Georgia Tech's
Energy Policy and Innovation Center and
Advanced Computational Electricity System Laboratory
present an original research study:

Assessment of Grid-Scale Energy Storage Scenarios for the Southeast: Benefits, Costs and Implications

Final Report

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Georgia Tech | Energy Policy and Innovation Center

About the Energy Policy and Innovation Center

The Energy Policy and Innovation Center (EPICenter) was launched in the Fall of 2016 with the mission of conducting technical research, providing information on various contemporary topics in the energy field, and coordinating activities among leaders and innovators across industries and sectors. The Center explores the intersection of policy and technology, while leveraging the extensive expertise present across firms, research institutions, policymakers, and other government and non-government organizations in the Southeastern United States.

In executing its mission, EPICenter draws upon voluntary contributions from external organizations. The center is funded by an endowment and annual cash gifts to the Georgia Tech Foundation, and receives additional support in the form of personnel time and other in-kind contributions. Input from external entities that accompanies support, including recommendations related to center studies or operations, is subject to the discretion of EPICenter leadership. Similarly, no particular work product, findings, or implied results of center deliverables shall be linked, or give the perception of being linked, to a specific donation by any individual entity. In addition, all report authors have completed the EPICenter conflict of interest (COI) disclosure form and have affirmed there are no financial interests or potential COIs in study outcomes.

The Center is the first known implementation of a regional partnership to focus on the interdependencies of energy policy and technology in developing and implementing significant, cost-effective, and market-based carbon reductions. An assortment of deliverables will be produced by the Center, including but not limited to work products, events, educational outreach, and workforce development. Through these outputs, the Center strives to help accelerate a variety of reliable, affordable, and low-carbon energy options in the Southeast.

Dr. Richard Simmons,
Director of EPICenter

About the Advanced Computational Electricity System Laboratory

Founded in 2009, the ACES Laboratory in the School of Electrical and Computer Engineering at Georgia Tech is an advanced environment for the development of transformational research to address challenging problems in electricity grids and distributed energy resources by the use of sophisticated software, algorithms, big data, and computation methods. The ACES Laboratory focuses on the systems aspects of the electricity grid at all scales, from bulk power systems to home appliances.

Project Research Team

Dr. Santiago Grijalva, Director
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Executive Summary

The objective of this project is to assess the economic benefits and system impacts for grid-scale energy storage in the Southeast region for informed investment decision-making and policy analysis. Energy storage is a dynamic field exhibiting considerable near term growth. Energy storage systems (ESS) can provide a wide range of services and benefits to the sector's entire value chain and, are therefore becoming an attractive technology among stakeholders.

The key to an increased deployment of energy storage projects is their economic viability. Because of the significant potential value of energy storage services as well as the complexity of related decision-making problems, sophisticated ESS evaluation tools and studies need to be utilized. Previous ESS studies show that the ESS assessment is site-specific, i.e. the economics and impacts are highly dependent on the region, policies, regulations, markets, incentives, use cases, etc. Most of the available studies focus on ESS within specific electricity market areas. While progress has been made in the determination of the value of ESS in some states, the value of ESS in the Southeast region is less well-understood, given the regulatory model and the lack of market signals for benefits and services. This study develops novel methodologies and software capability to understand the economics and system impacts of ESS in the Southeast region. A key goal of the proposed work is to help ensure that the region is prepared to accommodate such growth in an economically viable manner.

The methodologies disclosed in the present study are applied primarily to techno-economic assessments of ESS. While analyses of societal impacts are beyond our scope, the methodologies disclosed herein can form the basis of future work to test new hypotheses that consider social/environmental factors (e.g., ESS can have favorable welfare effects, or quantifiable impacts of CO2 emissions). The simulations in this study were performed based on the current capital costs of ESS but there is wide acknowledgement that these costs are decreasing every year. Thus, it is expected that ESS payback periods can decrease.

The study analyzes three scenarios for applications based on ESS ownership and operation models:

1. Owned and operated by an end use customer, i.e., Behind-the-meter (BTM)
2. Owned by an end use customer, but jointly operated by the customer and the utility
3. Owned and operated by the utility

The analysis of these scenarios has been conducted through advanced optimization models as well as realistic, historical, and publicly available datasets. Both the methodology and study input data have been developed to accurately represent ESS applications in the Southeast region. Below, we summarize the results of the study for these three key scenarios.

Scenario 1: ESS Owned and Operated by the End User (BTM)

Under the current tariff rates in Georgia, commercial and industrial (C&I) customers who are exposed to demand charges can benefit from BTM ESS investment. Cost savings are significant and can results in payback periods as low as 5 years for this class of customers. Residential customers exposed to demand charges can also benefit from BTM ESS where the payback periods are closer to 10 years. Although residential ESS is not as profitable as C&I, with the decreasing capital costs of ESS, it is expected that residential ESS may become more profitable for certain tariff classes and use profiles. In most BTM ESS scenarios, cost savings realized by the customer result in reduced revenues by the utility. In terms of system impacts, high penetration of BTM ESS can have significant impacts on the system net load. Tariff rates with demand charges result in smoother net load profiles that are more desirable from the system operator's perspective.

Scenario 2: ESS Owned by End Customer, but Jointly Operated.

Two joint operation strategies were proposed where utilities can operate BTM ESS jointly with the customers to hedge against their revenue loss, while customers can still benefit from BTM ESS. The first strategy, passing through wholesale prices, is generally not financially attractive and results in payback periods of more than 15 years. However, this strategy is revenue neutral for the utility. ***The second strategy, renting BTM ESS, has the same profitability for the customers as Scenario 1 and the utility can benefit from operating BTM ESS to maximize its own objective function.*** Optimization results show that significant revenues can be obtained by the utility from energy arbitrage depending on the price variability of the location. This strategy results in lower loss of utility's revenue compared to Scenario 1.

Scenario 3: ESS Owned and Operated by the Utility

Utility-owned and operated ESS results in the highest revenues and payback periods as low as 5 years using multiservice ESS optimization. The largest portion of the revenue is derived from frequency regulation. Simulations show that service co-optimization results in significant benefits and improve the financial viability of ESS projects. While spinning reserve service can increase the total revenue compared to the energy arbitrage only, it has minimal impact on the revenues for the cases that included frequency regulation. This is because the ESS capacity is better utilized to provide frequency regulation service, which is a bi-directional service compared the spinning reserve. Even under the most conservative simulation assumptions, multiservice ESS can reach a payback period of 5 years.

The present study can prove to be of service to utilities, policy-makers, researchers and other stakeholders. Several ***novel optimization methodologies*** have been developed that can be used to evaluate the relative economic merits of ESS under a range of scenarios, input conditions, and performance parameters. The methods and approaches can be extended to include additional parameters, such as CO2 costs, CO2 emission, and welfare effects. Finally, the project provides detailed insights into the comparative economic benefits of major ESS use cases from the perspective of residential customers, large commercial customers, and utilities. ***The results suggest there are significant opportunities and net economic benefits from ESS systems, whether owned and operated by large customers or utilities, or jointly-operated by both***. Taken together the methodologies and findings can contribute to informed investment decision-making and policy analysis in the Southeast region, and beyond.

Acknowledgements

The authors would like to thank selected researchers at the National Electric Energy Testing Research and Applications Center (NEETRAC), the National Renewable Energy Laboratory (NREL), and the Energy Storage Association (ESA), for providing informal consultation to the research team during this project. We would also like to thank Mark Philpot, an undergraduate student researcher at Georgia Tech, for his assistance in collecting and analyzing some of the open source and public data used in the study's analysis.

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1. Introduction

The Georgia Tech Energy Policy and Innovation Center (EPICenter) has performed a review of the literature, and of the inventory of energy storage (ES) projects, and a high-level initial assessment and potential outlook for grid-scale ES deployment in the Southeastern U.S. The initial findings suggested that ***grid-scale energy storage use cases and applications are highly diverse and difficult to combine. Furthermore, their benefits and costs are highly variable and dependent upon regional context and economic factors, particularly when societal perspectives are considered.*** Two critical variables that are evolving rapidly are battery costs and balance of systems costs. In addition, renewables integration and other shifts in the electricity generation mix are creating opportunities for greater decarbonization, with non-trivial implications on ES deployment. While selected private party approaches to behind the meter (BTM) energy storage deployments may yield modest returns for certain commercial and industrial (C&I) customers, the ***Southeast region is generally confronted by market and regulatory conditions which are substantially different*** than in states such as CA, WA, OR, NY and MA, where explicit state subsidies and/or procurement targets have been enacted, or where explicit market signals incentivize and compensate owners for grid services. That said, the vertical integration of the region's major utilities may provide certain economies of scale, operational efficiencies, or capital efficiency that are a result of single, centralized control authority from the point of generation, through transmission, to distribution.

This study extends Phase one EPICenter efforts to perform quantitative analyses that evaluate deployment scenarios of energy storage under key future conditions that the region may experience, while applying best practices from other regions and improved methods for addressing techno-economic uncertainty. Herein, we study conditions that incorporate current trends in energy storage costs, and adjustments in rates (including new rate case data and time of use rates), and increasing value and ability to monetize multiple use stacking (for both utilities and behind-the-meter private parties). The present report considers economic impacts under various projected generation supply and demand scenarios roughly approaching a 2030 horizon. The study team includes investigators from the School of Electrical and Computer Engineering (ECE): Mr. (now Dr.) Sadegh Vejdan and Prof. Santiago Grijalva, working in collaboration with the EPICenter Director, Dr. Rich Simmons. This project extends the previous development of the Energy Storage Evaluation Tool (NESET) sponsored by the Georgia Tech's National Electric Energy Testing, Research & Applications Center (NEETRAC).

Energy storage is a very dynamic field that is expected to grow considerably in the next two decades. A key goal of the proposed work is to contribute to the region's preparation to accommodate such growth in an economically viable, environmentally sound, and socially responsible manner. Substantial investments are being expended into the R&D, demonstration and deployment of energy storage for a variety of objectives and stakeholders, most of which are in states outside of the Southeastern U.S. This project considers technologies and best practices, state-of-the-art approaches, publications and evolving business models. ***A particular focus of the scenario assessment and envisioned implementation strategies, however, has been on strategic partners that have a Southeastern focus, and are evaluating energy storage within the context of a regulated, vertically-integrated utility structure. In addition, the team has strived to construct its methodologies in ways that can be more broadly applicable.***

As a primary objective, the results of the study are intended to provide insight into the benefits of energy storage for grid applications for various stakeholders. These benefits include:

For policy makers and civil society:

- Impact of energy storage on affordability and economic impact.
- Insights of energy storage performance that can inform resource planning, current and future trends in the generation mix, and in particular, approaches that may pair renewables plus storage.

For customers:

- Opportunities to deploy energy storage in ways that realize a favorable economic return or deliver other means of added value through various services.

For the research community:

- Identification of energy storage services trade-offs to inform new research priorities and potential sources of funding.
- Identification of new data sets and findings that can provide opportunities for interdisciplinary partnering.

For investors, technology companies, utilizes and OEMs:

- Results which may provide insight into the benefits, costs, risks, and trade-offs associated with deployments of energy storage under the scenarios studied.

2. Research Context and Scope

2.1. Chapter Overview

In this Chapter we developed the project scoping and conducted a literature review necessary to frame the problem and the various project tasks. The team validated the simulation requirements for energy storage systems and incorporated additional inputs for key use cases and scenarios of ownership and operation, including:

a) Behind the meter simulation,

b) Customer-sited and owned energy storage with joint operation, and

c) Utility owned and operated.

Previously, the NESET tool was developed by the Electrical and Computer Engineering team, by using a market environment assumption, and consequently it took inputs such as temporal energy marginal prices. In order to develop corresponding simulations for the Southeast, the NESET tool was expanded to receive inputs associated with specific rates structures. Other new simulation requirements were also validated in this task.

2.2. Simulation Scenarios, Inputs and Outputs

2.2.1. Simulation Scenario 1: Behind-the-Meter (BTM) Energy Storage

In this Scenario, energy storage is owned and operated by the end-use customer and therefore sited at the customer premises. This Scenario is identical to energy arbitrage and multi-variable revenue stream analysis, but it is implemented using regional economic data, and the inclusion of CO_2 as an output parameter of interest.

The required input data for this Scenario are:

i. Storage technology parameters:
   a. Technological parameters: Energy storage size (power and energy ratings), energy storage efficiencies, durability, capacity fade effect, duty cycle, degradation, life constraints
   b. Economic parameters: Capital costs including I) storage module costs (e.g. cost of purchasing or financing battery cells/modules), II) balance of system (BOS) costs (containerized DC system), III) power conversion system costs (Inverters, protection, EMS). Operation and maintenance (O&M) costs, End-of-life (EOL) costs.

ii. System parameters:
   a. Customer types: residential, residential with demand, C&I, etc. as well as their

penetration level in the system under study

b. Load profiles: e.g. time-series data (metered or synthesized) of load consumed by different type of customers
c. Prices and tariffs: e.g. energy and demand rates, real-time prices, time-of-use (TOU) rates, other fixed and overhead charges.
d. Time of use CO_2 intensity
e. Incentives and credits

The expected outputs of this Scenario are:

i. Benefit of energy arbitrage to the customer: savings in energy and demand charges
ii. Costs of customer's total investments
iii. CO_2 impacts
iv. Lost utility revenue
v. Load profiles after the energy arbitrage
vi. Other system and social benefits

2.2.2. Simulation Scenario 2: Customer-Sited and Owned, Jointly Operated Energy Storage

In this Scenario, energy storage is owned by the end-use customer and therefore sited at the customer premises as in Scenario 1. However, it is jointly operated by the customer and the utility in coordination. This Scenario leverages the previous Scenario 1 where the customer performs energy arbitrage to reduce the electricity bill charges but considers a hybrid control of the asset toward providing grid services as well, using approaches adopted in the wholesale markets. For this Scenario, grid ancillary services need to be defined for the Southeast region where there are no clear market signals/prices for frequency regulation, reserves, resilience, etc. A production cost modeling approach is proposed for this Scenario and is described more in detail in future steps of this project.

The required input data for this Scenario are:

i. Scenario 1 data
ii. Value of grid services: e.g. where an established market does not exist
iii. Marginal costs of generation mix (or their proxies) in the Southeast
iv. Control and command algorithms: How the utility informs the customer to change the energy storage operation, e.g. direct load control, critical pricing, etc.

The expected outputs of this Scenario are:

i. Scenario 1 outputs
ii. Benefits to the utility

2.2.3. Simulation Scenario 3: Utility Owned and Operated Energy Storage

In this Scenario we will simulate utility-owned and operated ESS, and determine benefits that are obtained exclusively in front of the meter to a utility. The utilization of input data such as LMPs is proposed with the inclusion of energy storage operation is proposed for this Scenario and is described more in detail in future steps of this project.

The required input data for this Scenario are:

i. Scenario 1 and 2 data
ii. Any other data required for additional energy storage services or "internalizable" benefits to the utility

The expected outputs of this Scenario are:

i. Benefits to the utility in a regulated context

2.3. Sources of Data and Assumptions

Energy storage is a disruptive technology that requires advances in interconnection processes, power system management, software analysis tools, and new policies in order to achieve broad penetration and to provide its full benefits to society. The timely execution of the proposed work relies upon the availability of and access to several datasets, including data that is currently excluded from the public domain or cannot otherwise be generated within the resources of the project team. Data and assumptions also depend highly on existing policies in each state as well as practices by utilities, vendors, and evolving customer needs. A study such as this one invariably has a level of uncertainty in the assumptions. The selection of conditions to a certain degree tries to address this uncertainty, but invariably, simplifications have to be made in order to make the simulation problem tractable.

A key feature of this project is providing analysis and simulation results based on the most reliable and accessible input data that can be easily used and accessed by ESS stakeholders and researchers. Thus, all the input data used for simulations are based on publicly available data bases. The following publicly available sources are explored for collecting each type of required data:

i. Storage technical and economical parameters are found publicly available at
   a. Department of Energy database: www.energystorageexchange.com
   b. Review papers and reports on energy storage technologies [1] – [22]
ii. System parameters are found at
   a. Customer type penetration level (publicly available): www.eia.gov
   b. Synthesized load profiles provided by Center of Distributed Energy at Georgia Institute of Technology
   c. Georgia Power tariffs (publicly available): www.georgiapower.com
   d. time-of-use carbon intensity: The IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation (Annex II), and www.eia.gov

All data required for Scenario 1 is completely collected and simulation scenarios are initiated in the next task of this project.

Other input data for Scenarios 2 and 3 are still being collected. Data privacy issues and their unavailability in publicly available sources requires lengthier data collection processes. These data include those required for production cost modeling (e.g. marginal costs) and command/control algorithms and the value of grid services in the Southeast.

2.4. Summary Table for Data Requirements

For each of the 3 simulation Scenarios, the specific data requirements were identified and outlined as illustrated in Table 1. Each data requirement is provided with a source of data. Also, the last column indicates whether the original version of NEETRAC Energy Storage Evaluation Tool (NESET) supported inputs to those parameters, or whether software modifications were needed in order to input the necessary data. In column "NESET", S denotes full support of that specific type of data, and U denotes that although the support is provided, it can be updated to become more user-friendly. This column indicates whether software changes were needed in the Input module of the tool for the tasks of this project.

Table 1 Data Requirements per Scenario

Scenario	Required Data	Source of Data	NESET
1. Behind-the-meter (BTM)			
	Storage technology parameters (technical and economical)		
	ESS size (power and capacity ratings)	energystorageexchange.com	S
	Battery efficiency, durability, fade, duty cycle, life constraints	NESET Report and References	S
	Battery and Balance of System (BOS) costs	Lazard Report, energystorageexchange.com	S
	Operation & Maintenance (O&M) Costs	NESET Report and References	S
	System parameters		
	Time of Use (TOU) rates	https://www.georgiapower.com/	U
	Demand charges	https://www.georgiapower.com/	U
	Other fixed/variable tariff factors	https://www.georgiapower.com/	U
	Time of Use CO2 intensity [CO2fn(t)]	EIA, The IPCC Report on Renewable Energy	U
	Customer load profiles (Residential and Industrial)	Sandia Load Data	S
	Penetration level of each customer in terms of tariffs within-each grid (for aggregation)	*	U
	Real-time prices	*	S
	Incentives/credits	*	S
2. Customer-sited & owned, jointly-operated with utility			
	Additional Data (+ Case 1 Data)		
	Value of grid services (e.g., where an established market does not exist)	*	U
	Command/Control Algorithms	https://www.georgiapower.com/	U
	Customer behavior and response	*	U
	Input data for a DCUC problem (Fuel prices, heat rates, marginal costs or proxies, network data)	Synthetic data	U
3. Utility owned and operated			
	Additional Data (+ Case 1, 2 Data)		
	Value of grid services, T&D benefit, etc. (e.g., to the extent it can be estimated in a vertically-integrated regulated market)	*	U

3. Methodology and Assumptions

In this Chapter, the methodologies and assumptions utilized for the simulation of energy storage scenarios are presented. The proposed workflow for analysis is described in Section 3.1. The optimization formulation is discussed in Section 3.2.

3.1. Simulation Workflow

An optimization-based approach is utilized extensively in this study in order to analyze all the scenarios of interest. The corresponding simulation workflow is shown in Figure 1. The analytical modules and input data are described in the following subsections.

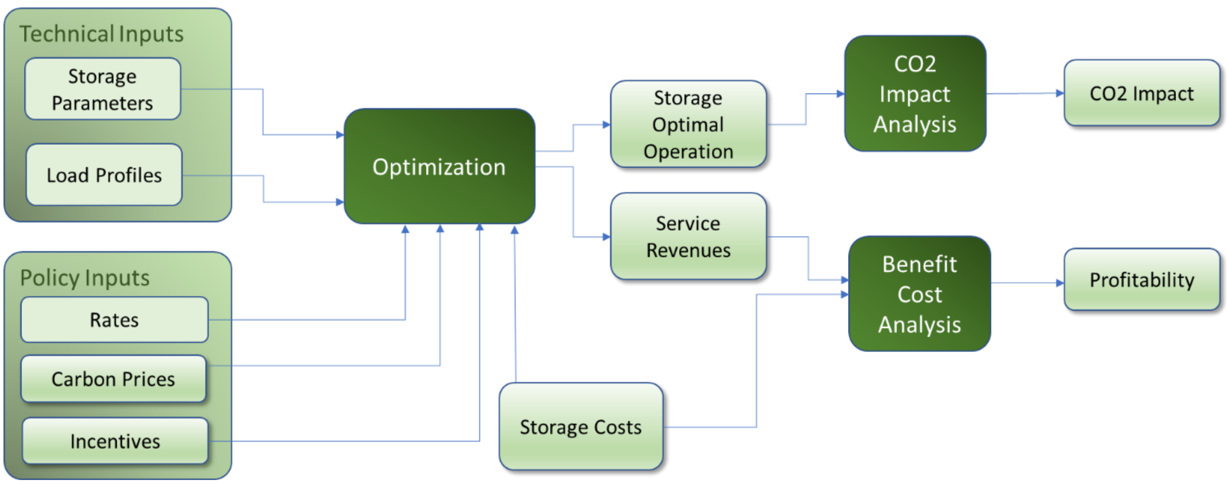

Figure 1: Simulation Workflow

3.2. Analytical Modules

There are three analytical modules in the proposed workflow as shown in Figure 1 colored in dark green:

- Optimization
- CO2 Impact Analysis
- Benefit Cost Analysis

3.2.1. Optimization

The core of the developed methodology is the temporal optimization module, which determines the optimal operation of ESS (output power and energy level at each time period *t*: $P_t^{dis}, P_t^{chg}, E_t$) that:

- Maximizes the total revenues from the energy storage services determined by the owner and operation mode at each scenario. Regardless of the scenario, this objective function can be generically modeled as in Equation (1).

- Subject to the following constraints:
  - Energy storage technical capabilities determined by storage parameters (Equation (2)),
  - Service requirements determined by mode of operation at each scenario (Equation (3)).

The optimization method is expressed mathematically as:

$$\underset{P_t^{dis}, P_t^{chg}, E_t}{\text{maximize}}\ Total\_Revenue = \sum_{s \in services} \sum_{t \in T} Revenue_{s,t}(P_t^{dis}, P_t^{chg}, E_t) \tag{1}$$

$$Lower\_Limits \le P_t^{dis}, P_t^{chg}, E_t \le Upper\_Limits \tag{2}$$

$$Revenue_{s,t}(P_t^{dis}, P_t^{chg}, E_t) \in Service\_Constraint\_Set \qquad \forall s,t \tag{3}$$

While the revenue is defined based on the requirements of each scenario, energy storage technical capabilities determined by its parameters are common among all scenarios. Despite the variety of energy storage technologies and their characteristics, the reliable operation of any storage technology should meet the following constraints and requirements for all the time periods within the operating horizon:

1. The charging and discharging powers are non-negative values and based on the capabilities of each storage technology, they are limited by the technology output power ratings that determine their maximum allowable value (Equation (4)).
2. Charging and discharging does not happen at the same time (Equation (5)).
3. The energy level at each time period is equal to the energy stored in the previous time period and available now plus the energy stored from charging at the current time period minus the energy depleted from discharging at the current time period (Equation (6)).
4. The energy level at each time period should not fall below a lower bound or exceed an upper bound to avoid deep discharging and overcharging, respectively. Otherwise, the useful life of the technology significantly degrades, and it might fail to operate reliably (Equation (7)).
5. For numerical purposes, the energy level at the end of the optimization horizon should be equal to the energy level at the beginning of the optimization horizon. In this project we developed a monthly optimization approach and assumed that the energy level at the beginning of the optimization horizon is equal to one-half of the full energy capacity of the storage technology (Equation (8)).

The previous requirements are represented mathematically by the following constraints, respectively:

$$0 \le P_t^{dis} \le P_{\max}^{dis}.u_t^{dis} \quad ; \quad 0 \le P_t^{chg} \le P_{\max}^{chg}.u_t^{chg} \qquad \forall t \in \mathrm{T} \qquad (4)$$

$$0 \le u_t^{dis} + u_t^{chg} \le 1 \qquad \forall t \in \mathrm{T} \qquad (5)$$

$$E_t = \eta_s E_{t-1} + \left(\eta_{chg} P_t^{chg} - P_t^{dis} / \eta_{dis} \right) \Delta t \qquad \forall t \in \mathrm{T} \qquad (6)$$

$$E_{\min} \le E_t \le E_{\max} \qquad \forall t \in \mathrm{T} \qquad (7)$$

$$E_T = E_0 \qquad \forall t \in \mathrm{T} \qquad (8)$$

Where:

Notation	**Type**	**Description**
T	set	Set of time periods
t	index	Index of time periods
T	index	Index of the last time period in the horizon
P_t^{dis}	variable	Power discharged to the grid at time period t -kW
P_t^{chg}	variable	Power charge from the grid at time period t -kW
u_t^{chg}, u_t^{dis}	variable	Binary variables representing the status of charging and discharging at time period t
E_t	variable	Energy level at time period t-kWh
$P_{\max}^{chg}, P_{\max}^{dis}$	parameter	Maximum charging and discharging power-kW
$E_{\min}, E_{\max}$	parameter	Minimum and maximum energy levels-kWh
η_s	parameter	Storage self-discharge rate
η_{chg}, η_{dis}	parameter	Charging and discharging efficiencies
Δt	parameter	Time interval-h

Depending on the energy storage technology, the values of these parameters may vary. Even for a specific technology, these values may differ from one storage project to another depending on the size and application of the project.

In optimizing the optimal operation (output power) of energy storage to maximize the service revenues, all of the above constraints (4) - (8) are considered as storage constraints (technical capabilities). As discussed, the definition of revenue and services are scenario-dependent and are described separately in each chapter.

3.2.2. CO2 Impact Analysis

One of the objectives in developing the present optimization methodology is to eventually simulate and quantify the relationship between energy storage and CO2 emissions. An analysis can either ignore or account for a price of carbon within the optimization model. The following provides a brief description of both approaches:

1. **Ignore Carbon Prices.** In this model, carbon prices are not included in the optimization model, and the optimal operation of ESS is determined by maximizing the service revenues only. In other words, any cost or market price associated with carbon is not considered in the objective function of the optimization. However, the CO2 emissions associated with the optimal operation of the ESS can be estimated as a post-optimization process. The operation of ESS changes the net demand shape and accordingly, the generation dispatch, which impacts emissions. For instance, the optimization of the ESS may charge with excess generation during off-peak periods, and re-inject this electric power during peak periods. This will impact the dispatch of generation, and therefore the system CO2 emissions. This net CO2 impact can be net positive, neutral or negative relative to the baseline, depending on what sources and at what levels are being utilized during charging periods, and what sources are being displaced during ESS discharge.

2. **Consider Carbon Prices.** In this model, carbon is considered to have a market value, and the optimal operation of ESS is determined by maximizing the sum of service revenues and the monetized benefits of avoided carbon costs. Carbon costs are directly considered in the objective function of the optimization. In other words, profitability and CO2 impact are both be considered in the optimization algorithm.

Figure 2 shows the workflow of this analysis, and how CO2 costs and impacts can be either considered or ignored in the optimization model.

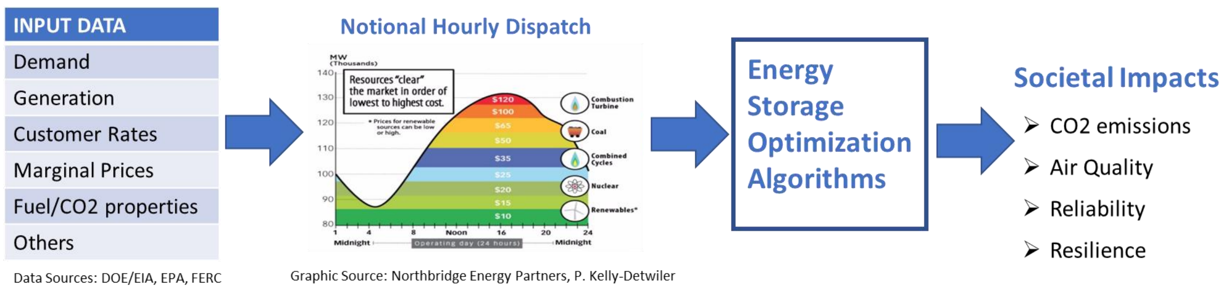

Figure 2 CO2 Impact Analysis[1].

In the ESS scenario assessments of the present study, we have elected to ***exclude an explicit price for CO2 from the analyses.*** This is primarily because at the time of publication, no explicit CO2 market exists in the Southeast region. Thus, the ROI of an ESS asset, as well as economic dispatch decisions at a system level are both independent of CO2 price, since that price is taken to be zero at the present time in the Southeast region. However, as noted above, the methodology has been developed such that ***CO2 costs could readily be added future optimization scenarios***. It would also be possible to determine the net impacts of CO2 emissions on an aggregated basis, for instance between modeled scenarios, provided adequate, temporally-resolved information is known about the particular dispatch of the regional system. Finally, if detailed dispatch information is not fully known, a rudimentary limits analysis could be performed on CO2 impacts based on heavily qualified assumptions (e.g., maximum and minimum shares of coal, natural gas, nuclear, renewables etc. in the generating mix). While inferior to a full production cost model approach and other methods of characterizing a true generation dispatch, the suggested limits analyses could be informative for planners and policy-makers, for instance, to determine the max and min projected CO2 emissions associated with a given level of ESS integration in a future deployment scenario, compared to a baseline condition. Its primary purpose would be to consider whether any unintended environmental consequences of ESS deployment are possible.

3.2.3. Measures of Project Worth and Benefit-Cost Analysis

After the maximum revenues are determined, a benefit-cost analysis is conducted and financial metrics such as net present value (NPV), rate of return, and payback period are determined. These quantities are defined as follows:

[1] Notional dispatch is illustrative; real generation dispatch is more complicated than a simple layered stack, and involves decision variables that extend beyond marginal operating and maintenance costs.

- **Net Present Value (NPV):** It is the sum of all years' discounted, after-tax, cash flows. The NPV method is a valuable indicator because it recognizes the time value of money. Projects whose returns show positive NPVs are attractive. For a discount rate (or in the case of NESET, EDR) *r*, it is calculated as:

$$NPV = \sum_{i=0}^{n} \frac{(Benefit_i - Cost_i)}{(1+r)^i} \tag{9}$$

where *n* is the project life in years and *i* is the year index.

- **Internal Rate of Return (IRR):** It is defined as the discount rate at which the after-tax NPV is zero. The calculated IRR is examined to determine if it exceeds a minimally acceptable return, often called the *hurdle rate*. The advantage of IRR is that, unlike NPV, its percentage results allow projects of vastly different sizes to be easily compared.

- **Payback Period:** A payback calculation compares revenues with costs and determines the length of time required to recover the initial investment. The following formula is used:

$$Payback\ Period = i\ ;\ NPV(i) = 0 \tag{10}$$

3.3. Input Data

3.3.1. Storage Costs

The costs associated with any ESS project can be captured by using parameters that include:

– **Capital Cost:** The capital needed to purchase energy storage assets and all of its other facilities such as converters, balance-of-plant, interconnection, and administrative costs. In the tool, it is formulated as:

$$\begin{aligned} Capital\ Cost = Fixed + Variable_{Power} \times Power\ Rating + \ Variable_{Energy} \\ \times Energy\ Rating \end{aligned} \tag{11}$$

– **Fixed Capital Cost:** Includes all the capital costs that are fixed and do not grow with the energy and power ratings of energy storage.

– **Variable Capital Cost (Power):** The coefficient ($/kW) at which the capital cost of storage grows with its power rating.

– **Variable Capital Cost (Energy):** The coefficient ($/kWh) at which the capital cost of storage grows with its energy rating.

– **Fixed Annual Operating Cost:** A cost or expense incurred without regard to whether or how much a respective service, facility or equipment is used (i.e., unlike variable costs; fixed costs are incurred irrespective of how much the service, facility or equipment is used). This is also known as fixed O&M cost and it is shown in the financial results for every year throughout the project life.

– **Variable Operating Cost:** Costs which change in proportion to the amount of energy generated or used. Variable costs may be associated with the cost for fuel, variable operating expenses, variable equipment and facility maintenance and depreciation from equipment wear. This number is multiplied by the actual energy output (determined by the tool as the optimal dispatch) and is shown in the financial results.

– **Replacement Cost:** This cost incurs when the energy storage has to be replaced before the end of project life (the end of last operating year).

– **Disposal Cost:** This cost incurs at the end of project life (the last operating year).

– **Expected Life:** Also known as the project life, the number of years that the energy storage is expected to be operating. All financial calculations are done up to the last year in the expected life.

All of these parameters depend of the ESS technology. Based on the requirements of each scenario, a proper ESS technology is selected. Further technological assumptions are documented in each scenario chapter.

3.3.2. Storage Technical Parameters

These parameters include:

- **Maximum charging and discharging power (kW)**

- **Minimum and maximum energy levels (kWh)**

- **Charging Efficiency:** Charging the energy storage is a process that is not perfectly efficient. This means that not all of that energy is actually stored. This is because of conversion losses. The ratio of the energy that is stored in the energy storage over the energy that is drawn for charging shows the charging efficiency. For example, an energy storage with the charging efficiency of 90% needs 1kWh of energy to increase its energy level by 0.9kWh.

- **Discharging Efficiency:** Discharging the energy storage is also not ideal. It means that not all of that energy is drawn from the energy storage is actually delivered externally. The ratio of the energy that is delivered externally over the energy that is drawn from energy storage (and decreases the energy level). For example, an energy storage with the discharging efficiency of 90% delivers 0.9kwh of energy while its energy level is decreased by 1kWh.

- **Self-Discharge Efficiency:** Storage discharge that occurs while energy storage is in an open-circuit condition. A self-discharge efficiency of 99% means that storage loses 1% of its total energy capacity at every time-step, regardless of its dispatch.

All of these parameters depend of the ESS technology. Based on the requirements of each scenario, a proper ESS technology is selected. Further technological assumptions are documented in each scenario chapter.

3.3.3. Load Profiles

Based on the requirements of each scenario, proper load profiles are collected and simulated. For instance, in scenarios 1 and 2, where ESS is sited at the customer's load, customer load profiles are used. Moreover, for scenario 3, where utility owns and operates the ESS, system aggregate load profiles are used. Further assumptions are documented in each chapter.

3.3.4. Rates

Based on the requirements of each scenario, proper rates are collected and simulated. For instance, in scenario 1, where ESS is sited at the customer's load, utility rates are used. For scenario 3, where utility owns and operates the ESS, marginal costs of generation are used. Further assumptions are documented in each scenario chapter.

4. Scenario 1: Behind-the-Meter ESS Simulations

The first of the three scenarios to be studied in this project is behind-the-meter (BTM) ESS where ESS is owned and operated by the end-use customer and therefore sited at the customer premises. This Scenario is identical to energy arbitrage and demand charge reduction in multi-service revenue stream analysis, but it is implemented using regional economic data, and the inclusion of CO_2 as an output parameter of interest. The expected outputs of this Scenario are:

vii. Benefits of energy arbitrage to the customer:
  a. Savings in energy charges
  b. Savings in demand charges
viii. Costs of customer's total investments
ix. CO_2 impacts
x. Lost utility revenue
xi. Load profiles after the energy arbitrage
xii. Other system and social benefits

In this section, the optimization problem is presented first, and the input data and respective assumptions are also provided. We note that the assumptions related to various input and data developed in Chapter 3 are utilized for this scenario.

4.1. Optimization

The objective function of the optimization problem for this scenario corresponds to minimizing the customer's monthly electricity bill charge (plus the cost of CO2 emissions). This is presented mathematically as:

$$\underset{P_t^{dis}, P_t^{chg}, P_r^{\max}}{\text{minimize}} \sum_{t=1}^{T} \pi_t^{ene} P_t^{net} \Delta t + \sum_{r=1}^{R} \pi_r^{dem} P_r^{\max} \left(+ \sum_{t=1}^{T} \pi_t^{CO2} P_t^{net} \right) \tag{12}$$

Subject to

- ESS technical constraints as in Equations (4) – (8),
- Customers net load with ESS,

$$P_t^{net} = P_t^{load} + P_t^{chg} - P_t^{dis} \tag{13}$$

- Demand requirement

$$P_t^{net} \le P^{\max} \tag{14}$$

4.2. Input Data

The required input data for this Scenario are:

iii. Storage technology parameters:
   a. Technical parameters,
   b. Economic parameters

iv. System parameters:
   a. Customer types,
   b. Load profiles,
   c. Prices and tariffs,
   d. Time of use CO_2 intensity

(Continued on page 26)

Table 2 summarizes the input data for scenario 1, data sources and assumptions. Each input data is discussed more in detail in the following subsections.

Table 2 Summary of Input Data for Scenario 1, Data Sources and Assumptions

Scenario	Required Data	Source of Data	Assumption(s)	Currently Available	NESET Model
1. Behind-the-meter (BTM)					
Storage technology parameters (technical and economical)					
	ESS size (power and capacity ratings)	energystorageexchange.com	500kW, 2hr(1MW)	Y	S
	Battery efficiency, durability, fade, duty cycle, life constraints	NESET Report and its references [26]	80% usable capacity, 95% charging efficiency, 95% discharging efficiency, no capacity fade effect	Y	S
	Battery and Balance of System (BOS) costs	Lazard Report [15] energystorageexchange.com			S
	Operation & Maintenance (O&M) Costs	NESET Report [26]			S
System parameters					
	Time of Use (TOU) rates,	georgiapower.com	General Service Tariffs for each customer type (3,4 rates per each scenario)	Y	U
	Demand charges,			Y	U
	Other fixed/variable tariff factors			Y	U
	Time of Use CO2 intensity [CO2fn(t)]	EIA.gov IPCC Report: iccp.ch			U
	Customer load profiles (Residential)	pecanstreet.org/dataport	No Georgia data, we take Texas	Y	S
	Customer load profiles (Commercial)	openeia.org	hourly, 1 year	Y	S
	Customer load profiles (Industrial)			N	S
	Incentives/credits				S

Since this scenario is centered around end-use customers, most of the input data is determined based on the customer's type. We identified two main customer's types:

- Residential and
- Commercial and Industrial (C&I)

Therefore, ESS technology, load profiles and rates are chosen for each of these customer types.

4.2.1. Storage Technology Parameters

- For residential customers, energy storage technology parameters are selected based on Tesla Powerwall[2]:
    - Technical parameters:7 kW maximum charging/discharging rates, 15 kWh total capacity, 13.5 kWh usable capacity (90% depth of discharge), and 90.25% roundtrip efficiency (= 95% charging efficiency × 95% discharging efficiency).
    - Economic parameters: the cost of Powerwall is 6700 $/module. We use this number as the fixed capital cost and assume no fixed or variable O&M costs.
- For C&I customers, energy storage technology parameters are selected based on the most common ESS parameters for BTM application available at Department of Energy, Energy Storage Database[3]:
    - Technical parameters: 500 kW maximum charging/discharging rates, 1000 kWh total capacity, 900 kWh usable capacity (90% depth of discharge), and 90.25% roundtrip efficiency (= 95% charging efficiency * 95% discharging efficiency).
    - Economic parameters: We assume that the total cost (sum of capital, O&M, disposal) is equal to 400 $/kWh as the incurred in the Capex year.

4.2.2. System Parameters

4.2.2.1 Customer types:

We identified two main customer's types:

- Residential and
- Commercial and Industrial (C&I)

4.2.2.2 Load profiles:

- For residential customer load profiles, we use the Pecan Street Database[4], which contains high resolution (1-minute) load data for more than 1,300 residential customers. Although none of these customers are in the Southeast region, we chose the customers located in Austin, Texas due to climate similarity. The average load size (annual demand or maximum load in a year) of these customers is 9.5 kW, and their average monthly energy consumption is about 900 kWh. The distribution of customers' load sizes and their average monthly consumption are plotted in Figures 3 and 4. The average daily load profile for summer and winter months, averaged on all customers and all summer (June through September) and

[2] https://www.tesla.com/powerwall
[3] https://energystorageexchange.com
[4] https://pecanstreet.org/dataport/

winter (October through May) days, are also plotted in Figure 5.

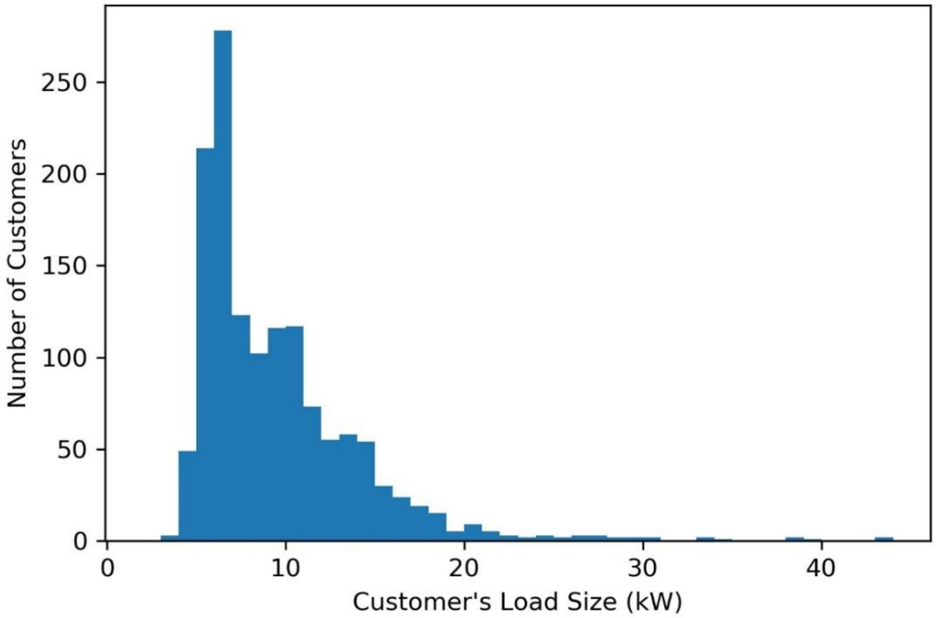

Figure 3 Histogram of the residential load sizes

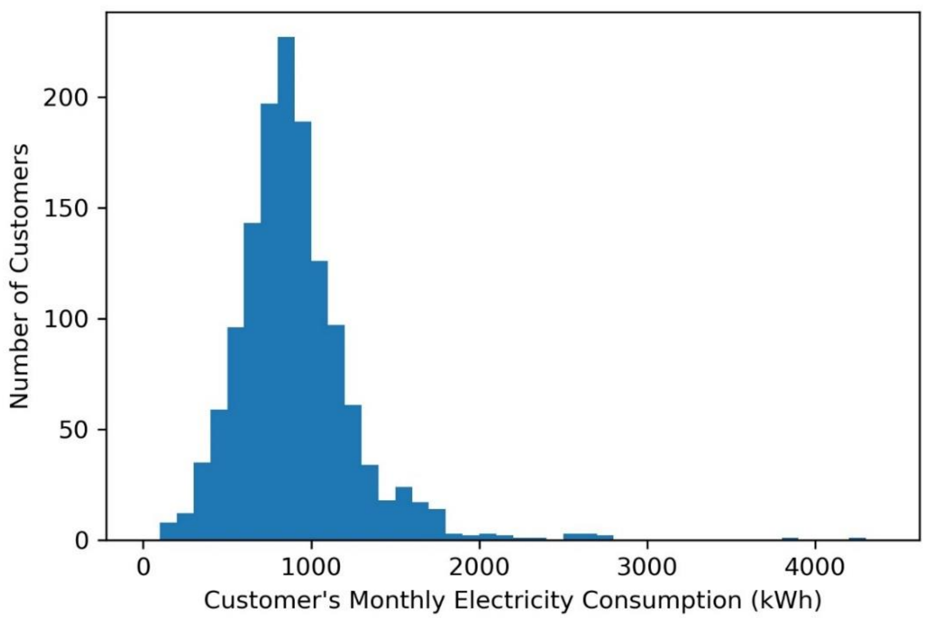

Figure 4 Histogram of averege monthly electricity consumption of residential loads

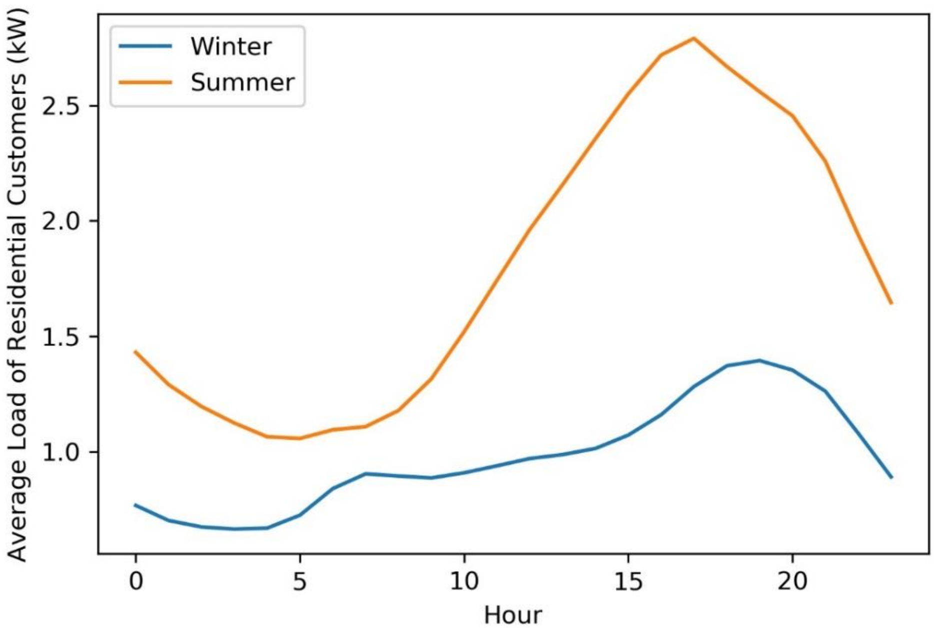

Figure 5 Average daily load profile of residential loads for summer and winter months

- For C&I load profiles, we use a publicly available data source supported by DOE that can be accessed at:
    - https://openei.org/datasets/files/961/pub/COMMERCIAL_LOAD_DATA_E_PLUS_OUTPUT/USA_GA_Atlanta-Hartsfield-Jackson.Intl.AP.722190_TMY3/

This database provides 1-year long hourly simulated load profiles for various locations and a set of commercial buildings, such as restaurants, offices, hospitals, etc. we have used the data simulated for Atlanta location to represent the Southeast region. A quick analysis of these data is plotted in Figures 6 and 7. Figure 6 shows the annual demand (load size in kW) and the average hourly consumption of each building type. It is seen that the dataset includes a diverse set of load profiles with a wide range of average and maximum consumptions and different load factors. Therefore, using this dataset is a realistic proxy for actual commercial loads and their variability. Figure 7 shows the average daily load profile for summer and winter months, averaged on all customers and all summer (June through September) and winter (October through May) days. Compared with average residential load profiles plotted in Figure 5, commercial load profiles show a different pattern and therefore, the optimal energy storage operation would be different in shifting the energy to off-peak hours as well as demand reduction. Thus, separating residential and commercial loads and performing separate energy storage analysis is imperative.

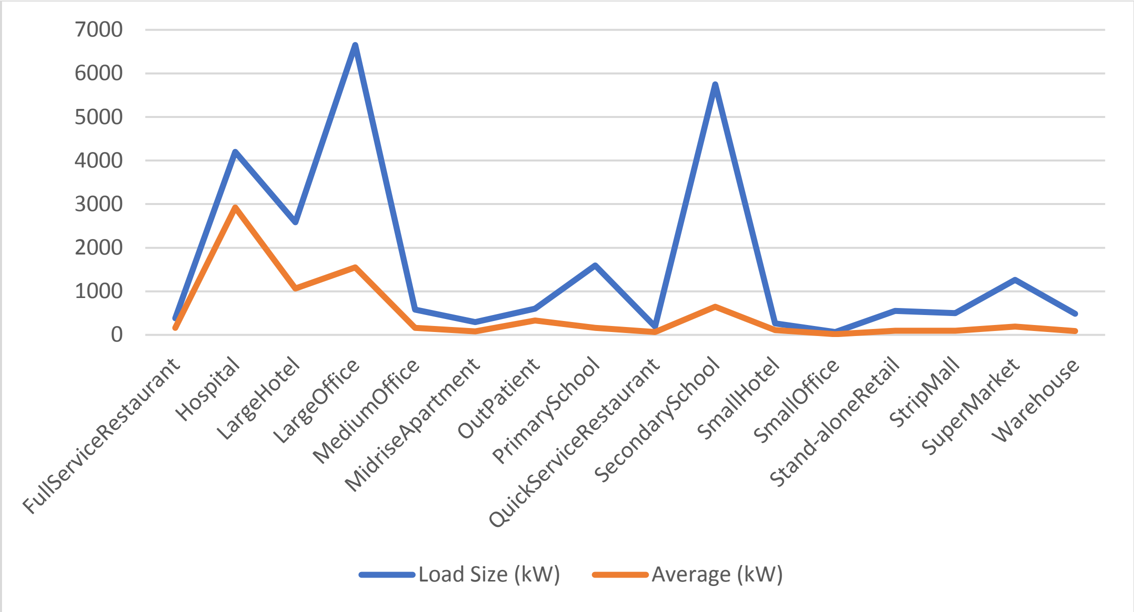

Figure 6 Maximum and average of C&I loads per each building type

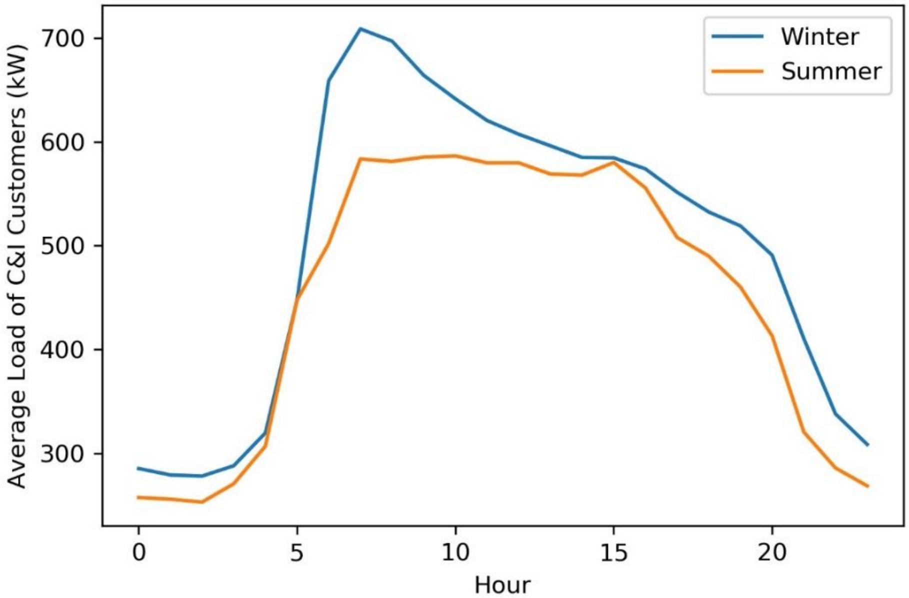

Figure 7 Average daily load profile of C&I loads for summer and winter months

4.2.3. Prices and Tariffs:

Because the focus of this project is on the Southeast region, we chose the Georgia Power rates and tariffs for all of the simulation studies. A comprehensive excel spreadsheet document was prepared including all the Georgia Power rates and links to documents. Figure 8 shows customer types, subtypes and tariffs based on Georgia Power data that were used in simulation studies.

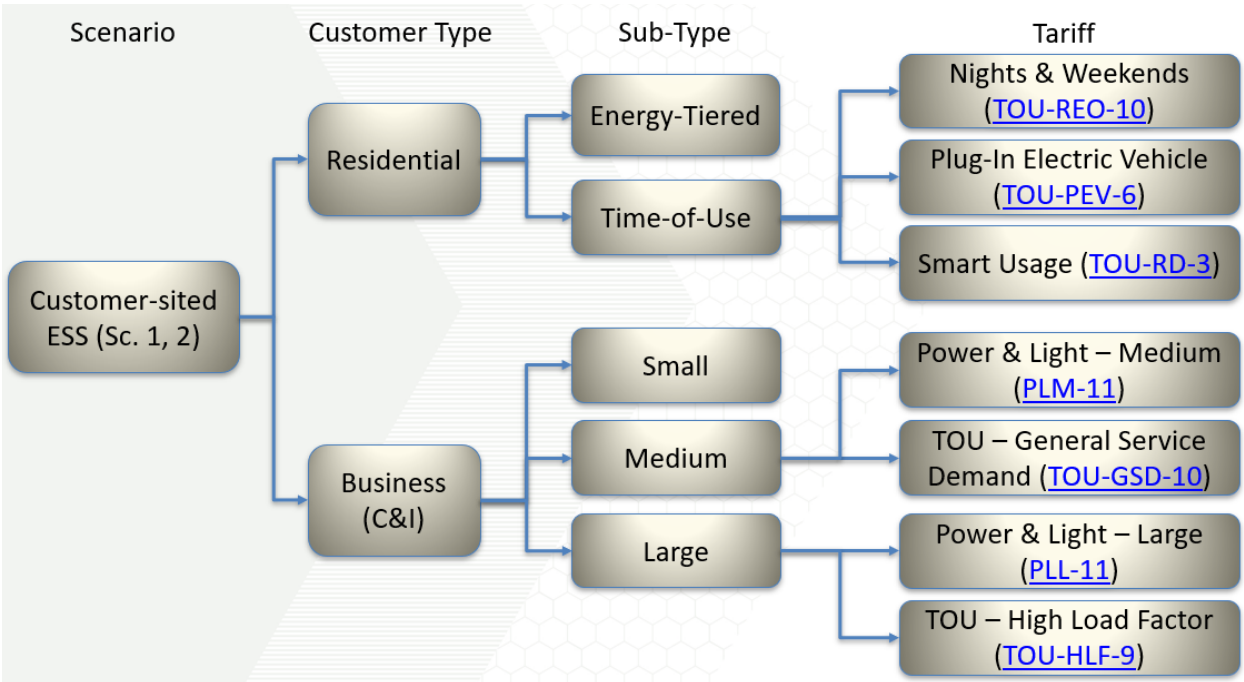

Figure 8 Customer types, subtypes and tariffs based on Georgia Power data

The energy-tiered tariffs are not considered for residential ESS simulation. In these tariffs, customers are charged based on their total net consumption. Because the impact of the ESS on the net consumption is negligible (ESS is an energy-neutral technology), ESS cannot reduce the energy charge of residential customers that are billed based on energy-tiered tariffs. Thus, only time-of-use (TOU) tariffs are provided for the residential ESS simulations.

For residential customers, energy-tiered tariffs do not include demand charge. However, for C&I customers, the demand charge is included in the tariff and therefore ESS can provide bill savings by smoothing the net load profile and reducing the demand.

For C&I customers, Georgia Power defines the subtypes as:

- Small: monthly demand not greater than 30 kW
- Medium: monthly demand greater than 30 kW and not greater than 500 kW
- Large: monthly demand greater than 500 kW

Small C&I customers are not included in ESS simulations since it is less likely to see large-scale deployment of ESS for those customers compared to medium and large C&I customers.

Medium and large C&I customers are provided with a few tariff options. However, in this project only the two most common tariffs for each of them are used. One is energy-tiered with demand charge (Power and Light) and the other is TOU.

Analyzing the TOU tariffs shown in Figure 8, showed that regardless of the customer type or subtype, the breakdown of the customer's monthly bill charge based on Georgia Power rates is as follows:

- Monthly Bill Charge = Base Rate + Other Schedules + Municipal Franchise Fee + Sales Taxes
  - Base Rate = Basic Service Charge + Energy Charge + Demand Charge
    - Basic Service Charge = Fixed
    - Energy Charge = Energy**rate* where *rate*[c/kWh] depends on time of use and customer type
    - Demand Charge = Demand**rate* where *rate*[$/kW] depends on time of use and customer type
  - Other Schedules = ECCR + NCCR + DSM + FCR
    - ECCR = 12.768% of the Base Rate
    - NCCR = 9.7357% of the Base Rate
    - DSM = 2.4471% of the Base Rate
    - FCR = Energy**rate* where *rate*[c/kWh] depends on month and customer type
  - Municipal Franchise Fee = 2.9989% (Inside City Limits) or 1.1525% (Outside City Limits) of sum of all above
  - Sales Taxes = e.g. 6% of sum of all above

4.3. Simulation Results

Simulation results for residential and C&I customers are presented in the following subsections.

4.3.1. Residential

Using the optimization problem, residential load profiles and TOU tariff rates, the customers' energy and demand savings and the ESS optimal operation are determined in 6 test cases including 3 TOU tariff rates below:

- Nights & Weekends: Energy only, On-Peak (20c/kWh) and Off-Peak (5c/kWh)
- Plug-In Electric Vehicle: Energy only, On-Peak (20c/kWh), Off-Peak (7c/kWh) and Super Off-Peak (1c/kWh)
- Smart Usage: Energy and Demand, On-Peak (10c/kWh), Off-Peak (1c/kWh), Maximum kW (6.64 $/kW)

Also, two cases per each rate is assumed where customer can or cannot sell to the grid (*s*=1 or *s*=1). The sell price is the same as buy price (tariff rate). For each test case, the summary of results for the benefit-cost analysis is presented in Table 3. These economic results can help customers and the utility for decision making about BTM ESS installations. Plug-In Electric Vehicle and Smart Usage rates show more promising results in terms of revenue and payback period.

Table 3 Results Summary for BTM Residential ESS

Test Case #	Rate	**Annual Cust Savings ($)**		**Payback Period (years)**	
		Median	**Maximum**	**Medium**	**Minimum**
1	Nights & Weekends (*s*=0)	248	277	27.0	24.2
2	Nights & Weekends (*s*=1)	277	277	24.2	24.2
3	Plug-In Electric Vehicle (*s*=0)	600	643	11.2	10.4
4	Plug-In Electric Vehicle (*s*=1)	643	643	10.4	10.4
5	Smart Usage (*s*=0)	289	635	23.2	10.5
6	Smart Usage (*s*=1)	305	688	21.9	9.7

It should be noted that most customers would generally not consider a payback period of greater than 10 years economically viable. This is in part because estimates of the lifespan of current ESS systems (based on today's lithium ion batteries), while dependent upon utilization, are frequently in the 10-year range.

The optimal ESS dispatch in each test case is averaged over all the available customers and plotted as in Figure 9. Positive values correspond to discharging while negative values correspond to charging. Since the Nights & Weekends tariff is flat for winter months, there is no arbitrage value and therefore the ESS does not operate in these months. ESS discharges in peak hours, which are 2-7 pm of summer months. The difference between case 1 (s=0) and 2 (s=1) is that since customer can sell its excess power back to the grid, the discharging power of ESS is greater in case 2 than in case 1.

Since the Plug-In Electric Vehicle tariff has super-off-peak rates at nights, we expect more charging activities from the ESS during night hours as seen in Figures 9(3) and 9(4). The peak hours are also evident from these plots where ESS discharges at higher rates.

Although the Smart Usage tariff has a flat rate for energy for winter months, ESS dispatch is nonzero. This is because of the demand charge reduction operation. The ESS operation for winter months is fairly similar to the average winter load of customers shown in Figure 5. For summer months, however, both energy and demand charge reduction control the ESS operation. As in Figures 9(5) and 9(6), during the peak hours of summer months, ESS discharges at higher rates.

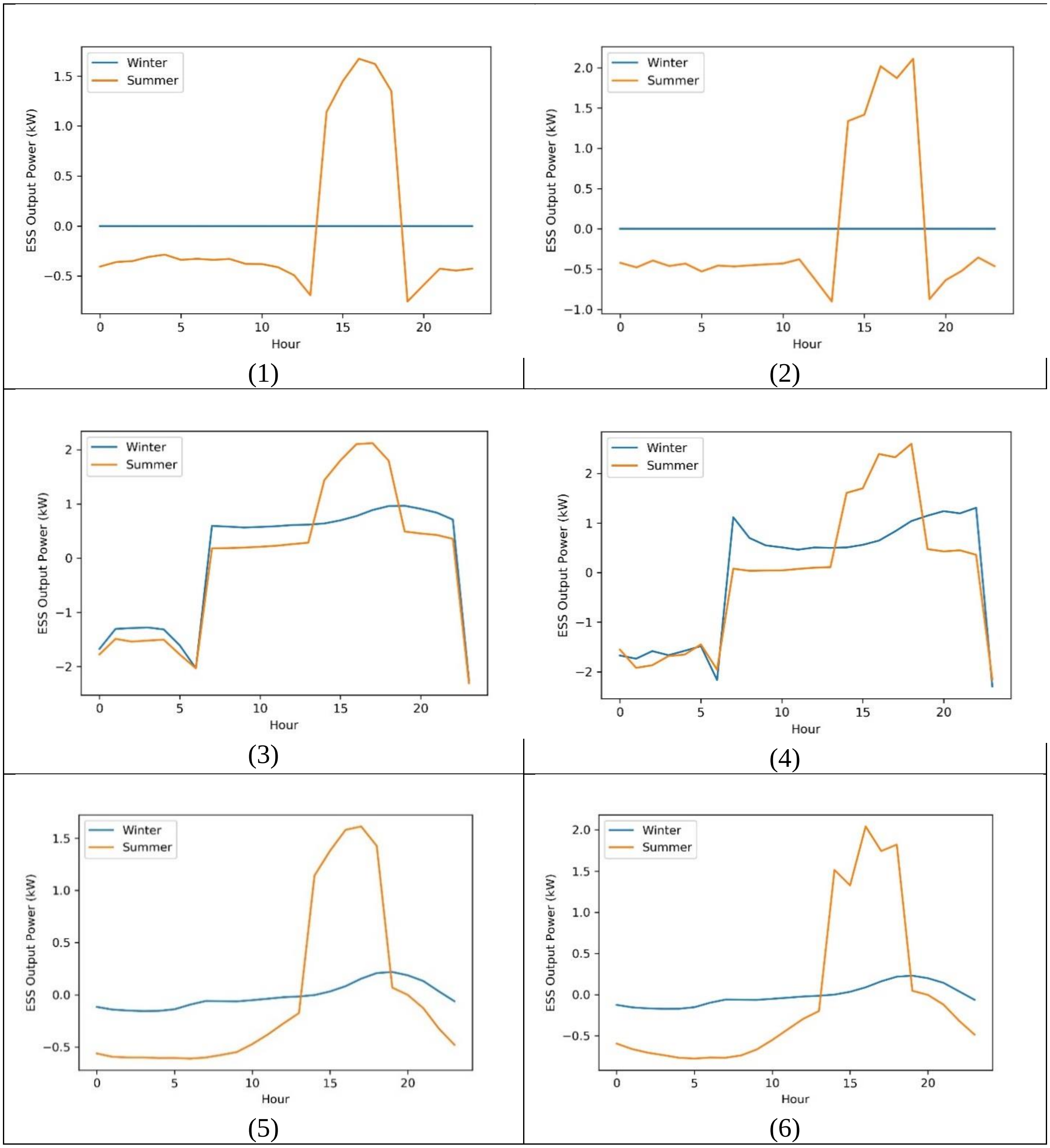

Figure 9 Average Optimal ESS Dispatch for 6 Test Cases of the Residential BTM Scenario

These ESS operation results are helpful for utilities to analyze the impact of large-scale BTM ESS deployment. Using the developed optimization algorithm, they can understand how ESS customers will respond to each tariff signals and impact the net load of the system as well as the emissions and other system parameters.

4.3.2. Commercial and Industrial Customers

For this optimization problem, C&I load profiles and Georgia Power tariff rates, the customers' energy and demand savings and the ESS optimal operation are determined for six test cases including the four tariff rates below:

- Power and Light – Medium:
    - Energy charge: First 3,000 kWh at 11.2561¢ per kWh, Next 7,000 kWh at 10.3091¢ per kWh, Next 190,000 kWh at 8.8885¢ per kWh, Over 200,000 kWh at 6.8955¢ per kWh
    - Demand charge: 8.24 $/kW in excess of 30 kW.
- TOU – General Service Demand:
    - Energy charge: On-Peak kWh at 12.2372¢ per kWh, Shoulder kWh at 6.2514¢ per kWh, Off-Peak kWh at 2.3541¢ per kWh
    - Demand charge: On-Peak kW at 15.66 per kW, Economy kW at 5.23 per kW, Maximum kW at 5.23 per kW
- Power and Light – Large:
    - Energy charge: First 3,000 kWh at 13.2655¢ per kWh, Next 7,000 kWh at 12.0303¢ per kWh, Next 190,000 kWh at 10.2607¢ per kWh, Over 200,000 kWh at 7.9109¢ per kWh
    - Demand charge: 9.53 $/kW.
- TOU – High Load Factor:
    - Energy charge: On-Peak Rate at 12.9222¢ per kWh, Off-Peak Rate at 3.4249¢ per kWh
    - No demand charge.

For TOU tariffs, two cases per each rate were considered: a) The customer can sell to the grid, and b) the customer cannot sell to the grid. The sell price is the same as the buy price if applicable based on the tariff rate structure. However, since power and light tariffs are energy-tiered and they do not specify a price, the ability of the customer to sell or to not sell does not apply to these tariffs.

For each test case, the ESS annual revenues for each building were calculated by solving the optimization problem. The summary of results for the benefit-cost analysis is presented in Table 4. These economic results can help customers and the utility for decision making about BTM ESS installations. All the rates, other than TOU – Large, show promising results in terms of revenue and payback period. TOU – Large does not provide enough revenues since the energy time-shift is limited to only about 22% of the days in a year. Also, there is no demand charge included in this tariff. Demand reduction usually provide a great portion of the total revenue.

Table 4 Results Summary for BTM C&I ESS

Test Case #	Rate	Customer Can Sell?	Mean of Annual Customer's Savings (k$)	Maximum of Annual Customer's Savings (k$)	Median of Payback Periods (Years)	Minimum Payback Period (Years)
7	Power & Light - Medium	N/A	23.6	61.1	14.2	9.7
8	TOU - Medium	NO	39.8	79.3	16.0	6.7
9	TOU - Medium	YES	40.9	79.3	15.8	6.7
10	Power & Light - Large	N/A	27.4	70.9	25.8	7.8
11	TOU - Large	NO	7.3	9.0	Very High	Very High
12	TOU - Large	YES	9.0	9.0	Very High	Very High

The payback period for each test case (TC) of each building is provided in Table 5. All the numbers are in years. It is assumed that the ESS used for all these buildings are identical (500kW, 2hr) and the capital cost is $400,000 incurred at the Capex year. Discount rate is assumed to be 8%.

Note that these customers are grouped to Medium (M) and Large (L) customers based on Georgia Power definition. Also, since TC 7, 8, and 9 are applicable to Medium customers and TC 10, 11, and 12 are applicable to Large customers, the ESS revenues for the other group (not applicable by that rate) are reported (for the sake of completeness) in orange color. Results show promising payback periods for ESS deployed at large hotels, schools and large offices that are exposed to "Power and Light – Large" tariff.

The optimal ESS dispatch in each test case is averaged over all the available customers and plotted as in Figure 10. Positive values correspond to discharging while negative values correspond to charging.

Table 5 ESS Payback Periods (in years) for each C&I building

Building	Size	Sc 7	Sc 8	Sc 9	Sc 10	Sc 11	Sc 12
Strip Mall	M	18.3	10.9	10.7	15.8	51.3	44.7
Stand-alone Retail	M	18.7	10.8	10.7	16.1	47.3	44.7
Medium Office	M	21.8	10.4	10.2	18.8	50.1	44.7
Warehouse	M	26.9	13.7	12.5	23.2	102.6	44.7
Outpatient	M	28.9	10.9	10.9	24.9	44.7	44.7
Full-Service Restaurant	M	34.1	12.1	12.1	29.3	44.7	44.7
Small Hotel	M	42.5	14.8	14.1	36.5	59.2	44.7
Midrise Apartment	M	47.4	15.9	15.1	40.8	61.8	44.7
Quick-Service Restaurant	M	55.7	22.7	19.5	47.9	92.9	44.7
Small Office	M	238.4	60.0	31.8	117.1	338.1	44.7
Large Hotel	L	6.5	5.0	5.0	**5.6**	44.7	44.7
Secondary School	L	8.0	7.0	7.0	**6.9**	44.7	44.7
Primary School	L	9.7	7.9	7.8	**8.4**	51.0	44.7
Large Office	L	10.5	6.1	6.1	**9.1**	44.7	44.7
Super Market	L	13.1	9.4	9.2	11.3	48.7	44.7
Hospital	L	14.9	7.5	7.5	12.8	44.7	44.7

Although the Power and Light tariffs (both Medium and Large) are energy tiered and not suitable for energy time-shift, the ESS dispatch is nonzero as seen in Figure 10(7) and 10(10). This is because of the demand charge reduction operation. The ESS operation is fairly similar to the average load of customers shown in Figure 7.

The TOU – Medium tariff provides opportunities for both energy time shift and demand charge reduction services in summer months and demand charge reduction in winter months. The high discharging rate at peak hours illustrated in Figure 10(8) and 10(9) shows the energy time-shift operation.

Since the TOU – Large tariff is flat for winter month and the demand charge is zero, there is no energy time-shift or demand charge reduction value and therefore ESS does not operate in these months. However, ESS discharges in peak hours, which are 2-7 pm of summer months. For those test cases where the customer can sell its excess power back to the grid, the discharging power of ESS is greater than that of the case where the customer cannot sell back to the grid.

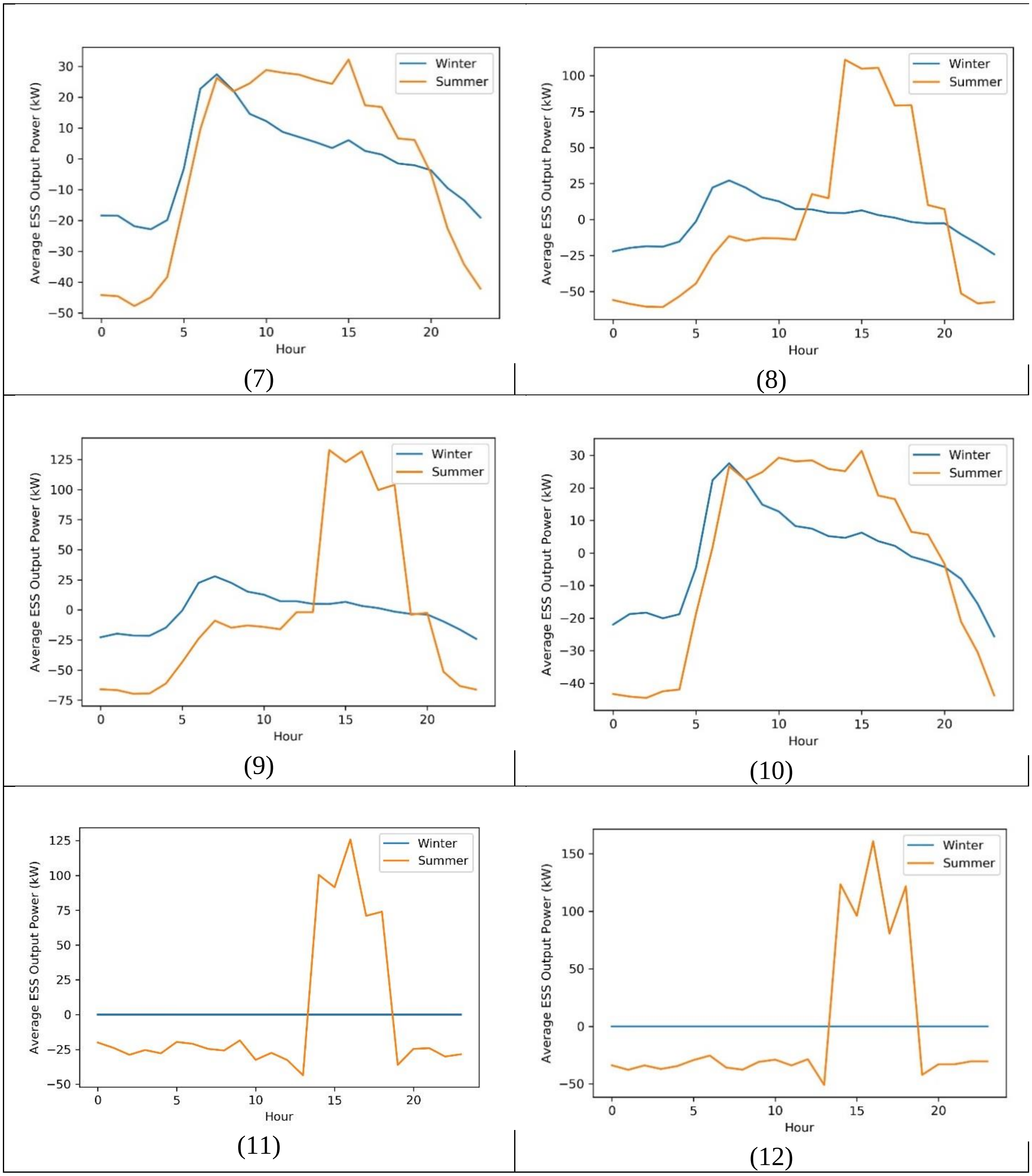

Figure 10 Average Optimal ESS Dispatch for 6 Test Cases of the C&I BTM Scenario

4.4. Scenario Conclusion

Simulation results provided in this chapter show that under the current GP tariff rates, C&I customers who are exposed to demand charges can benefit from BTM ESS investment. The significant cost savings result in payback periods of as low as 5 years for these customers. Residential customers exposed to demand charges can also benefit from BTM ESS where the payback periods are around 10 year. Although residential ESS is not as profitable as C&I, with the decreasing capital costs of ESS, it is expected that residential ESS become more profitable. In terms of system impacts, high penetration of BTM ESS can have significant impact on the system net load. Tariff rates with demand charges result in smoother net load profiles that are more desirable from the system operator's perspective.

5. Scenario 2: Customer-Sited and Jointly Operated ESS Simulations

5.1. Introduction and Objective

The second of the three scenarios studied in this project considers an ESS sited at the end-use customer premises (BTM), with the potential to be jointly operated by the customer and the utility. The motivation for considering this scenario is to better understand how the two factors of ownership and control authority can be approached when multiple parties are involved. Therefore, the objective of this Section is to develop a joint operation strategy for BTM ESS that provides value to both customers (energy users and energy storage owners) and the utility. Specifically, we answer *how BTM ESS can be operated so that the customers and the utility will benefit from the ESS* or more generally, we consider how the costs and benefits might be shared between the two parties, such that both parties are motivated to cooperate.

5.2. Methodology Overview

Optimization models are developed to analyze the ESS operation strategies and operators' (customers' and the utility's) objective functions. The customer's objective is to minimize their electricity bill, while the utility seeks to maximize its net profit. The customer's objective function is expressed as:

$$\underset{P_t^{ess,chg},P_t^{ess,dis}}{minimize} \sum_{t=1}^{T} \pi_t^{ene}\left(P_{t,n}^{load} + P_{t,n}^{ess,chg} - P_{t,n}^{ess,dis}\right)\Delta t + \sum_{r=1}^{R} \pi_r^{dem} P_r^{max} \tag{15}$$

where the decision variables $P_t^{ess,chg}$ and $P_t^{ess,dis}$ denote the energy storage charge and discharge powers at time step *t*.

The utility's objective function includes the sum of customers' bill payments minus the costs of operating utility's generation and wholesale transactions. This is expressed as:

$$\begin{aligned} \underset{P_t^{wh},P_t^{g}(,P_{t,n}^{ess,chg},P_{t,n}^{ess,dis})}{maximize} \sum_{n=1}^{N} \left[\sum_{t=1}^{T} \pi_t^{ene}\left(P_{t,n}^{load} + P_{t,n}^{ess,chg} - P_{t,n}^{ess,dis}\right)\Delta t + \sum_{r=1}^{R} \pi_r^{dem} P_{r,n}^{max}\right] \\ - \sum_{b=1}^{B}\sum_{t=1}^{T} \pi_{t,b}^{g} P_{t,b}^{g} \Delta t - \sum_{t=1}^{T} \pi_t^{wh} P_t^{wh} \Delta t \end{aligned} \tag{16}$$

where P_t^{wh} is the power purchased by the utility at the wholesale level and $P_{t,b}^{g}$ is the power generated by utility's generation. Index *b* shows the blocks of energy generated at different marginal costs. Index *n* denotes the number of customers served by the utility. Also, $P_t^{wh} + \sum_{b=1}^{B} P_{t,b}^{g} = \sum_{n=1}^{N} P_{t,n}^{load} + P_{t,n}^{ess,chg} - P_{t,n}^{ess,dis}$ shows that the total customers' net load is met from the utility's generation as well as the wholesale market. Note that in this formulation, the customers' ESS charging and discharging powers ($P_{t,n}^{ess,chg}, P_{t,n}^{ess,dis}$) are or are not the utility's decision variables depending on the assumption of joint-operation where the utility has or does not have direct control over BTM ESS.

In Scenario 1, BTM ESS is operated exclusively to minimize the customers' bill using Eq. (15). This strategy impacts the utility's profit in two ways: First, the total energy sales will decrease since the ESS customers' bills are minimized as in Eq. (15). Second, the change in the time-of-use of the system's net load caused by the ESS may change the cost of the utility's local energy generation as well as wholesale purchases. In this scenario, Eq. (16) can be used with the customers' ESS charging and discharging powers ($P_{t,n}^{ess,chg}, P_{t,n}^{ess,dis}$) as parameters (and not decision variables) to quantify the utility's profit.

In this Section, as an initial baseline, we first analyze the impact of customer-owned and operated BTM ESS (in Scenario 1 where ESS is operated to minimize customer's electricity bill) on the utility's revenue in Subsection 4.1. and show that this strategy results in a net loss for the utility. Next, we propose two independent optimization-based approaches for the joint operation of BTM ESS. The two approaches are defined as parts of Scenario 2:

- Scenario 2A: "Passing-through" wholesale prices for BTM ESS: the utility sends the wholesale energy prices to BTM ESS customers. ESS customers are billed based on their load profile and the applicable tariff rates (no change compared to the case with no ESS) but they can benefit from the energy arbitrage at the wholesale level prices. Therefore, the utility's net profit will not be impacted. Note that a regulated utility may or may not elect to use this approach and may or may not be able (technically or according to regulations) to do this. However, we are making this assumption to baseline the analytical approaches.
- Scenario 2B: "Renting" BTM ESS: utility rents the capacity of BTM ESS and operates it to minimize the costs of the utility's generation and wholesale transactions. ESS customers are paid based on the maximum revenue that they could have obtained if they had operated their ESS.

These approaches are described and analyzed separately and provide simulation results. We are considering either one approach or the other. While it might be interesting to consider some hybrid approach, it is considered beyond the scope of this analysis.

5.3. Input Data and Assumptions

The required input data for this Scenario are:

v. Storage technology parameters:
    a. Technical parameters,
    b. Economic parameters
vi. System parameters:

a. Customer types,
b. Load profiles,
c. Price Signals,

These are almost identical to Scenario 1 input data except for Price Signals that will be discussed more in detail.

5.3.1. Storage technology parameters

- For residential customers, energy storage technology parameters are selected based on Tesla Powerwall[5]:
    - Technical parameters: 7 kW maximum charging/discharging rates, 15 kWh total capacity, 13.5 kWh usable capacity (90% depth of discharge), and 90.25% roundtrip efficiency (= 95% charging efficiency × 95% discharging efficiency).
    - Economic parameters: We utilize the same cost parameters that were used for Scenario 1. The cost of Powerwall is $6700/module. We use this number as the fixed capital cost and assume no fixed or variable O&M costs.

- For C&I customers, energy storage technology parameters are selected based on an extensive literature review of research paper as well as real-world BTM ESS projects available at Department of Energy, Energy Storage Database[6]. Typical parameter values for this case are selected as:
    - Technical parameters: power rating (=max charging and discharging rates) of 20% yearly peak load, capacity of 2 hours at the maximum power rating, with 90% usable capacity (90% depth of discharge), and 90.25% roundtrip efficiency (= 95% charging efficiency * 95% discharging efficiency).
    - Economic parameters: We utilize the same cost parameters that were used for Scenario 1. We assume that the total capital cost is equal to $400/kWh as the incurred in the Capex year. The capital cost includes the Li-ion Battery cells and packing cost ($200/kWh) as well as balance-of-system (BOS) cost ($200/kWh). The values of these cost parameters are selected based on estimates of Bloomberg New Energy Finance[7] and NREL Report[8], respectively. We assume that the O&M cost is captured in the BOS cost parameter.

In both residential and C&I cases, we assume that there is no salvage/residual value after the storage end-of-life. This is a conservative estimate since the literature discusses end of life value for ESS. Also, the life cycle of the above batteries is understood and considered in this study.

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[5] https://www.tesla.com/powerwall
[6] https://energystorageexchange.com
[7] Bloomberg New Energy Finance: Sustainable Energy in America Factbook, 2019
[8] 2018 U.S. Utility-Scale Photovoltaics-Plus-Energy Storage System Costs, National Renewable Energy Lab, Technical Report NREL/TP-6A20-71714 Nov 2018

5.3.2. System parameters

5.3.2.1. Customer types:

We identified two main customer's types:

- Residential and
- Commercial and Industrial (C&I)

5.3.2.2. Load profiles:

Similar to Scenario 1, the load profiles from the Pecan Street Database were used for residential cases. Also, the load profiles from the DOE building load database were used for C&I cases. For more information about the load profiles please refer to Scenario 1 section on load data.

5.3.2.3. Prices:

We have used wholesale electricity market energy prices as well as System Lambda of the Southern Company. The various price data are used to compare the impact different energy prices have on ESS outputs and potential customer revenues and payback periods. Hourly prices from 2018 are collected from ISO websites and other publicly available sources. The price signals of the following ISO/locations are used for comparison:

- Midwest Independent Transmission System Operator (MISO) Arkansas Hub
- New York ISO
    - Reference bus
    - Gowanus, Brooklyn, NY
- Pennsylvania New Jersey Maryland Interconnection (PJM) Aggregate node
- ISO New England
- California ISO, city of San Jose
- Electric Reliability Council of Texas (ERCOT)

Figure 11 shows the hourly energy prices from the above markets as well the Southern Company's System Lambda during month of January 2018.

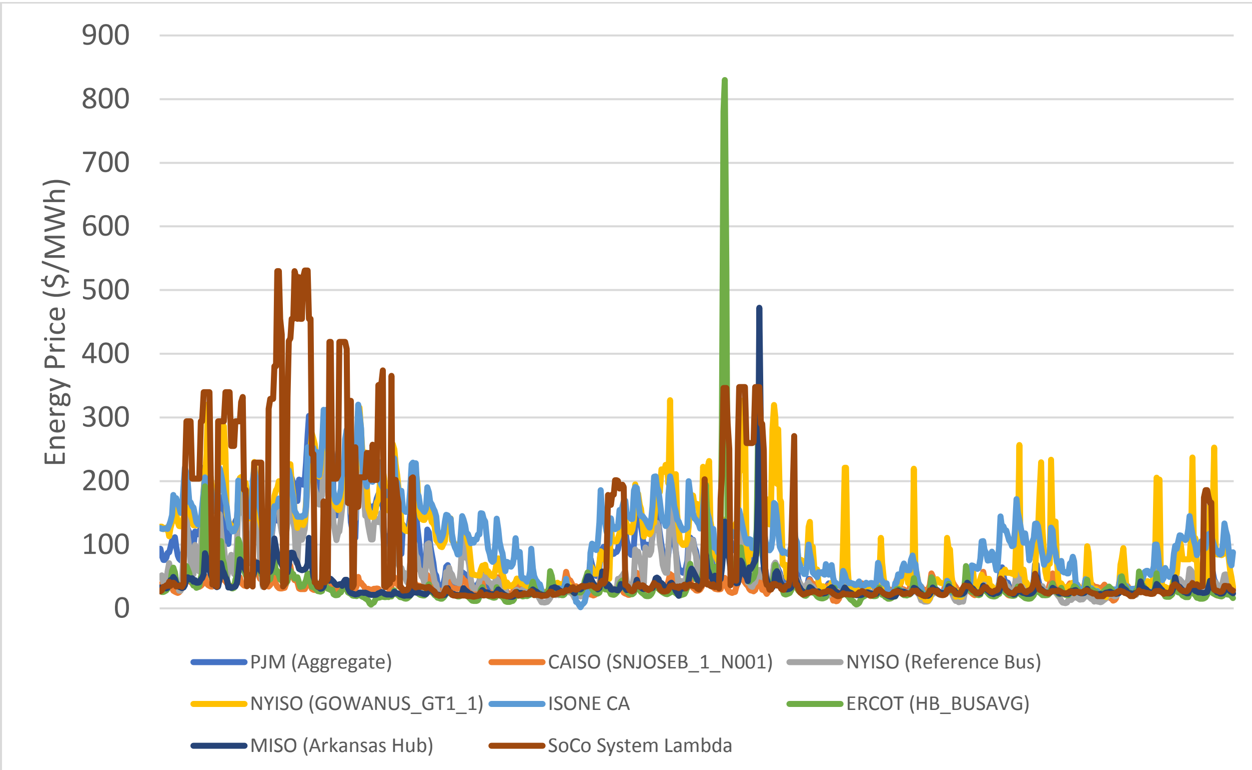

Figure 11 Hourly day-ahead energy prices from the selected markets in January 2018

5.4. Impacts of BTM ESS operated to minimize customer's bill on the utility's revenue

This subsection provides numerical results for the impacts of BTM ESS operated to minimize customer's bill on the utility's revenue based on results from Scenario 1 and the state/regional generation and market data collected for Scenario 2. In Scenario 1, the BTM ESS is operated just to minimize the customers' bill. This strategy impacts the utility's profit in two ways:

- First, the total energy sales will decrease since the ESS customers' bills are minimized as in (1).
- Second, the change in the time-of-use of the system's net load by ESS may change the cost of utility's local energy generation as well as wholesale purchases.

For each of the residential and C&I rates used in simulating Scenario 1, the financial results (annual customers' revenues) and the optimal dispatch results (hourly output power of ESS) are normalized based on the kW power rating of the ESS. This parameter was chosen as 7kW (Tesla PowerWall rating) for all residential customers and assumed to be 20% of the maximum annual load[9] for each

[9] I. Alsaidan, W. Gao, A. Khodaei, "Battery energy storage sizing for commercial customers," in *IEEE Power & Energy Society General Meeting*, Chicago, IL, USA, July 2017.

of the C&I customers. These results are then averaged among all the customers of the same type to calculate how much the utility's net revenue will be impacted on average by a 1kW BTM ESS (having a capacity of 2.1h for residential, and 2h for C&I). The following parameters are then calculated from the utility's perspective:

1) Annual net change in total energy sales: which is equal to the average normalized annual revenues of the customers.
2) Annual net change in costs of local generation: This parameter is calculated assuming all the ESS charge and discharge energy is provided by the local generation. The average normalized dispatch of ESS is multiplied by the simulated prices from Georgia generation data.
3) Annual net change in costs of wholesale energy market transactions: This parameter is calculated assuming all the ESS charge and discharge energy is provided by the utility from participating in the wholesale energy market. The average normalized dispatch of ESS is multiplied by the wholesale day-ahead energy market prices.

Table 6 presents the results of the BTM ESS impact analysis. Rates are denoted with the following convention. The numbers after the letter "R" define the tariff rate's code based on Georgia Power tariffs. CS1 determines if the customer "can sell" back to the grid (at the same purchase price) while CS0 does not allow a reverse power flow from the customer to the grid. The changes in the cost of wholesale markets are reported only for two representative markets for brevity and for their proximity to the state of Georgia. The total change in the utility's objective function ("Delta Utility's Revenue column") compared to the case without energy storage is reported as a range in Table 6. This total change is the sum of changes in the energy sales (the "Delta Energy Sales" column) and one of the alternative generation options, either local generation ("Delta Local Generation Cost" column) or either of the wholesale markets ("Delta Cost PJM/MISO Market" column). In this scenario (Scenario 1), <u>the total change in the utility's revenue is always a negative number under all the tariff rates showing that the utility's revenue will always decrease with increasing BTM ESS operated by the customers</u>**.** Note that the numbers are calculated based on a 1kW BTM ESS and they have a linear relationship with the kW power.

Table 6 Utility's Change of Revenue in the Case of Customer-owned and Operated ESS

Rate	Delta Energy Sales ($)	Delta Local Generation Cost ($)	Delta Cost PJM Market ($)	Delta Cost MISO Market ($)	Delta Utility's Revenue ($)
R220CS0	-19.5	-0.6	2.2	1.9	[-21.1, -17.3]
R220CS1	-23.4	-0.7	2.6	2.2	[-24.1, -20.8]
R230CS0	-49.1	-1.9	7.0	5.7	[-51, -42.1]
R230CS1	-55.2	-2.1	7.6	6.2	[-57.3, -47.6]
R240CS0	-44.9	-1.2	2.9	2.4	[-46.1, -42]
R240CS1	-47.9	-1.3	3.4	2.9	[-49.2, -44.5]
R400CS0	-80.3	-0.5	1.6	1.0	[-80.8, -78.7]
R410CS0	-117.3	-0.8	4.0	3.0	[-118.1, -113.3]
R410CS1	-117.4	-0.9	4.0	3.0	[-118.3, -113.4]
R500CS0	-93.4	-0.5	1.6	0.9	[-93.9, -91.8]
R520CS0	-17.8	-0.5	3.2	2.6	[-18.3, -14.6]
R520CS1	-17.9	-0.5	3.2	2.5	[-18.4, -14.7]

The significance of this analysis is underlined in the following example. Currently, Georgia Power serves more than 2.2M residential and 0.3M commercial customers[10]. Assume 1% residential and commercial customers have installed BTM ESS. The total kW of BTM ESS would be:

$$2{,}200{,}000 * 0.01 * 7kW \ + \ 300{,}000 * 0.01 * 325kW \ = \ 1{,}129{,}000kW$$

where 7kW and 325kW are average kW ratings for residential and commercial BTM ESSs. Using the results from Table 4, Georgia Power will lose a significant revenue of **M$20 to M$123** in annual revenues. Therefore, although BTM ESS can provide reasonable savings for the customers, it will decrease the utility's revenues drastically. Thus, other operation strategies for BTM ESS should be explored so that both customers and utilities may benefit from BTM ESS under multi-party control strategies.

[10] https://www.georgiapower.com/company/about-us/facts-and-financials.html

5.5. Joint Operation Strategy A (Scenario 2A): "Passing-through" wholesale prices for BTM ESS

In this case, the utility "passes-through" the wholesale energy prices to BTM ESS customers. It is assumed that such customers are billed based on their load profile and the applicable tariff rates (no change compared to the case with no ESS) but they can benefit from the energy arbitrage at the wholesale prices. Therefore, the utility's net profit will not be impacted. A regulated utility may or may not elect this approach and may or may not be able to do this. However, we are making this assumption to baseline the analytical approaches. Also, note that from the market services that can be provided by ESS, only energy arbitrage is modeled since we assume that those services require costly infrastructure that are not available at the current state of the distribution grid as well as electricity markets.

5.5.1. Optimization

The objective function of the optimization problem for this scenario corresponds to minimizing the customer's monthly electricity bill charge. Unlike, scenario 1, there is no demand charge. The objective function is presented mathematically as:

$$\underset{P_t^{ess,chg},P_t^{ess,dis}}{minimize} \sum_{t=1}^{T} \pi_t^{ene} \left(P_t^{load} + P_t^{ess,chg} - P_t^{ess,dis}\right) \Delta t \qquad (17)$$

Subject to

- ESS technical constraints as in Equations (4) – (8),

$$0 \le P_t^{dis} \le P_{\max}^{dis}.u_t^{dis} \quad ; \quad 0 \le P_t^{chg} \le P_{\max}^{chg}.u_t^{chg} \qquad \forall t \in \mathrm{T} \qquad (18)$$

$$0 \le u_t^{dis} + u_t^{chg} \le 1 \qquad \forall t \in \mathrm{T} \qquad (19)$$

$$E_t = \eta_s E_{t-1} + \left(\eta_{chg} P_t^{chg} - P_t^{dis} / \eta_{dis}\right)\Delta t \qquad \forall t \in \mathrm{T} \qquad (20)$$

$$E_{\min} \le E_t \le E_{\max} \qquad \forall t \in \mathrm{T} \qquad (21)$$

$$E_T = E_0 \qquad \forall t \in \mathrm{T} \qquad (22)$$

- If the customer cannot sell net energy back to the grid then the following constraints is enabled,

$$P_t^{load} + P_t^{chg} - P_t^{dis} \ge 0 \qquad (23)$$

5.5.2. Simulation Results

The seven regional prices are used to simulate arbitrage results. Also, results from three Georgia Power Residential rates are provided for comparison. Simulation results for the residential and C&I customers using variable price signals are presented in the following subsections.

5.5.2.1. Residential

Using the optimization problem formulation, residential load profiles, and the seven different price signals from the ISOs, the optimal ESS operation is determined for 14 test cases (a customer can sell and cannot sell for each of the seven price signals) and compared with the results from the six test cases using Georgia Power Tariffs from Scenario 1. When using a variable price signals the only source of revenue is energy arbitrage (EA) since no other incentives are included. For each test case, the summary of results for the benefit-cost analysis is presented in Table 7. These economic results can help customers and the utility make decisions about the economic impact that results from the installation of ESS.

Just as in Scenario 1, when it is assumed that the customer can sell energy back to the grid at an identical price as the current buying price, the revenue becomes independent of the load profile and converges to a single value. However, when switching from the "can sell" case to "cannot sell", the payback period for Scenario 2A increases in the range of 60% to 90%, which is significantly higher than the 10%-20% seen in Scenario 1. This is because the optimal time window for discharging with price signals occurs at an hourly level, and if the customer does not have a large load to offset, a significant portion of the revenue is lost in comparison with the tariff rates with much larger windows of peak price. This demonstrates that when operating on a variable price signal the ESS needs to be able to sell energy back to the grid to remain competitive with an ESS operating under a tariff.

While none of the payback periods for the ISO price signals compete with the Plug-In Electric Vehicle Rate, both the ERCOT and CAISO price signals demonstrate that when customers can sell energy back to the grid, price signals can result in payback periods that are competitive with the Smart Usage and Nights & Weekends Rates.

Table 7 Residential Payback Period

	ERCOT (HB_BUSAVG)		CAISO (SNJOSEB_1_N001)		NYISO (GOWANUS_GT1_1)		ISONE CA		PJM Aggregate	
	CS0	CS1	CS0	CS1	CS0	CS1	CS0	CS1	CS0	CS1
mean	35.3	18.5	36.6	21.2	49.5	29.1	73.4	40.8	72.2	43.0
median	34.9	18.5	36.1	21.2	48.7	29.1	72.7	40.8	70.7	43.0

	NYISO		MISO (Arkansas Hub)		Georgia Power Tariff					
	CS0	CS1	CS0	CS1	R220CS0	R220CS1	R230CS0	R230CS1	R240CS0	R240CS1
mean	81.3	49.1	103.7	61.1	29.0	24.2	11.7	10.4	21.3	20.0
median	80.0	49.1	101.2	61.1	27.0	24.2	11.2	10.4	23.2	21.9

The average optimal ESS dispatch for the CAISO (1-2), MISO (3-4) and Georgia Power Plug-In Electric Vehicle rates R230 (5-6) are plotted in Figure 12, with positive values corresponding to discharging and negative values corresponding to charging. The average of all 1379 customer discharge rates was taken.

Cannot Sell **Can Sell**

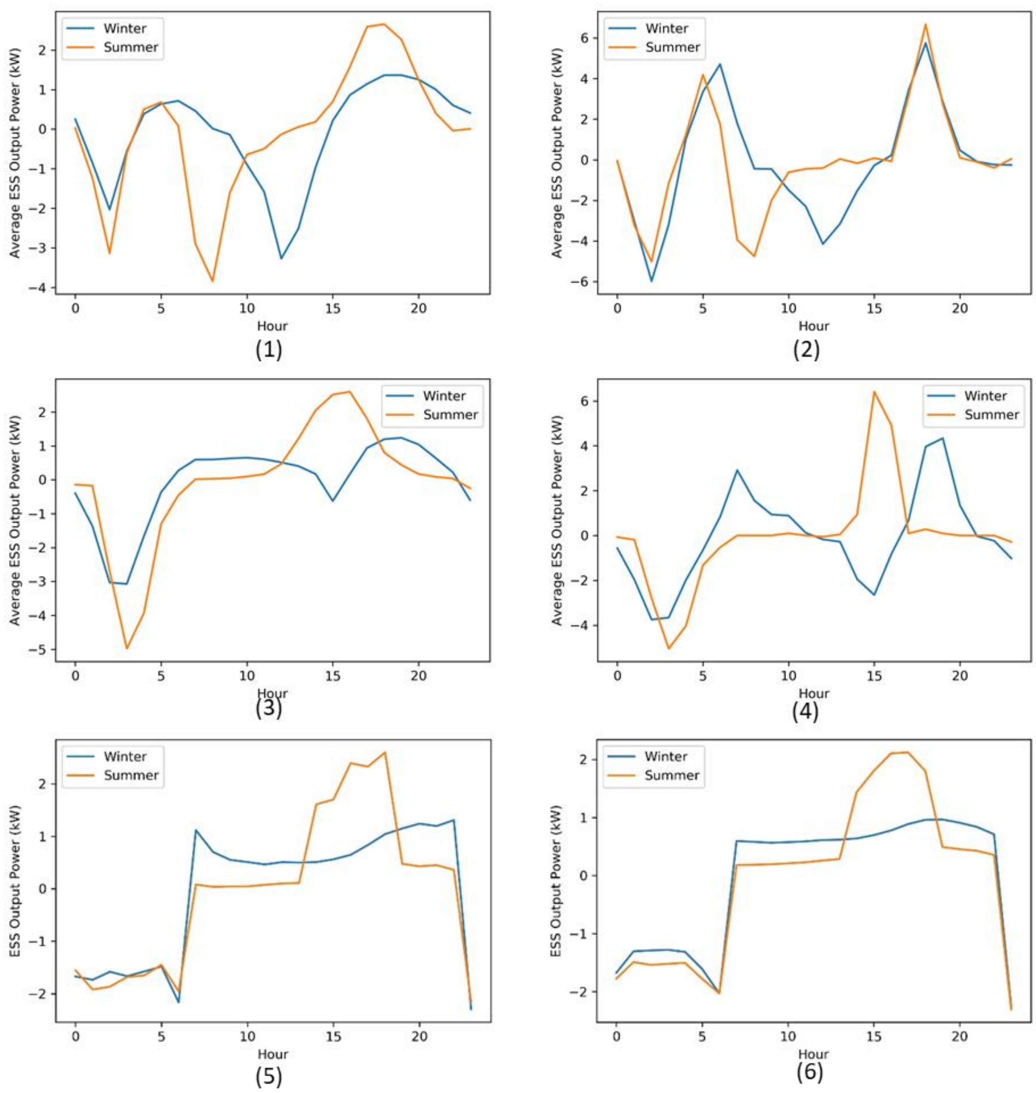

Figure 12 Residential ESS Dispatch for CAISO (1,2), MISO (3,4), and GA Power (5,6)

The optimal ESS operation with wholesale market price signals is more variable than that with utility tariff rates. In the case of wholesale prices, higher charging and discharging values occur over smaller windows as the system tries to capitalize on the individual hours with peak and minimum prices instead of the multi-hour windows seen in the Georgia Power Rates. In other words, wholesale market prices vary hourly and can create arbitrage opportunities during shorter periods, e.g. all ESS would discharge during the one hour with maximum price. While utility tariff rates are usually flat for several hours of the day, e.g. peak hours and off-peak hours, and ESS can charge or discharge during longer periods of time. When the operator can sell to the grid, both the max discharge and charge are dependent on the battery parameters, however when the operator cannot sell the max discharge is limited by the customers load profile instead, which is seen when comparing cases 1 and 3 with cases 2 and 4.

These results demonstrate that the profitability of an ESS under this scenario is dependent on the specific price signals and rate used. In addition, the optimal operation of an ESS under a variable price signal as in wholesale prices generally involves higher rates of discharge and charging and is much more dependent on being able to sell energy back to the grid than existing Georgia tariffs.

5.5.2.2. C&I

For the C&I case, the same seven variable price signals are used as in the residential case. For each price signal, two cases are again considered, where the customer can sell back to the grid and where the customer cannot sell back to the grid. The payback period for the 15 building types are seen below in Table 8.

Similar to the residential test cases, when the customer can sell back to the grid the payback period converges to a single value for all cases. Unlike the residential case, for the C&I case the payback period only increases between 0%-25% in most cases when switching from can sell to cannot sell. This occurs because the peak load of each user type is used to size the battery, and, since the battery can discharge in 2 hours, not much revenue is lost when operating with smaller optimal pricing windows. This makes the **C&I test cases much less dependent on the ability to sell energy to the grid than the residential cases**. This ability is denoted by CS1 and the inability is denoted by CS0 in Table 8. As seen in Table 8, the ERCOT and CAISO price signals results in favorable payback periods for most users, while the other price signals generally result in payback periods in excess of 25 years.

Table 8 C&I Pay Back Periods Average and Standard Deviations

Price Data Location	**ERCOT (HB_BUS AVG)**	**CAISO (SANJOSE)**	**NYISO (GOWANUS)**	**ISONE CA**	**PJM Aggregate**	**NYISO (Reference Bus)**	**MISO**
Average (CS0)	17.04	20.1	27.06	38.16	39.56	45.33	56.07
Average (CS1)	16.4	18.7	25.7	36.1	38.2	43.6	54.2
Std Deviation (CS0)	1.06	1.95	1.68	2.62	1.92	2.36	2.61
Std Deviation (CS1)	0	0	0	0	0	0	0

The optimal ESS dispatch for the CAISO (7-8), ERCOT (9-10), and MISO (11-12) is seen below with positive values representing ESS discharge and negative values representing charge in Figure 13. The average discharge of all building types was taken. Similar to the residential results, comparing cases (1), (3), and (5) with cases (2), (4), and (6) shows that the peak discharge is significantly higher when the ESS operator can sell energy back to the grid. Also like the residential cases, the C&I cases show an increased amount of variance between charging and discharging as the optimization function maximizes revenue with a price signal that changes by the hour.

Cannot Sell **Can Sell**

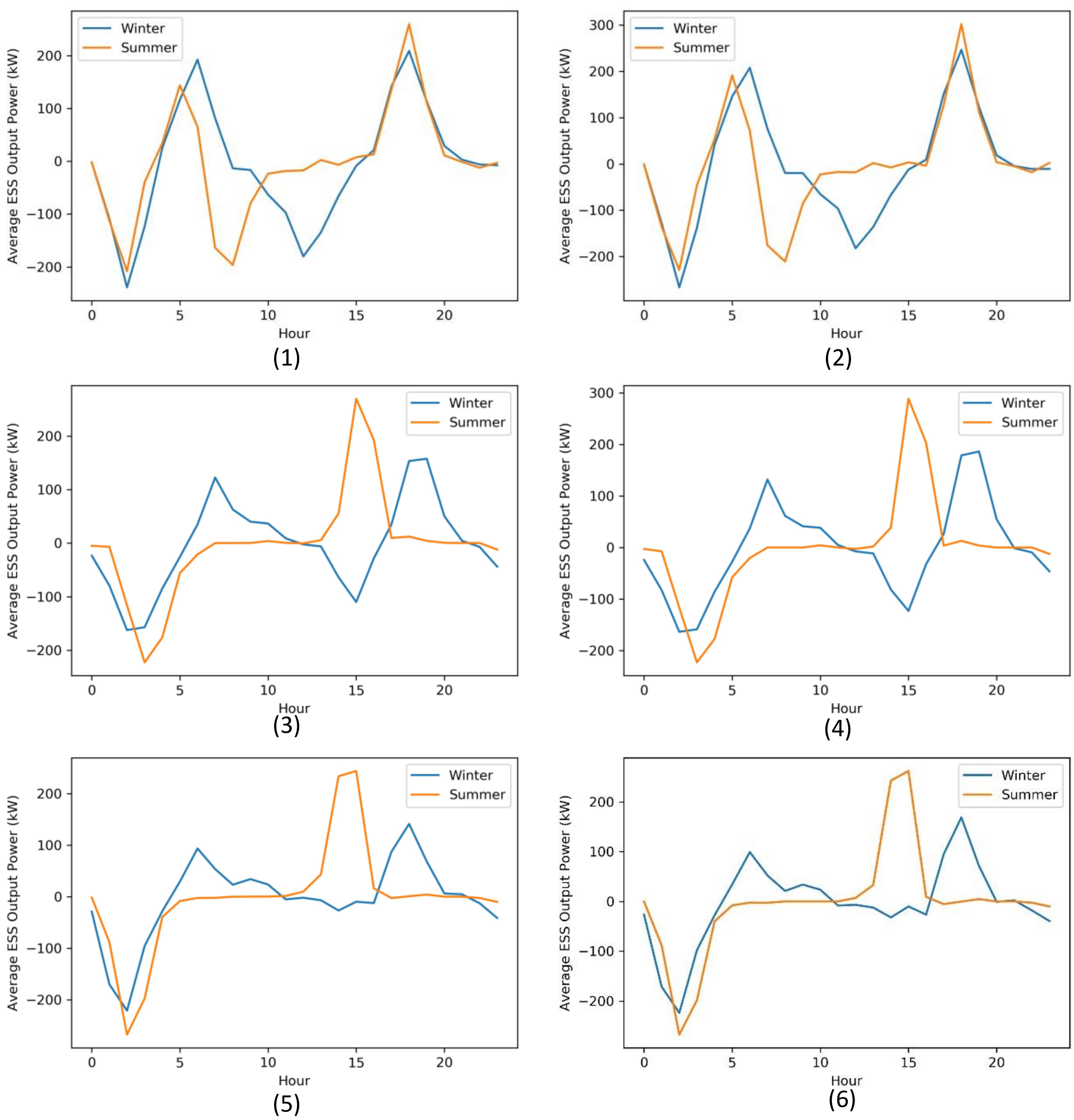

Figure 13 C&I ESS Dispatch for CAISO (1, 2), ERCOT (3, 4), and NYISO (5, 6)

These results show that while in some cases an ESS operation may be profitable when working with varying price signals, it is important to examine the specific price signal that will be used in order to determine if EA will generate enough revenue in that specific use case.

5.5.3. Joint Strategy Analysis

In this strategy where ESS customers are exposed to wholesale prices, the customers' revenues, which is the reduction in their energy bills, from wholesale energy arbitrage are significantly lower than scenario 1 with Georgia Power Tariffs. Therefore, this strategy is less favorable for customers. Very long payback periods will also demotivate customers to own BTM ESS. As shown by results, payback periods are above 15 years that is much longer than the normal calendar life of many battery technologies (5 to 10 years)[11,12]. From a utility's perspective, however, this strategy is revenue neutral since customer is directly transacting at the wholesale price. Note that, this strategy has some implementation cost to send wholesale market prices to BTM ESS. Analyzing the implementation cost is out of the scope of this work. Moreover, the total system load would have more spikes due to sharp variabilities of ESS operation.

5.6. Joint Operation Strategy B (Scenario 2B): "Renting" BTM ESS

In this strategy, the utility rents the capacity of BTM ESS and operates them to minimize the costs of operating utility's generation and wholesale transactions (Equation 2). ESS customers are paid based on the maximum revenue they could have obtained if they had operated their ESS.

5.6.1. Optimization

The optimization model used in this strategy is almost similar to the one in the joint strategy #1 but for the aggregate of all the customers' BTM ESSs. The model is described in Equations (24) – (29).

$$\underset{P_{t,n}^{ess,dis},P_{t,n}^{ess,chg}}{maximize} \sum_{n=1}^{N} \left[\sum_{t=1}^{T} \pi_t^{ene} \left(P_{t,n}^{ess,dis} - P_{t,n}^{ess,chg} \right) \Delta t \right] \tag{24}$$

[11] B Zakeri, S Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," Renewable and sustainable energy reviews, 2015

[12] J, Tant, et al., "Multiobjective battery storage to improve PV integration in residential distribution grids," *IEEE Transactions on Sustainable Energy*, *4*(1), 182-191.

Subject to

- ESS technical constraints:

$$0 \le P_{t,n}^{dis} \le P_n^{dis,max} u_{t,n}^{dis} \quad ; \quad 0 \le P_{t,n}^{chg} \le P_n^{chg,max} u_{t,n}^{chg} \qquad \forall t \in \mathcal{T}, \forall n \in N \qquad (25)$$

$$0 \le u_{t,n}^{dis} + u_{t,n}^{chg} \le 1 \qquad \forall t \in \mathcal{T}, \forall n \in N \qquad (26)$$

$$E_{t,n} = \eta_{s,n} E_{t-1,n} + \left(\eta_{chg,n} P_{t,n}^{chg} - P_{t,n}^{dis} / \eta_{dis,n}\right) \Delta t \qquad \forall t \in \mathcal{T}, \forall n \in N \qquad (27)$$

$$E_n^{min} \le E_{t,n} \le E_n^{max} \qquad \forall t \in \mathcal{T}, \forall n \in N \qquad (28)$$

$$E_{\mathcal{T},n} = E_{0,n} \qquad \forall t \in \mathcal{T}, \forall n \in N \qquad (29)$$

In Equation (24), the hourly price of energy (π_t^{ene}) is either the marginal cost of local generation (simulated price of Georgia) or the hourly price of the wholesale market (π_t^{wh}).

5.6.2. Simulation Results

The optimization model in Eqns. (24) – (29) is simulated with all the seven wholesale prices as well as the Georgia System Lambda. Results are normalized for a total of 1kW 2hr aggregate battery with 90% usable capacity and 95% roundtrip efficiency. Table 9 presents the results of utility annual revenues from participating in the wholesale markets with the normalized BTM ESS.

Table 9 Utility Annual Revenues in Joint Strategy B (Scenario 2B)

Price Location	ERCOT	CAISO	NYISO Ref	NYISO NYC	ISONE	PJM	MISO	Georgia System Lambda
Annual Revenue ($/kW)	48.3	42.1	18.2	30.7	21.9	20.8	14.6	11.4

As in Subsection 4.4, assuming 1% residential and commercial customers have installed BTM ESS, the total kW of BTM ESS would be 1.129GW that will result in up to **M$54.5 of annual revenue**. Note these market revenues of the utility from BTM ESS using this “renting” strategy **has increased 3 to 10 times** compared to the case where customers operating their ESS based on tariffs. This is because BTM ESS is operated by the utility to maximize the market revenue.

5.6.3. Joint Strategy Analysis

In this strategy, BTM ESS is rented by the utility from the customers who own the ESS outright. The renting price is calculated based on the maximum customer benefits as in Scenario 1. Since those benefits are considerable under most of the tariff rates, the customers will still have enough financial motivation to invest in a BTM ESS and let the utility operate the ESS. The utility will take the full control of the BTM ESS operation and maximize the energy arbitrage value from all the distributed BTM ESS. Optimization results show significant revenues can be obtained by the utility from energy arbitrage depending on the price variability of the location. This strategy will always result in lower losses of utility's revenue compared to Scenario 1. In some cases, there are financial opportunities for utilities using this strategy based on various tariff rates and wholesale market prices. For example, if utility rents BTM ESS from large commercial customers under tariff rate R520 and transacts at ERCOT, the normalized renting price is $17.8/kW while the energy arbitrage revenue is $48.3/kW. This will yield in a net profit of $30.5/kW. Higher utility revenues are expected if ancillary market participation is also considered. More on this will be provided in Scenario 3. Moreover, **this strategy is also more desirable from a system operation perspective since the system operator has more flexibility to compensate the uncertainties of the grid**. Implementation of this strategy requires communication infrastructure to send and receive control and feedback signals. However, it does not require significant software update in the electricity market operator compared to joint strategy #1 since all the distributed bids are aggregated at the utility's point of connection. Again, the implementation details are out of scope of this project.

5.7. Scenario Conclusion

Simulation results provided in this chapter show that BTM ESS owned and operated by ESS can have negative impacts on the utility's revenue. Thus, two joint operation strategies were proposed that utilities can operate BTM ESS jointly with the customers to hedge against their revenue loss while customers can still benefit from BTM ESS. The first strategy, passing through wholesale prices, is not financially attractive and result in payback periods of more than 15 years. However, this strategy is revenue neutral for the utility. The second strategy, renting BTM ESS, has the same profitability for the customers as Scenario 1 and the utility can benefit from operating BTM ESS to maximize its own objective function. Optimization results show significant revenues can be obtained by the utility from energy arbitrage depending on the price variability of the location. This strategy will always result in lower losses of utility's revenue compared to Scenario 1.

6. Scenario 3: Utility-owned and Operated ESS

6.1. Introduction and Objective

The third of the three scenarios studied in this project considers an ESS owned and operated by the electric utility. We simulate this scenario to determine the benefits to a utility that are obtained from ESS exclusively "before the meter". For this scenario, the utilization of system-wide input data such as system lambda is proposed to drive the optimal operation of ESS. The results provide insights on the maximum potential value of a utility-owned and operated ESS in the Southeast.

The methodology maximizes the benefits for the utility using realistic and publicly available data from the Southeast U.S. Specifically, we answer the following question: *how utility-owned and operated ESS should be optimally operated so that the utility will obtain the maximum benefit from the ESS services*. The analysis methodology involves the following steps described in the next subsections:

- Identifying utility's objectives and applicable ESS benefits and services
- Developing the optimization model for ESS service revenue maximization
- Collecting the required input data
- Developing an ESS software and performing the simulations
- Analyzing the simulation results

6.2. Utility's Objective and Applicable ESS Services

In this scenario, the utility seeks to maximize the monetary benefits of ESS applications i.e. service revenues. Thus, identifying the applicable services is a key step. While many ESS applications and potential services have been discussed in the literature[13], we analyze the most important services, including services that have been studied in other regions in the U.S. We apply analysis methodologies and optimization models specifically developed for publicly available data for the Southeast region to study the following ESS services:

- System Supply Capacity
- Energy Arbitrage
- Ancillary Services
- Transmission and Distribution (T&D) Upgrade Investment Deferral
- Reliability Improvement and Outage Mitigation

Each service and the corresponding optimization model are described in the next Section.

[13] EPRI, "Electric Energy Storage Technology Options: A White Paper Primer on Applications, Costs and Benefits," 2010

6.3. Optimization Methodology for ESS Service Revenue Maximization

This section introduces applicable ESS service and proposes optimization models that maximize the service revenues. Significant research effort has been taken to develop such optimization methodologies that require only publicly available data and can best describe the ESS service revenues and dispatch operation. Each service is described next.

6.3.1. System Supply Capacity

ESS can be used to provide system supply capacity. This service ensures that enough available generation can meet the peak load requirement in the next few years. This requirement is based on available and forecasted generation, load, renewables, retired plants and system reliability calculations. A simple proxy for this requirement can be specified by having the installed capacity be no less than the system forecasted peak load plus a 15% margin. In this project, we define this capacity requirement as:

$$Currently\ Installed\ Capacity\ \geq\ Max\ Annual\ Load\ *\ 1.15 \tag{30}$$

This is reasonable, given previous studies and IRPs [23], and the presence of large conventional units in the South. Evaluation of the monetary benefits of this service is usually done by capturing the investment deferral in alternative supply resources for peak conditions, e.g. gas turbines. With the available forecast data for system future annual peak load of the region (described in Section 6.5.3), the currently installed capacity already meets the requirement for more than 20 years. Therefore, no additional capacity is required, and hence no capacity value is modeled in this study.

6.3.2. Energy Arbitrage

Energy arbitrage is known as the “buy-low, sell-high” service where ESS buys energy and charges during off peak periods with low-cost energy and sells and discharges during peak periods with high-cost energy. The service optimal dispatch and revenue are conventionally modeled with an optimization problem that maximizes the net profit of ESS from energy arbitrage at the Locational Marginal Price (LMP) of the ESS pricing node (π^{ene}):

$$\underset{P_t^{ess,chg},P_t^{ess,dis}}{maximize} \sum_{t=1}^{T} \pi_t^{ene}\left(P_t^{ess,dis} - P_t^{ess,chg}\right)\Delta t \tag{31}$$

where the decision variables $P_t^{ess,chg}$ and $P_t^{ess,dis}$ denote the energy storage charge and discharge powers at time step *t*.

LMPs are the outputs of wholesale market clearing process done by ISOs/RTOs. They are publicly available data and can be access through ISO/RTO’s websites. However, the supply of energy in the Southeast is different from the wholesale market areas. As a substitute for LMPs, the Southeast hourly system cost of energy supply is captured in the “System Lambda” that is the output of the utility’s unit-commitment and real-time dispatch optimization problems solved to determine the lowest system operational cost to meet the expected load with the available generation. To evaluate the ESS energy arbitrage in the Southeast, we use system lambda a) instead of and b) besides LMPs in the above maximization problem in the two following cases, respectively:

6.3.2.1.Isolated Southeast

In this case, we assume that the utility buys and sells ESS energy at a price equal to the system lambda (λ) instead of LMP:

$$\underset{P_t^{ess,chg},P_t^{ess,dis}}{maximize} \sum_{t=1}^{T} \lambda_t \left(P_t^{ess,dis} - P_t^{ess,chg}\right)\Delta t \tag{32}$$

Subject to ESS power and energy constraints as in equations (4) – (8).

6.3.2.2.Southeast and Wholesale Markets

In this case, we assume that the utility buys and sells ESS energy at the system lambda (λ) besides the LMP. In other words, the utility has the option to buy and sell energy not only in its own system, but also to other neighboring ISOs/RTOs at their LMPs. Each ISO/RTO market is indexed with *m*:

$$\underset{P^{ess,chg},P^{ess,dis}}{maximize} \sum_{t=1}^{T} \left[\begin{array}{c} \lambda_t \left(P_{t,0}^{ess,dis} - P_{t,0}^{ess,chg}\right) + \\ \sum_{m=1}^{M} \left(\pi_{t,m}^{ene} - C_m^W\right) P_{t,m}^{ess,dis} - \left(\pi_{t,m}^{ene} + C_m^W\right) P_{t,m}^{ess,chg} \end{array} \right] \Delta t \tag{33}$$

C_m^W is the transaction cost with other wholesale markets, which includes “wheel-through” and congestion costs. The total purchased energy for charging and sold energy for discharging are defined as below and are subject to ESS power and energy constraints as in equations (4) – (8).

$$P_t^{ess,dis} = P_{t,0}^{ess,dis} + \sum_{m=1}^{M} P_{t,m}^{ess,dis} \tag{34}$$

$$P_t^{ess,chg} = P_{t,0}^{ess,chg} + \sum_{m=1}^{M} P_{t,m}^{ess,chg} \tag{35}$$

We note that unlike many conventional ESS evaluation studies in market areas, a degradation model is used for ESS operation in this Scenario. The model uses a linear penalty cost for ESS output power, which fits well for Li-ion batteries, the most common technologies in new ESS deployments. The term corresponding to this linear penalty cost is subtracted from the objective function of the above maximization problems. This term can be expressed as:

$$Degradation\ Cost = C^{deg}(P_t^{ess,dis} + P_t^{ess,chg}) \tag{36}$$

The linear degradation coefficient is calculated based on the ESS capital cost and the number of full cycles the ESS can provide before its end of useful life[14].

6.3.3. Ancillary Services

Ancillary services include a few services that support the reliable delivery of energy. Depending on the region/market these services may vary in definition, requirements, pricing and dispatch. Based on our previous studies[15], the two most important and common ancillary services studied in this Scenario are:

- Frequency Regulation: This service is one of the ancillary services specified by FERC under Order 888. It is a market-based service where participants offer their output power capacity to be responsive to the regulation signal, which is a measure of frequency deviation. The signal shows how much of the offered capacity should be dispatched. In some markets such as PJM, it is one product (regulation), while in some other markets such as CAISO it is two separate products for frequency regulation up and down.
- Operating Reserve: Also known as spinning or synchronized reserve, is another market-based ancillary service where participants offer their output power capacity to be able to respond in case of an emergency for an unplanned outage. Resources participating in this service must be dispatched in a short period of time based on the market, usually less than ten minutes.

While these services are generally defined as market-based, other utilities in non-market regions such as the Southeast U.S. still buy or sell such services based on their local requirements and production as well as other systems in the interconnection.

To evaluate the revenue of these services, the following optimization objective function is used:

$$\underset{P^{AS},P^{chg},P^{dis}}{maximize} \sum_t \lambda_t^{AS} P_t^{AS} - \lambda_t \left(P_t^{chg} - P_t^{dis}\right) - C^{deg}\left(P_t^{chg} + P_t^{dis}\right) \tag{37}$$

[14] S. Vejdan and S. Grijalva, "Maximizing the revenue of energy storage participants in day-ahead and real-time markets," *IEEE Clemson University Power Systems Conference 2018*, Charleston, SC, Sept 2018.
[15] S. Vejdan and S. Grijalva, "Analysis of Multiple Revenue Streams for Privately-Owned Energy Storage Systems," *2018 IEEE Power and Energy Conference at Illinois (PECI)*, Feb 2018.

where the first term denotes the ESS revenue from allocating a capacity (P_t^{AS}) for the specific ancillary service at each time step *t*, *AS* indexes the set of ancillary services: frequency regulation and spinning reserve, the second term is the dispatch cost of ancillary service that is calculated based on the energy price (system lambda), and the third term is the degradation cost as described before.

The dispatch of ancillary services is based on real-time control signals that the system operator sends to the resources that have allocated a non-zero capacity for ancillary services. For frequency regulation, a high-resolution (2-second) signal from the historical system data of PJM is used. This signal provides the deviation from the nominal 60 Hz frequency. During normal operation, and assuming no slow frequency oscillations are present, the system frequency can be considered uniform in the interconnection. Thus, the frequency signal provides a proper regulation signal for the Southeast as well. The spinning reserve service is infrequently dispatched and thus, no real-time dispatch signal is associated provided for this service[3].

6.3.4. Transmission and Distribution (T&D) Upgrade Investment Deferral

This service is defined as delaying (and in some cases as entirely avoiding) utility investments in transmission and/or distribution asset upgrades (e.g. substation, feeder, transformer, etc.), using relatively energy storage[16]. Consider a T&D system whose peak electric loading is approaching the system's load carrying capacity (design rating). In some cases, installing a small amount of energy storage downstream from the nearly overloaded T&D node will defer the need for a T&D upgrade. To do so, the storage dispatch (output power and duration) should meet the following requirements:

- ESS discharge output power is high enough to reduce the peak load, so that the net load (load minus storage output power) does not exceed a threshold (the ratings of current T&D assets),
- ESS discharge duration is long enough to keep the maximum load below the upgrade threshold for the peaking periods.

Accordingly, ESS provides the benefit of deferring an investment in upgrading T&D assets. This deferred cost is quantified as the service revenue. The proposed optimization model for evaluating the maximum revenue of this service has the same structure as in ancillary services except that λ_t^{ID} and P_t^{ID} are used instead of λ_t^{AS} and P_t^{AS} to denote the avoided cost per unit of power and deferred upgrade power values, respectively.

The steps to quantify λ_t^{ID} are as follows:

[16] J. Eyer and G. Corey, "Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide," SANDIA Report SAND2010-0815, Feb 2010.

- Forecast the T&D asset peak loading conditions: This can be done for each individual asset. However, due to limited publicly available data for each asset, we use a fraction of the system peak load to represent a plausible constrained peak load of a T&D asset in the system.
- Find the maximum deferrable period as a function of ESS maximum output power.
- Calculate the upgrade cost with a conventional alternative: using a price (e.g. a new small-scale gas turbine may cost about 1500$/kW) multiplied by power rating of the alternative to fully relieve the peak conditions.
- Find the present value of the upgrade cost based on the maximum deferrable period and utility's discount rate.

The conventional models assume this service operation as a pre-dispatch process where ESS provides this service at the highest priority and its residual power and energy are dispatched for other services, e.g. energy arbitrage. However, the proposed approach relies on the optimization model to decide whether to discharge and provide this service or not. This decision is made by comparing the service revenues and results in higher total revenues.

6.3.5. Reliability Improvement and Outage Mitigation

This service entails using ESS to provide highly reliable electric service. In the event of a complete power outage lasting more than a few seconds, the ESS provides enough energy to ride through outages of extended duration to complete an orderly shutdown of processes, and/or to transfer to on-site generation resources[4]. Utilities can benefit from this service to minimize the loss of revenue from energy sales to the customers during outages and minimize the cost of customer's claims for unplanned outages.

The proposed optimization model used for evaluating the maximum revenue of this service has the same structure as for the ancillary services except that λ_t^{RI} and P_t^{RI} are used instead of λ_t^{AS} and P_t^{AS} to denote the avoided revenue loss per power and the sustained power during an outage, respectively:

$$\underset{P^{RI},P^{chg},P^{dis}}{maximize} \sum_t \lambda_t^{RI} P_t^{RI} - \lambda_t^{outage}\left(P_t^{chg} - P_t^{dis}\right) - C^{deg}\left(P_t^{chg} + P_t^{dis}\right) \quad (38)$$

Note that in this service, the ESS dispatch variables (P_t^{chg}, P_t^{dis}) are multiplied by the price λ_t^{outage} which is equal to:

- System lambda during normal conditions

- Zero during outage (islanding)

The steps to quantify the service revenue are as follows:

- Using historical outage data and reliability metrics, outage scenarios are generated as the percentage of customers (load size) impacted by the outage and the duration of outage.
- Using historical energy sales data and estimates of avoided reconnection costs, λ_t^{RI} is determined.
- ESS is dispatched to maximize this service revenue and to mitigate the outage impacts.

We note that the conventional methods for evaluating this service use the Value of Loss Load (VOLL) metric, which depends on the customer type, size and location, which is difficult to quantify accurately. Moreover, VOLL is not the source of a collectible revenue for the utility-owned ESS. Thus, we use the avoided loss of revenue from utility energy sales instead of the VOLL. This approach provides a more accurate and insightful model for the service revenue estimation.

6.4. Simulation Assumptions and Input Data

The important assumptions regarding the simulation of this scenario are described as follows.

- Optimization: Mixed Integer Linear Programming (MILP) model, daily optimization with hourly granularity.
- Forecasting: For future parameters, e.g. load growth rate, we use forecast data published by agencies such as the EIA. If future parameters are not available, we use historical data with the back-casting approach to represent future parameters. In the latter case, results represent the maximum expected value of ESS if they had been deployed in the past. Forecasting future parameters as a part of this task is out of scope, but can prove to be beneficial in a future study.
- Horizon: the study uses a 10-year horizon, where all investments are made at year zero. We assume that there is no salvage/residual value after the storage end-of-life. This is a conservative estimate since the literature discusses end-of-life value for ESS. Using optimization, we maximize the utilization of ESS for 10 years so that at the end of the horizon it reaches its end-of-life. Note that if any timeseries input data has a horizon of less than 10 years (e.g. load and system lambda) we rollover the data to cover the 10-year horizon.
- ESS technical parameters: Fixed throughout 10 years horizon. Sensitivity analysis is performed with respect to a few of them.
- No grid model: all the generation, load and ESS are connected to one node with infinite capacity. This is based on the information that the Southeast region does not currently face critical transmission capacity constraints or congestion. Thus, the assumption of an infinite

transmission capacity is reasonable. In addition, simulation of distribution grid is out of scope.

The required input data for this scenario are described in the next subsections.

6.4.1. Utility-scale ESS parameters

- Technology: Li-ion with the following parameters: lowest-cost battery ESS, 95% charge and discharge efficiency (90.25% roundtrip), negligible leakage, linear degradation cost with respect to energy throughput
- Power rating: 80 MW as described by the 2019 Georgia Power (GP) Integrated Resource Planning (IRP)
- Capacity rating: No information from Georgia Power IRP. We assume 2 hours (most common duration among current BESS based on Department of Energy, Energy Storage Database[17]) at 80 MW (160 MWh) and perform sensitivity analysis.
- Maximum and minimum ESS state-of-charge (SOC) are assumed to be 90% and 10%, respectively, to minimize the overcharging and over discharging stresses on battery's useful life.
- Economic parameters: We utilize the same cost parameters that were used for Scenario 1 and 2. We assume that the total capital cost is equal to $400/kWh as the incurred in the Capex year. The capital cost includes the Li-ion Battery cells and packing cost ($200/kWh) as well as balance-of-system (BOS) cost ($200/kWh). The values of these cost parameters are selected based on estimates of Bloomberg New Energy Finance[18] and NREL Report[19], respectively. We assume that the O&M cost is captured in the BOS cost parameter.

6.4.2. System parameters

The following data has been collected from publicly available databases, e.g. EIA, FERC, GP website, etc.

- System historical hourly load data, peak periods (GP data, usu. hours 13 – 16 weekdays in July and August)
- System load forecast, annual peak demand (GP ~16.4 GW in 2019), annual load growth rate (GP ~0.4%/year)
- System total generation capacity (20.4 GW sum of powerplants available capacities at hour of annual peak demand),

[17] https://energystorageexchange.com
[18] Bloomberg New Energy Finance: Sustainable Energy in America Factbook, 2019
[19] 2018 U.S. Utility-Scale Photovoltaics-Plus-Energy Storage System Costs, National Renewable Energy Lab, Technical Report NREL/TP-6A20-71714 Nov 2018

- Historical system lambda (Southern Company data, 2016 – 2018 at hourly granularity),
- Historical energy sales data (EIA form 861 for GP),
- Historical ancillary service transactions data (FERC form 1 for GP purchases and sales of ancillary services, used to calculate average ancillary service prices (λ_t^{AS}).),
- Historical outage data and reliability metrics (EIA form 861 for GP).

6.5. Simulation Results and Analysis

This Section provides numerical results for Scenario 3 simulated with the developed optimization models and collected data under several important simulation cases and input parameters. For each simulation case, the net present value (NPV) of ESS is calculated as in equation (9), where the total cost is $64 MM all incurred at the CapEx year (year 0). Since this cost includes all the O&M costs, the OpEx years do not include any costs. The cashflows in OpEx years include the ESS service revenues. Simulation cases start with single service analysis. Next, all services are co-optimized with each other using optimal service stacking[3]. For NPV calculation, the discount factor is assumed to be 8%. After each case is simulated, the annual revenues are discounted and used to calculate NPV. Results help decision makers understand the potential benefits and financial viability of ESS in the Southeast region.

6.5.1. System Supply Capacity Revenue

Figure 14 shows the available 10-year forecast data for system summer and winter peak load and the capacity requirement (1.15*annual peak load as in equation (30)) in the Georgia Power territory, as well as the currently installed capacity which already meets the capacity requirement. Therefore, no additional capacity is required, and capacity value of ESS is assumed to be zero in this study.

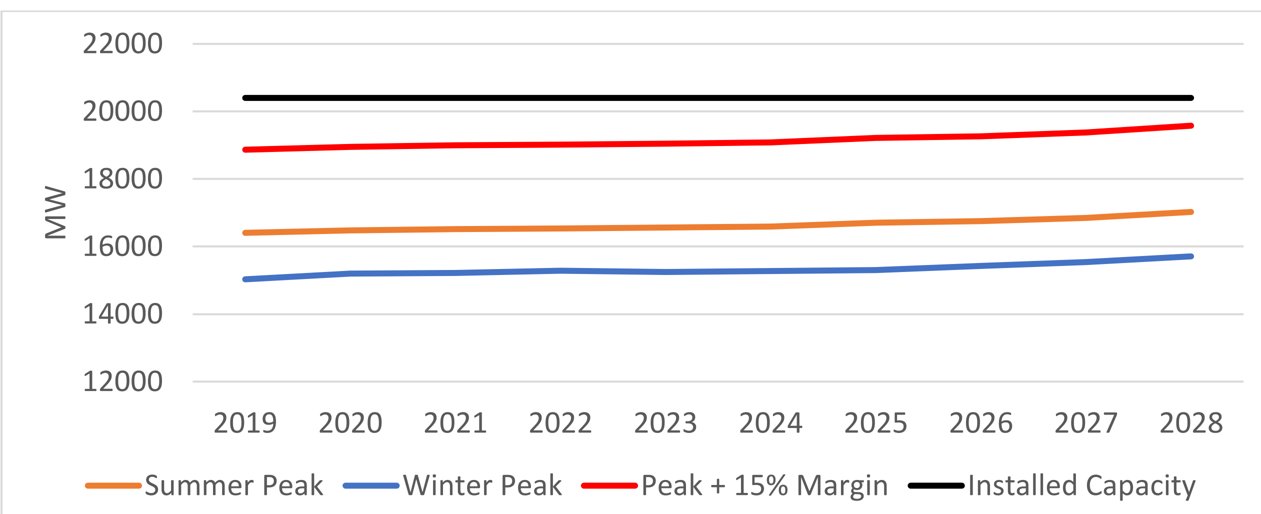

Figure 14 Generation Capacity vs. System Peak Load

6.5.2. Energy Arbitrage Revenue

The energy arbitrage revenue is analyzed in the two cases of isolated Southeast and with the wholesale markets . For the second case, various wheel-through costs are simulated. Results are presented in Table 10. We determined NPV for each case, with an assumption of 8% discount rate. None of the simulated cases provide positive NPV, which is aligned with other studies on Energy arbitrage revenue. However, the simulation results show the potential added value of intermarket arbitrage. We also provide the simple average annual revenue in the Table, as a rough barometer for comparison among the various simulation cases. If Georgia Power can only transact with one market, PJM is shown to be more profitable. Moreover, the cases where Georgia Power transacts with both PJM and MISO result in the highest revenues. Although wheel-through costs in intermarket arbitrage cases decrease the arbitrage revenues, intermarket arbitrage can still significantly increase the revenue compared to the case with arbitrage only within Georgia Power.

Table 10 Energy Arbitrage Results

Sim. Case #	Energy Price Region(s)	Wheel-through Cost(s) (% Energy Price)	Average Annual Revenue (M$)	NPV (M$)
1	GP	0	0.9	-58.0
2	GP, MISO	0, 0	2.6	-46.6
3	GP, MISO	0, 10	2.1	-50.1
4	GP, MISO	0, 20	1.7	-52.5
5	GP, PJM	0, 0	2.7	-46.0
6	GP, PJM	0, 10	2.1	-50.1
7	GP, PJM	0, 20	1.6	-52.9
8	GP, PJM, MISO	0, 0, 0	3.6	-39.9
9	GP, PJM, MISO	0, 10, 10	2.8	-45.1
10	GP, PJM, MISO	0, 20, 20	2.2	-49.2

6.5.3. Ancillary Services Revenue

Ancillary service revenues are analyzed for both frequency regulation (FR) and spinning reserve (SR) services. Analyzing FERC form 1 provides monthly costs of these services for each utility including Georgia Power (GP). Using this data, we calculate the average hourly price of these services for one year. Using PJM RegD signal as a proxy for frequency deviation and dispatch signal in the Southeast, we calculate the hourly averaged dispatch-to-contract ratios that show how much of the allocated capacity are dispatched in real-time. These values are usually between 0.1 to 0.2 for both charge and discharge signals. The spinning reserve service is very infrequently dispatched and thus, no real-time dispatch signal is associated with this service. For the case with multiple regions, the ESS participates in the various markets.

Results are presented in Table 11 where cases with the frequency regulation service have positive NPVs. Note that cases 15 and 16, co-optimize both ancillary services[20]. For the multi-region case, ESS performs arbitrage across time given prices of the various regions. While spinning reserve service can increase the total revenue compared to the energy arbitrage only, it has minimal impact on the revenues of the cases with frequency regulation. This is because the ESS capacity that is not used by energy arbitrage is better utilized in the frequency regulation service which is a bi-directional service compared the spinning reserve (only discharge). In addition, average frequency regulation prices are higher than those for the spinning reserve service. In summary, FR's bi-directional nature and higher market prices explain why FR dominates over SR, when compared as revenue generating ancillary services.

Table 11 Ancillary Service Results

Sim. Case #	Energy Price Region(s)	Ancillary Service(s)	Average Annual Revenue (M$)	NPV (M$)
11	GP	FR	16.7	48.2
12	GP, PJM, MISO	FR	18.6	61.0
13	GP	SR	2.6	-46.4
14	GP, PJM, MISO	SR	4.8	-31.6
15	GP	FR, SR	16.7	48.2
16	GP, PJM, MISO	FR, SR	18.7	61.2

Finally, it should be noted that the market for Frequency Regulation in other regions of the U.S. is very dynamic. There are indications that many ESS systems were deployed to capitalize on revenue streams from this specific ancillary service in the 2013-2018 timeframe. Caution is advised because some studies [25] have observed that Frequency Regulation may eventually plateau or saturate in other markets.

[20] This co-optimization generates a new result that is not merely a simple, additive sum of the two services, since the delivery of multiple services must be coordinated, resulting in some constraints compared to independent cases.

6.5.4. T&D Investment Deferral Revenue

Figure 15 shows the 10-year forecast of GP system annual peak load in per unit (p.u.). Using a linear interpolation, the average annual peak load growth is 3.6%/year. We assume that a specific T&D asset that needs upgrade has the same peak load growth rate as shown in Figure 16 (red plot). Once the ESS is installed to reduce the net load (blue plot in Figure 16), it can defer the T&D upgrade investment. The deferral period can be calculated based on the maximum peak shaving capability of ESS ($P^{ess,dis,max}$), which is determined based on the historical hourly load data and the ESS ratings, as well as the peak load growth rate (r) and the T&D upgrade threshold ($P^{T\&D}$) as:

$$Deferral\ Period\ (DP) = \frac{P^{ess,dis,max}}{rP^{T\&D}} \tag{39}$$

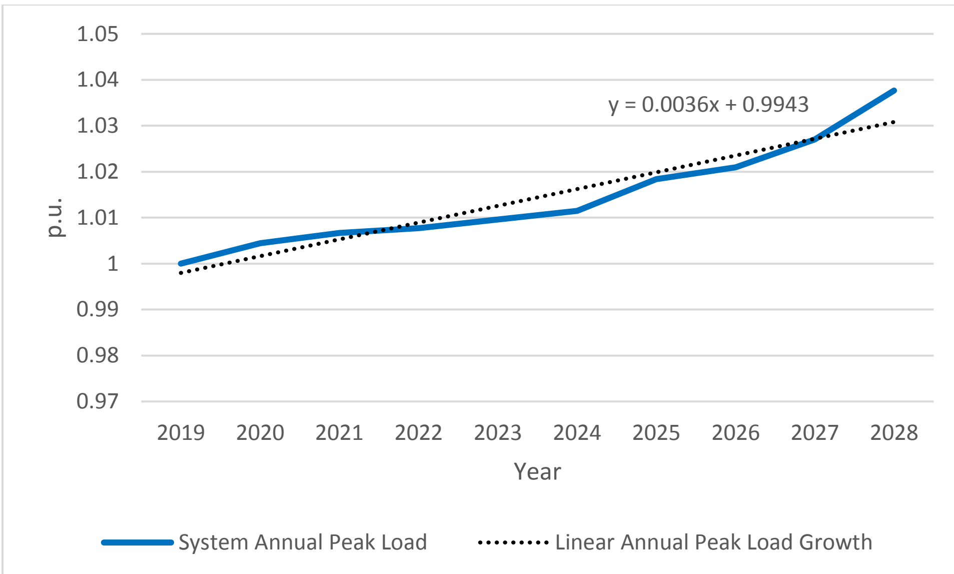

Figure 15 10-year forecast of GP system annual peak load in per unit (p.u.)

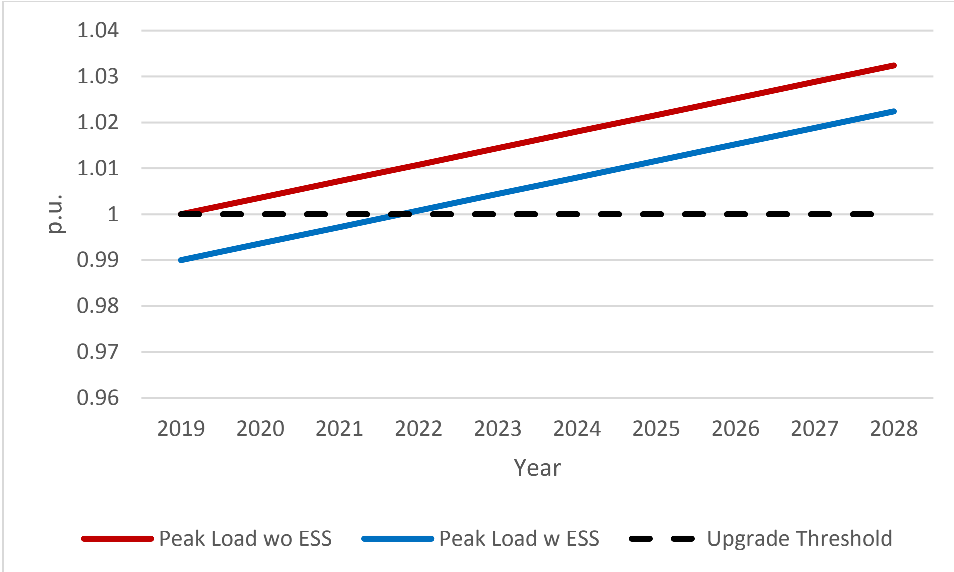

Figure 16 Linearized Peak Load Growth with and without ESS

The present value of the per unit deferred investment cost (λ_t^{ID}) is then calculated as:

$$\lambda_t^{ID} = C^{upg}\left(1 - \frac{(1+i)^{DP}}{(1+d)^{DP}}\right) \tag{40}$$

where *i* and *d* are inflation and discount rates, respectively assumed to be 2.5% and 8%. Parameter C^{upg} is the per unit cost of upgrade investment, which we assume to be \$1.5 MM/MW[21].

We assume that ESS is distributed optimally so that it can shave the system peak effectively. The forecasted system peak for 2019 is 16406 MW which we assume is the T&D upgrade threshold. Also, using the historical hourly load data and the simulated 80 MW / 2 hr ESS, $P^{ess,dis,max}$ is 73MW. Thus, the deferral period is calculated as $\frac{73}{0.0036\times16406} = 1.2$ years which is rounded to 1 year. Thus, λ_t^{ID} is \$76,388/MW. Simulating this service with the developed optimization model and calculated parameters is performed for several cases varying in the size of the T&D asset as a percentage of the sum of T&D peak loads relative to the system peak load. For simplicity, we do not include energy arbitrage in these cases, but the services are co-optimized further in this chapter. Simulation results for the investment deferral service revenue are presented in Table 12.

[21] Cost of a medium size (a few MW) natural gas generator based on National DER Reports

Table 12 Investment Deferral Results

Sim. Case #	Percentage of the T&D Peak Load Relative to the System Peak Load	Deferral Period (years)	λ_t^{ID} ($/MW)	10-year Revenue (M$)	NPV (M$)
17	100	1	76,388	5.6	-58.4
18	50	2	148,888	6.0	-58.0
19	25	5	344,974	6.9	-57.1
20	10	10	610,610	4.9	-59.1
21	5	10	610,610	2.4	-61.6
22	1	10	610,610	0.5	-63.5

Results show that when ESS is used to peak-shave a bigger aggregated load (100% of the system load in case 17) it may not have enough capacity to do so and since the load is large, the deferred period might be very short, e.g. only 1 year in case 17. However, as the T&D load size decreases, ESS can fully peak shave it and defer the investments to further years, e.g. 5 years in case 19. This results in higher avoided costs or revenues. Moreover, if the T&D load size further decreases, the value of the deferred investment decreases much more than increase in the added value of a longer deferred period. Note that since the ESS project horizon and its end-of-life is assumed to be 10 years, the maximum deferred period is 10 years.

A key takeaway from these simulation results is that a distributed ESS (case 19) can provide higher revenues in this service compared to an aggregate ESS (case 17). Thus, the optimal placement of distributed ESS can have significant impacts on the economics of the project, which is out of scope of this study. Another key takeaway is that while Investment T&D Deferral can deliver some benefits, it would generally need to be stacked with other value streams to contribute to an economically viable ESS investment.

6.5.5. Reliability Improvement Revenue

Reliability data for electric utilities in the U.S. are provided in EIA form 861. The GP reliability data in 2018 shows that the System Average Interruption Duration Index (SAIDI) is 227.4 minutes with 2,456,340 total number of customers. This translates to 9,309,528.6 hours of total customer interruption duration in the GP territory. The same data base provides energy sales data where the average electricity sales for GP is $0.09/kWh. An average customer consumes 33.7 MWh per year. Assuming a constant load, the average hourly load of each customer in GP is 3.847 kW. Using this data, the annual GP loss of revenue from interruptions is calculated as $3,223,486. ESS can save some of this lost revenue by providing backup power. Results for cases with different ESS capabilities in saving the lost revenues are provided in Table 13. Note these results are conservative since interruptions impose many charges, e.g. reconnection, customer claims, etc., on the utilities and using ESS a utility can avoid those costs and adds to the service revenue. However, the provided conservative results serve as the worst-case lower bound for the revenue of this service.

Table 13 Reliability Improvement Results

Sim. Case #	Percentage of the Interruption Mitigation	Annual Revenue (M$)	10-year Revenue (M$)	NPV (M$)
23	100	3.2	21.6	-42.4
24	50	1.6	10.8	-53.2
25	25	0.8	5.4	-58.6
26	10	0.3	2.2	-61.8

6.5.6. All Service Revenues Co-optimized

Cases where all the studied services are co-optimized are presented in Table 14. For a better insight, 4 cases are simulated where two of use GP system lambda as energy price (cases 27 and 29) and the other two enable intermarket energy arbitrage (cases 28 and 30). Also, other service parameters such as wheel-through costs (0, 20%), percentage of T&D peak load (25%, 1%), and percentage of interruption improvement (100%, 10%) are assumed to be equal to their “best” and “worst” values that result in the highest and lowest revenues, respectively. These are shown under the column “Other Parameters” in the Table.

The results presented in Table 14 shows that multiservice ESS optimization can provide significant economic benefits and improve the ESS project financial viability. Even though the results report aggregated results, it should be noted that the largest portion of the revenue is from the frequency regulation service. This is consistent with other research studies, such as [3], where frequency regulation service provides the highest revenue among services under wholesale market territories. Payback periods are as low as 4 years. Even under the worst simulation case, the payback period is 5 year which is equal to the half of the ESS useful life. This small difference between payback periods and estimated revenues (between highest and lowest simulations) is reassuring, and provides a compelling justification for the economic viability of utility-owned ESS value stacking.

Table 14 All Services Co-Optimized Results

Sim. Case #	Energy Price Region(s)	Other Parameters	10-year Revenue (M$)	NPV (M$)	Payback Period (Years)
27	GP	Best	133.1	69.2	4
28	GP, PJM, MISO	Best	146.0	82	4
29	GP	Worst	114.5	50.5	5
30	GP, PJM, MISO	Worst	111.2	45.1	5

6.6. Scenario Conclusion

This chapter has developed simulation of various ESS services. The simulation of service co-optimization results in significant benefits and improve the ESS project financial viability.

While spinning reserve service can increase the total revenue compared to the energy arbitrage only, it has minimal impact on the revenues of the cases with frequency regulation. This is because the ESS capacity is better utilized in the frequency regulation service, which is a bi-directional service compared the spinning reserve. The largest portion of the revenue is derived from frequency regulation.

The simulation results provided in this chapter show that even under the most conservative simulation assumptions, multiservice ESS can reach a payback period of 5 years. The simulations were performed based on the current capital costs of ESS while these costs are decreasing every year. Thus, it is expected that the multiservice ESS payback periods can further decrease.

7. Conclusions and Future Work

7.1. Study Conclusions

The economic benefit and impact of energy storage systems depends on the technology properties, the regional generation and grid characteristics, as well as key policies, regulatory structures, and rate designs.

Emerging advanced optimization methods, coupled with integrated modeling and publicly available data enable the assessment of energy storage for a number of relevant use cases and applications. In this study, tree scenarios have been studied: 1) ESS Owned and operated by end use customer, 2) ESS owned by end use customer, but jointly operated by the customer and the utility, and 3) ESS owned and operated by the utility.

The Simulation results for Scenario 1, ESS owned and operated the customer, show that under the current tariff rates, C&I customers who are exposed to demand charges can greatly benefit from BTM ESS investment. The significant cost savings result in payback periods of as low as 5 years for these customers. Residential customers exposed to demand charges can also benefit from BTM ESS where the payback periods are around 10 year. Although residential ESS is not as profitable as C&I, with the decreasing capital costs of ESS, it is expected that residential ESS become more profitable. In terms of system impacts, high penetration of BTM ESS can have significant impact on the system net load. Tariff rates with demand charges result in smoother net load profiles that are more desirable from the system operator's perspective.

In the case of Scenario 2, ESS owned by the customer but operated jointly with the utility, the simulation results show that ESS can have negative impacts on the utility's revenue. Two joint operation strategies were proposed that utilities can operate BTM ESS jointly with the customers to hedge against their revenue loss while customers can still benefit from BTM ESS. The first strategy, passing through wholesale prices, is not financially attractive and result in payback periods of more than 15 years. However, this strategy is revenue neutral for the utility. The second strategy, renting BTM ESS, has the same profitability for the customers as Scenario 1 and the utility can benefit from operating BTM ESS to maximize its own objective function. Optimization results show significant revenues can be obtained by the utility from energy arbitrage depending on the price variability of the location. This strategy will always result in lower losses of utility's revenue compared to Scenario 1.

In Scenario 3, Utility Owned and Operated ESS, simulations show that service co-optimization results in significant benefits and improve the ESS project financial viability. While spinning reserve service can increase the total revenue compared to the energy arbitrage only, it has minimal impact on the revenues of the cases with frequency regulation. This is because the ESS capacity is better utilized in the frequency regulation service, which is a bi-directional service compared the spinning reserve. The largest portion of the revenue is derived from frequency regulation.

The simulation results provided in this chapter show that even under the most conservative simulation assumptions, multiservice ESS can reach a payback period of 5 years. The simulations were performed based on the current capital costs of ESS while these costs are decreasing every year. Thus, it is expected that the multiservice ESS payback periods can further decrease.

This study can valuable to utilities, policy-makers, researchers and other stakeholder for several reasons. First of all, several novel optimization methodologies have been developed that can be used to evaluate the relative economic merits of ESS under a range of scenarios, input conditions, and performance parameters. Second, the methods and approaches can be extended to include additional parameters, such as CO2 costs, CO2 emission, and welfare effects. Finally, the project provides detailed insights into the comparative economic benefits of major ESS use cases from the perspective of residential customers, large commercial customers, and utilities. The results suggest there are significant opportunities and net economic benefits from ESS systems, whether owned and operated by large customers or utilities, or jointly-operated by both. Taken together the methodologies and findings can contribute to informed investment decision-making and policy analysis in the Southeast region, and beyond.

7.2. Study Limitations

The study assumptions are limited to currently known parameters and uses a 2030 horizon. This time horizon will permit us to compare key scenarios at a sufficient scale for decision-makers, yet maintain confidence in key technology and systems assumptions, such as ESS performance attributes, tariffs, and generating resources. The study has not conducted sensitivity analysis for these parameters.

Battery costs have experienced a rapid decline in the last decade. The study however, assumes that the decision is made at present costs, without including the impact of storage cost forecasting on financing parameters.

For reasons of simplicity and lack of data and CO2 market signals in the Southeast, we did not assume a cost for CO2, nor did we did consider CO2 in the optimization. We also did not estimate emissions change by scenario. However, the methodologies would readily lend themselves to such analyses for future optimization studies.

7.3. Future Work

Future work on the analysis of ESS in the Southeast can follow several directions:

- Inclusion of the impact of emissions, which requires corresponding development of production costing and generation dispatch simulations with energy storage.
- Sensitivity analysis, most notably, considering implications of expected cost reduction on ESS.
- Expansion of the study to analyze additional rates that are present in the Southeast.
- Analyze the impact of modification to rate design on the benefit of ESS and their allocation.

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