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Comparison Between Grid-Scale Batteries and Flexible Loads for Combined Value-Added Services

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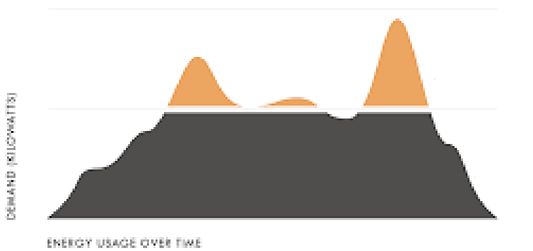
Introduction and Motivation

- Battery costs are declining.
- Traditionally dormant demand-side of the grid is becoming more active due to various technological advancements and increasing energy awareness.
- Policies supporting participation of DERs in wholesale markets are gaining more traction e.g. FERC Order 841, FERC Order 2222 etc.
- Load Serving Entities (LSE) can use batteries and flexible loads for multiple services simultaneously.

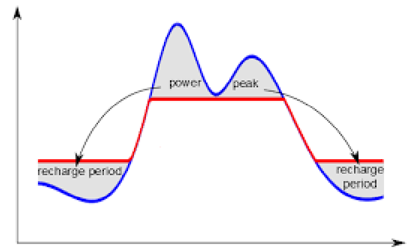
Given favorable market conditions, policies and customer willingness, should an LSE invest in grid-scale batteries or the control of flexible loads (residential HVACs and water heaters) for multiple services?

Widely available

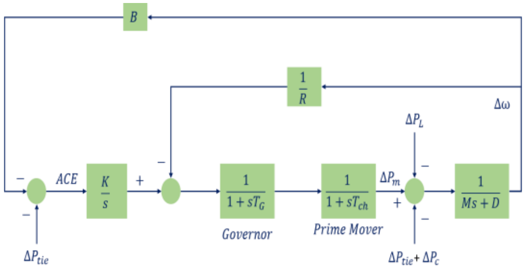
Services of Interest



Peak Shaving



Energy Arbitrage



Frequency Regulation

- Well studied and established concept
- Directed at reducing electricity demand during peak hours
- Results in reduced capacity charges for an LSE within a competitive market environment

- Similar to peak shaving
- Increases consumption (or charges storage) when prices are low
- Reduces energy consumption (or discharges storage) when prices are high
- Results in reduced energy costs for LSE

- Balances electricity supply and demand in real time
- Most electricity markets have regulation markets
- Batteries and aggregations of flexible loads can participate
- Provides attractive extra renumeration for LSE

Methodology

Step 1: Establish capacity of flexible loads and grid-scale battery storage system using a cost-based equivalence approach.

$$Initial\ Cost = N_{HVAC}(N_{EWH} + M_{HVAC}) + N_{EWH}(E_{EWH} + M_{EWH}) + PD_{EWH}(P_{r,EWH}) + PD_{HVAC}(P_{r,HVAC})$$

$$Battery\ system\ size = \frac{Initial\ Cost}{\lambda_{batt.\ system}}$$

Where $N_{HVAC(EWH)}$ = *number of HVACs/water heaters,* $E_{HVAC(EWH)}$ = *equipment costs,* $M_{HVAC(EWH)}$ = *marketing costs,* $PD_{HVAC(EWH)}$ = *program development costs and* $P_{r,HVAC(EWH)}$ = *unit power rating,* $\lambda_{batt.\ system}$ = *battery system unit cost*

Step 2: Use novel mathematical optimization model to estimate annual profits from energy arbitrage and frequency regulation for each option (i.e. grid-scale battery and flexible loads) based on historical demand and electricity market price data.

Step 3: Estimate annual capacity charge savings from peak shaving depending on the wholesale market environment. Add to results from Step 2

Step 4: Use NPV analysis (and results from Step 3) to establish equivalent worth over the lifetime of each option (i.e. grid-scale battery and flexible loads)

Methodology – Optimization Model Structure

- A generic form of the novel optimization model for estimating annual profits for the flexible load option is as shown below.

$$\begin{aligned}
&Maximize\ [LSE's\ Revenue\ - LSE's\ Costs\ (including\ customer\ compensations)]\\
&subject\ to \left\{\begin{array}{c}
Peak\ Shaving\ Constraints\\
Energy\ Arbitrage\ Constraints\\
Frequency\ Regulation\ Constraints\\
Aggregated\ HVAC\ Unit\ Dynamics\ Constraints\\
Aggregated\ Water\ Heater\ Unit\ Dynamics\ Constraints
\end{array}\right\}
\end{aligned}$$

- The optimization model is solved for each day of the year.
- For efficient computation, the residential HVAC units are grouped into different clusters and the thermal dynamics for the units within a cluster is represented by an equivalent HVAC model. A similar approach is also used for the water heating units.

Methodology – Optimization Model Structure

- A generic form of the novel optimization model for estimating annual profits for the grid-scale battery option is as shown below

$$Maximize\ [LSE's\ Revenue\ - LSE's\ Costs]$$

$$subject\ to\ \left[\begin{array}{c} Peak\ Shaving\ Constraints \\ Energy\ Arbitrage\ Constraints \\ Frequency\ Regulation\ Constraints \\ Battery\ Storage\ System\ Constraints \end{array}\right]$$

- Customer compensation functions are not included in the model because the battery is owned by the LSE.

- The optimization model is also solved for each day of the year.

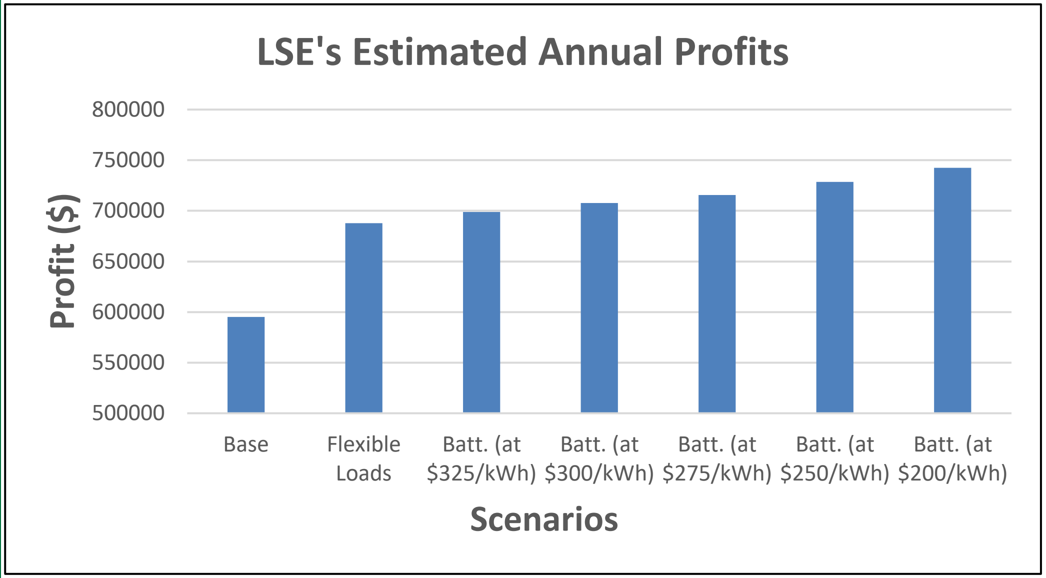
Case Study - Parameters

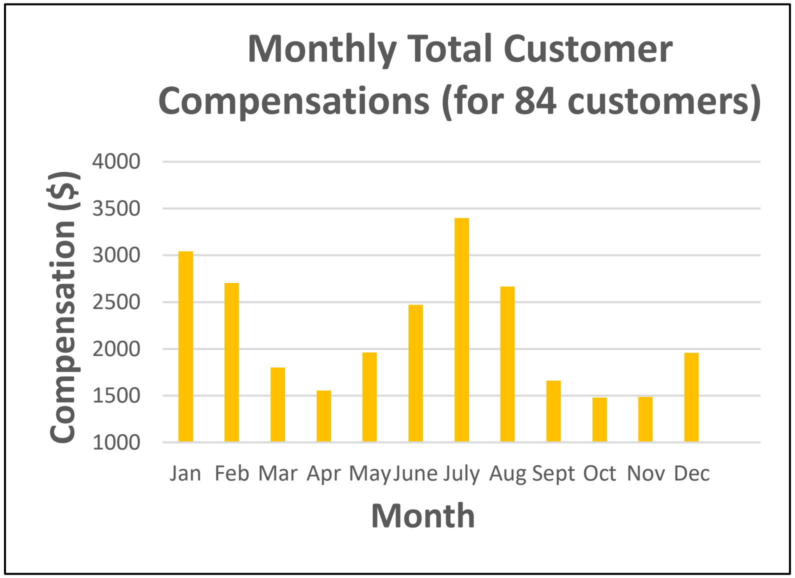
- The case study focuses on a hypothetical LSE operating within the New York City (N.Y.C) load zone of the NYISO wholesale market environment.
- Demand data was generated using the GridLAB-D software and electricity market prices (energy and regulation prices) were obtained from NYISO.
- Some of the parameters for the case study are shown in the table below.

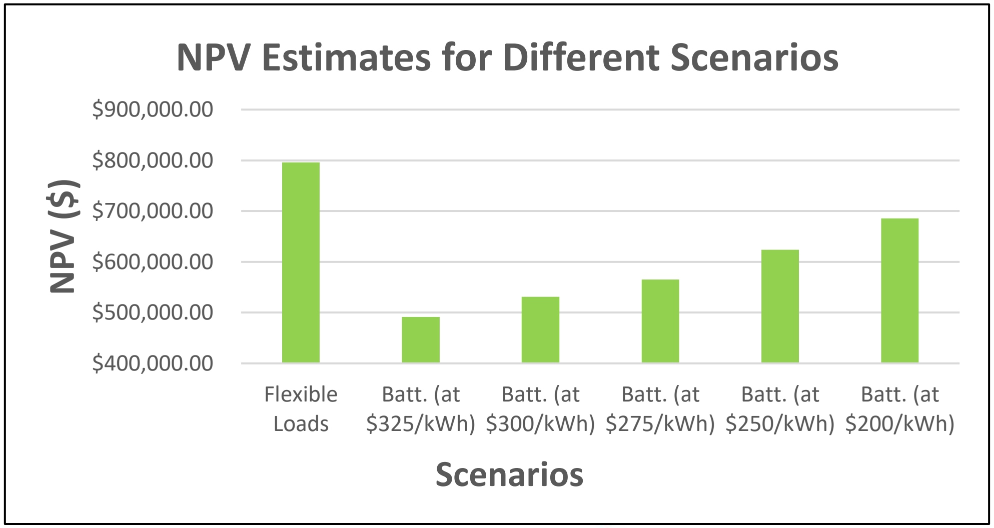
Parameters	Value	Parameters	Value
N_{HVAC}	42 (single cluster)	$P_{r,EWH}$	4.5 kW
N_{EWH}	42 (single cluster)	$P_{r,HVAC}$	4.2 kW
$M_{HVAC/EWH}$	$25/participant*	*Initial Cost*	$28,248
E_{EWH}	$315/unit*	$\lambda_{batt.\,system}$ ($/kWh)**	325, 300, 275, 250 and 200
E_{HVAC}	$215/unit*	*Battery sys. capacity (kWh)*	87, 94, 103, 113 and 141
PD_{EWH}	$12/kW*	*Flexible loads capacity (kW)*	365
PD_{HVAC}	$9/kW*	*Life span (years)*	5 for battery; 10 for flexible loads

**Values obtained from [7].*
***Values obtained from [8]. Five battery system cost scenarios were considered.*

Case Study - Results







Conclusions

- Both control of flexible loads and grid-scale storage options provide more annual profits for the hypothetical LSE when compared with the base case.
- For the hypothetical LSE considered, the control of flexible loads is the best option considering a 10-year life span.
- Longer life span of flexible loads compared to batteries is a major factor.
- Average annual compensation for each flexible load is approximately $310 which is significantly higher than existing DSM programs.
- As battery costs decline, the total revenue from using battery storage resources for multiple services will increase.
- The developed optimization model and proposed approach can be employed by any other LSE interested in conducting a similar analysis.

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