern computing system, OpenDSS can solve an 8500 node distribution network in less than a second. Consequently, from a computing time-cost perspective, the power system feasibility constraint in the optimization model is relatively "cheap" to compute when adopted for small-scale problems.

B. Solution Methodology

The optimization problem formulated in (4) is a non-linear, non-convex binary integer program with non-linear constraints. Problems of this form are notoriously intractable and require solution techniques that are specialized for the individual application [16]. Three solution algorithms, local search, simulated annealing and a combined method were implemented and their relative merits were compared.

1) Local Search Heuristic

The local search algorithm is a greedy heuristic that quickly arrives at a local minimum and terminates without trying non-improving moves. The algorithm first sorts loads in terms of outage cost and then, starting with no loads served, iteratively selects the next best load to ride through the outage. This approach builds up a priority list until adding one more load will cause the energy storage system's available energy capacity to be exhausted mid-outage or no more loads can be feasibly served. The first of the two stopping criteria is included because all customers experience a relatively large economic loss for short duration outages, and in general, greater aggregate savings can be realized if less loads are served so that high-priority loads are allowed to ride through the entire outage.

- **Algorithm Outline**

1. Starting with initial configuration $X = \{0 \ldots 0\}$, sort loads in terms of outage cost.
2. While $t_{storage} < t_{out}$
   - 2.1. For all disconnected loads in X
     - 2.1.1. Serve the next highest cost-of-outage load and get solution S' associated with new configuration X'.
     - 2.1.2. If infeasible, increment counter and go to 2.1.
     - 2.1.3. Else:
       - 2.1.3.1. If $t_{storage} > t_{out}$, set $X = X'$ and go to 2
       - 2.1.3.2. Else, increment counter and go to 2
   - 2.2. If counter is equal to number of disconnected loads, break
3. Return the last solution and associated configuration, X

2) Simulated Annealing

Simulated annealing is a probabilistic meta-heuristic modeled after a metallurgical process. It controls the issues of cycling and local minimum termination by accepting non-improving moves according to probabilities tested with computer generated random numbers. In addition to problem data, simulated annealing algorithms use additional input parameters to tune algorithm performance and limit computation time. The stopping criterion checks to see if a better solution has been found after a given number of iterations, L.

- **Algorithm Parameters**
  - Initial Configuration, $X = \{X_1, X_2, \ldots X_n\}$
  - Temperature, T: Constant used in determining the probability of accepting non-improving moves
  - Annealing Rate, ρ: Factor by which to reduce temperature
  - Loop Size, L: Number of iterations before reducing temperature

- **Algorithm Outline**

1. Starting with initial configuration X, calculate initial solution, S
2. While best solution has improved:
   - 2.1. Loop L times
     - 2.1.1. Pick a random feasible neighbor S' of S
     - 2.1.2. Let $\Delta = f(S') - f(S)$
       - 2.1.2.1. If $\Delta \leq 0$, set $S = S'$ and save solution as best to date
       - 2.1.2.2. If $\Delta \geq 0$, set $S = S'$ with probability $exp(-\Delta/T)$
   - 2.2. Set $T = \rho T$ (i.e. reduce the temperature)
3. Return the best solution found and associated configuration, X

3) Combined Approach

In order to further improve solution quality, the final configuration, X, of the local search algorithm is fed into the simulated annealing algorithm to accept non-improving moves and continue looking for better solutions outside of the local minimum. As we will see, this combined approach offers an improved solution quality to performance ratio than either of the two algorithms alone.

V. PRIORITY RIDE-THROUGH SIMULATIONS

The IEEE 123 Node Distribution Test System is a three-phase unbalanced radial distribution feeder with 85 loads [17]. Test system data include technical parameters for loads, substation transformers, regulators, lines, etc. In addition to power system data, the authors developed data for the number of customers, customer type and average annual kVA demand of each load point (i.e. distribution transformer) according to the following assumptions:

- **Assumption 1**: The load factor of all customers is 0.45, a value that is typically used for distribution transformer loading assumptions [18]. Hence, the average kVA demand is 0.45 times nominal peak load, which is provided in the test feeder data.
- **Assumption 2**: All loads are assumed to remain constant during the outage and equal to their average kVA demand. This is a reasonable assumption for planning purposes over long time horizons.
- **Assumption 3**: Residential, small C&I and large C&I customer sub-classes are assumed to each represent 36%, 35% and 29% of all load, respectively and each sub-class average per customer kW consumption is 1.33kW, 8.7kW and 75kW, respectively. These values are in close agreement with nationwide data [19], except for industrial customer average demand, which was assumed to be half the average value since large industrial customers typically connect directly to the sub-transmission network and since the transformer kVA ratings provided in the test system would not support very large loads.

High-level system characteristics are summarized in Table I.

TABLE I
KEY SYSTEM CHARACTERISTICS

Power System Parameters	Value
Base Voltage (kV)	4.16

Voltage Magnitude max. (*pu*)	1.05
Voltage Magnitude min. (*pu*)	0.95
Feeder Head Phase Current Rating (*A*)	600
Loads	85
Customer Data	**Value**
Type I customers	441
Type I average annual demand (*kVA*)	1.33
Type II customers	62
Type II average annual demand (*kVA*)	8.7
Type III customers	10
Type III average annual demand (*kVA*)	75

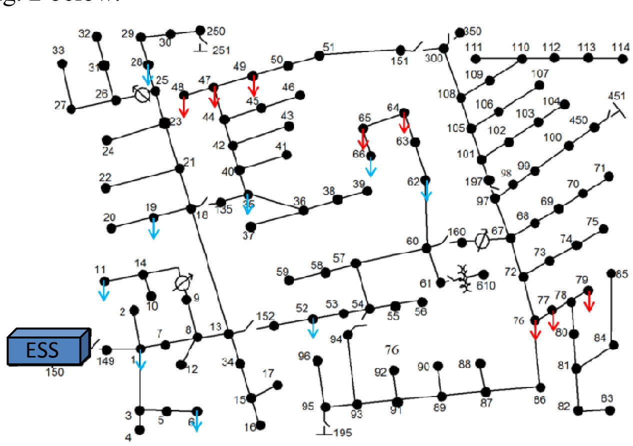
A. *Outage Cost Comparison*

An outage on the high side of the substation transformer (node 150) is simulated, leading to a 120 minute feeder-wide interruption. Without emergency backup service, all customers experience the entire outage duration and the net interruption cost is $155,060, which is borne primarily by C&I customers. If a 1500 kVAh energy storage system located at the substation is used to provide emergency backup service to all loads, it will need to supply the entire feeder load of 1797 kVA. Assuming the storage system rated discharge power is sufficient, its available energy capacity will be exhausted after only 50 minutes and all loads will be dropped mid-outage, resulting in a net outage cost of $100,890. Now, implementing the local search method, 26 high priority C&I customers at 17 load points are selected to ride through the entire outage, and aggregate outage costs are reduced to $57,783. The net demand on the storage system is reduced to 740 kVA. These results are summarized in Table II.

TABLE II
OUTAGE SCENARIO COMPARISONS

	No Load Served	**All Loads Served**	**Subset* Served**
Total loads served	0	85	17
Feeder head load (*kVA*)	0	1797	740
Discharge time (*min*)	N/A	50	122
Type I outage costs (*$*)	2,215	1,708	2,215
Type II outage costs (*$*)	82,027	53,067	55,567
Type III outage costs (*$*)	70,822	46,114	0
Net outage costs (*$*)	155,060	100,890	57,783

Due to the scarcity of loads served, no power system voltage or current constraints are violated. The loads that do receive emergency backup service are physically depicted in Fig. 2 below.



Type II: ↓ Type III: ↓

Fig. 2. 123 Node Test Feeder Optimal Outage Ride-Through Loads

B. *Algorithm Performance*

To compare algorithm performance, a 2500 kVAh, 500 kVA energy storage system is again placed at the substation to provide emergency backup service during the 120 minute outage. With 85 loads total, the feasible set contains over $3.8\text{x}10^{25}$ combinations, making the computation of the global minimum solution prohibitively time consuming. Consequently, solution methodologies are examined according to their solution quality as well as the number of iterations that they take to converge. Table III shows three sets of simulated annealing tuning parameters used in the simulations.

TABLE III
SIMULATED ANNEALING PARAMETER SETS

Set	**Temperature**	**Annealing Rate**	**Loop Size**	$\mathbf{X_{init}}$
SA1	70,000	0.95	15	{0,…,0}
SA2	200,000	0.99	35	{0,…,0}
SA2_Xinit	200,000	0.99	35	Local Search best solution

Since the simulated annealing algorithm contains a probabilistic component, it is run (sampled) ten times to get a best solution, a solution mean and a standard deviation. Table IV summarizes the results.

TABLE IV
ALGORITHM COMPARISON

Algorithm	**Best Solution ($)**	**Solution Mean ($)**	**σ ($)**	**Iteration Mean**	**σ**
Local	92,448	N/A	N/A	113	N/A
SA1	95,383	101,969	5,269	146	45
SA2	87,300	91,760	4,786	827	133
SA2_Xinit	86,815	90,267	2,112	897	110

The results show that the local search heuristic terminates at a local minimum after a relatively few number of iterations. SA1 also solves quickly, but the solution quality is poor. On average, the SA2 simulation achieves a lower objective function value than the local search method, but at the expense of additional iterations. Using the final solution of the local search solution as the initial solution to the SA2 simulation consistently provides the best solution quality for a total of approximately 1000 iterations. SA2_Xinit is also guaranteed to be at least as good as the local search heuristic.

C. *Energy Storage System Considerations*

A range of power ratings and energy capacities were simulated for the same two-hour outage to determine the effects of the storage system parameters on aggregate outage cost reduction. Results are shown in Fig. 3. One can see that when one constraint is tight and the other is slack, the objective function value varies approximately linearly with the storage system parameter in question. For example, if rated power is sufficient and only energy capacity is limiting outage ride-through capability, then adding additional capacity will lead to a proportional reduction in outage cost.

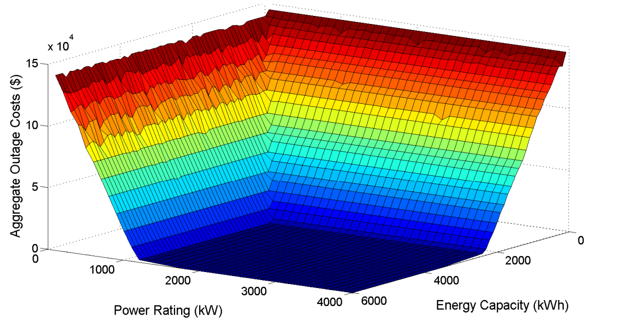


Fig.3. Energy Storage System Parameter effects on Outage Cost Minimization

D. Power System Considerations

We saw previously in Section A that there were no power system constraints violated in the 17 load ride-through scenario due to the fact that only serving a subset of customers brings the system to a lightly loaded state. While phase currents are significantly reduced, the operation of downstream reactive power and voltage regulation equipment needs to be taken into consideration. Switched-in shunt capacitor banks, for instance, can produce excessive VARs in lightly loaded systems, resulting in poor power factor (leading) and downstream voltage increases. This can be exacerbated voltage regulators configured for line drop compensation on regularly loaded systems. Fig. 4 illustrates this phenomenon for the simulated scenario shown in Fig. 2. The x-axis represents distance from the substation and the y-axis is voltage in per unit. The A phase is the black trace, the B phase is the red trace, and the C phase is the blue trace.

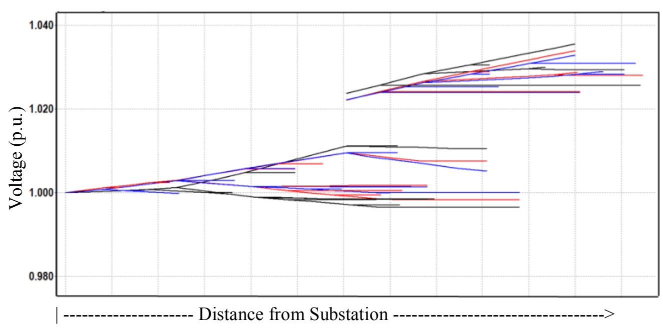


Fig.4. Voltage Drop Diagram – Priority Ride-Through Operation

In addition to voltage and reactive power considerations, phase imbalances could also pose issues as many loads selected are single-phase. A more rigorous treatment of power system operating constraints would include phase imbalance in addition to phase current and voltage limits.

E. Discussion

The outage cost comparison results developed in section A indicate that greater aggregate savings can be achieved by allowing a small group of high priority customers to ride through outages and that, in general, C&I customers have the largest outage cost per average kVA demand. High priority loads and candidate groups for pooled local backup resources can be identified at a high level. In general, supplying a subset of customers is also beneficial in terms of reducing demand on the storage system as well as the power system, although adverse effects need to be taken into consideration, as shown in section D.

VI. Optimal Mix and Placement of Storage Resources for Islanded Operation

The 123 node system contains four downstream sectionalizing switches on the three phase portion of the feeder. Assuming that the system is fed from the substation at node 150, the three phase system topology can be depicted as in Fig. 5, where M1-M5 represent the five sectionalizable feeder sections with their respective nominal peak loads and load counts.

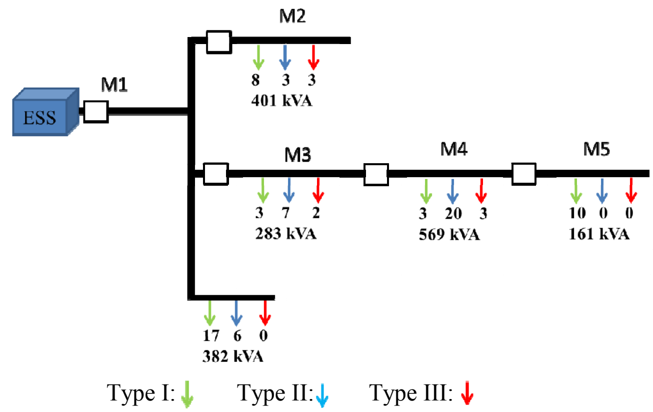


Fig.5. 123 Node System Sectionalizable Feeder Sections

Microgrids and advanced distribution systems necessarily contain advanced protection schemes that allow local generation/storage resources to support islanded operation in the case of bulk power system outages. Assuming that the switches on the 123 node system are outfitted with the necessary high-speed, coordinated outage detection and isolation technology, one can determine the optimal mix and placement of energy storage resources at various sub-networks for emergency backup service during a given outage.

A. Optimization Model

The optimization problem can be stated as follows: *Given an outage of duration t_{out} and $i \in \{1 \dots I\}$ candidate storage systems of capacity W_i, power rating S_i and cost C_i, respectively, determine the optimal mix and placement of resources to minimize aggregate outage costs subject to a global budget constraint.*

$$\underset{X}{\text{minimize}} \sum_{n=1}^{N} AOC_n \left(\sum_{i=1}^{I} X_{n,i} W_i, \sum_{i=1}^{I} X_{n,i} P_i \, , t_{out} \right) \quad s.t. \qquad (5)$$

$$\sum_{n}^{N} \sum_{i}^{I} X_{n,i} \, C_i < Budget$$

$$X_{n,i} \in +\mathbb{Z}^n$$

Where $n \in \{1 \dots N\}$ is the sub-network index and AOC_n is the aggregate outage cost of priority ride-through service at node n, which is a function of the capacity and power rating of local storage systems in parallel as well as outage duration and is the output of (4). $X_{n,i}$ is a positive integer selection variable representing the number of unit i storage systems to be placed at location n.

B. Solution Methodology

The problem formulated above is again a non-linear, non-convex constrained integer program where the decision variables are now open to the set of all positive integers. For small problem sizes, explicit enumeration may be possible. An alternative method is to again implement a local search heuristic, where one storage unit is chosen at a time until the budget limit is met. The algorithm is summarized as follows:

- **Algorithm Outline**

1. While budget is not exhausted
    1.1. Calculate aggregate outage savings for each candidate system at each node
    1.2. Choose the system and location that achieves the greatest Return on Investment (savings/capital cost) and fix at that location
    1.3. Update available budget
2. Return the systems and locations and minimum aggregate outage cost

This algorithm has the added benefit of building up a list of candidate storage technologies, regardless of the budget constraint, which can then be used to examine incremental cost effectiveness. As note, power system constraints are handled in solving (4), hence they are not necessary in the formulation of the optimal mix and placement problem.

C. Simulations

This paper adapts energy storage system operating parameters and costs from an EPRI white paper [20], which lists energy storage systems designed for large C&I customer-premise applications. Based on this data, six candidate systems, shown in Table V, are created for prioritized outage ride-through applications in distribution sub-networks since they will most likely be serving a small subset of C&I customers. Storage systems are assumed to be modular and include the necessary communications and control subsystems to support real-time operations.

TABLE V
CANDIDATE ENERGY STORAGE SYSTEMS

Storage System	Maturity	Capacity (kVAh)	Power (kVA)	Cost ($/kVAh)
Advanced Lead Acid 1	Demo-Commercial	5000	1000	600
Advanced Lead Acid 2	Demo-Commercial	1000	200	720
Sodium Sulfur (NaS)	Commercial	7200	1000	500
Zinc Bromine (Zn-Br) Flow	Demo	625	125	480
Vanadium Flow	Demo	1000	285	1085
Lithium Ion	Demo	625	175	1085

A 120 minute outage is again simulated on the 123 node test feeder system and all five feeder sub-sections are considered potential locations for one or more energy storage system. Table VI shows the result of the local search heuristic for a $1.2 million dollar (USD) budget constraint.

TABLE VI
OPTIMAL MIX AND PLACEMENT PRIORITY LIST

Order	Unit Selected	Location	Outage Cost ($)
0	N/A	N/A	155,060
1	Zn-Br	4	135,269
2	Zn-Br	3	116,113
3	Zn-Br	2	101,163
4	Zn-Br	1	86,555

Of the candidate storage systems, the Zinc Bromine flow battery consistently achieves the greatest ROI for this outage simulation.

Table VII summarizes cost reductions and loads served by customer type and location.

TABLE VII
SAVINGS BY CUSTOMER TYPE

Feeder Section	Type II Loads Served	Type II Savings	Type III Loads Served	Type III Savings
1	6	14,573	0	0
2	0	0	1	14,951
3	4	13,036	1	6,100
4	6	10,598	2	9,197
5	0	0	0	0
Total	16	30,248	4	38,207

D. Discussion

We see that the algorithm chooses a small subset of high cost-of-outage customers to serve at each location and is able to reduce outage costs by $68,455. 69 loads are left unserved and no residential customers are selected for outage ride-through. From a high level, we can see that the order of locations is determined based by the density of C&I loads, although medium and large C&I loads are not preferred to small C&I loads, and a comparatively larger number of small C&I customers are served overall.

VII. Conclusion

This paper presents optimization models and solution methodologies for determining the optimal implementation of energy storage resources in the power distribution system for emergency backup applications. First, an optimal subset of loads is selected to ride through an interruption. Simulations indicate the superiority of conserving precious backup resources for high priority customers. Next, this same approach is applied to a larger resource allocation problem of selecting and placing storage technologies at different points in the distribution system. The heuristic approach builds a priority list of energy storage system placements based on Return on Investment for a given outage scenario, and clearly chooses the smaller, lower cost technology for targeted ride-through over larger, more expensive systems.

It is important to note that small C&I customers experience large outage costs per average annual kW demand in comparison to other load types. The optimization simulations weigh this customer class similar to medium and large C&I customers, which are traditionally associated with emergency backup systems. While from a utility perspective, it may not be acceptable to use a rate payer-funded investment for selective service improvements. However, the techniques developed in this paper provide a framework for identifying groups of customers that would benefit from pooled emergency backup resources, and hence provide a tool for targeting potential investors of jointly-owned storage systems.

Furthermore, long term planning assessments could combine the techniques developed in this paper with the results of distribution reliability assessments, which provide outage statistics for individual load points. Due to the radial nature of distribution networks and coordinated protection schemes, simulations would most likely favor downstream customer groups for islanded service and upstream locations for aggregate service. Further work remains to be done in this area.

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