Behind-the-Meter Energy Storage: Economic Assessment and System Impacts in Georgia

Sadegh Vejdan, Adam Kline, Mason Totri, and Santiago Grijalva
School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, GA, USA

Richard Simmons
Strategic Energy Institute
Georgia Institute of Technology
Atlanta, GA, USA

***Abstract*—This paper presents an optimization approach to maximize the value of behind-the-meter energy storage that is owned and operated by customers. The objective of the optimization problem is to minimize the customer's electricity bill under various utility tariff rates. Each rate structure results in different options for the formulation of the optimization problem. Publicly available utility tariff rates from Georgia Power are used. The investment cost assumptions are derived from the latest market reports and from available vendor data. The impact of utility tariffs on the energy storage economics and system impacts are quantified. The simulation results show that different categories of behind-the-meter customers can obtain benefits from the installation of energy storage in this region. Moreover, tariffs with demand charges are usually more profitable for customers with energy storage and more desirable for the system operators to achieve a smoother net load curve.**

***Index Terms*--Behind-the-meter, cost-benefit analysis, energy storage, optimization.**

NOMENCLATURE

A. Sets and Indices

$\mathcal{T}$	Set of time periods 1 to T indexed by t
$\mathcal{L}$	Set of demand levels 1 to L indexed by l
$\mathcal{T}_l$	Set of time periods for each demand level l
$\mathcal{B}_e$	Set of energy blocks 1 to B_e indexed by b
$\mathcal{B}_d$	Set of demand blocks 1 to B_d indexed by b
n	Index of customers 1 to N
y	Index of years 1 to Y

B. Variables

$P^{dis/chg}$	Discharging/charging power of energy storage
$u^{dis/chg}$	Binary state variables for discharging/charging
E^s	Stored energy in the energy storage
P^{net} / E^{net}	Net power/energy consumed by the customer
P^{dem}	Customer's demand, i.e. maximum net consumed power
$u^{ene/dem}$	Binary variables for stepwise energy/demand charges

C. Parameters

π_t^{ene}	Energy price at time t
π_l^{dem}	Demand price at level l
$C_b^{ene/dem}$	Energy/demand price at block b
Δt	Duration of each time step in hours
P^{load}	Customer's load
$P_{\max}^{dis/chg}$	Maximum discharging/charging power of energy storage
s	Status parameter showing whether net metering is applicable (1) or not (0)
η	Leakage efficiency of energy storage
$\eta_{dis/chg}$	Discharging/charging efficiency of energy storage
$E_{\max/\min}^s$	Maximum/minimum allowable stored energy
$E_{0/T}^s$	Stored energy at the beginning/end of the time horizon
$E_b^{\max}$	Maximum monthly customer's net energy consumption in block b
$P_b^{\max}$	Maximum monthly customer's power demand in block b
ε	A small positive number

I. INTRODUCTION

Energy Storage Systems (ESS) can provide several services that can benefit industry stakeholders, including the customer, the electric utility, and ESS providers [1]. They can compensate the variability of renewable energy sources smoothing their output, and provide other grid services including load shaping, backup, and frequency regulation [2]. The use cases for ESS and their economics vary significantly depending on the ESS technology, regulatory regimes, rate structures, and incentives in various regions. For instance, the Southeast region is generally confronted by market and regulatory conditions, which are substantially different from other states, where explicit state subsidies and/or procurement targets have been enacted, or where explicit market signals incentivize and compensate owners for grid services. Analysis of the benefits of behind-the-meter (BTM) ESS hence requires

This work is partially supported by the Georgia Tech Energy Policy and Innovation (EPI) Center Grant "Assessment of Grid-Scale Energy Storage Scenarios for the Southeast".

978-1-7281-0407-2/19/$31.00

detailed modeling of the rate structures and specific regulatory aspects of each region.

In this paper, we propose a generic optimization method for determining the economic benefits of BTM battery ESS for the customers. The method covers diverse and realistic utility tariff rates, which is an innovative feature in software tools for ESS studies. The economics and system level impacts of BTM ESS are assessed using the optimization approach. The specific contributions of the paper are:

a) Proposing a generic optimization approach considering various tariff rates including energy charges, time-of-use, demand rates, and real-time pricing,

b) Assessment of both BTM use benefits as well as system level impacts,

c) Insights on the economic viability of BTM ESS for customers in the Southeast region, yet with generalized models that can be applied in other regions, and

d) Mechanism to analyze the interplay between rates and EES impacts. This research provides insights into the impact of regulatory policies associated with BTM ESS deployment in a region.

The rest of this paper is organized as follows: Section II presents a literature review focusing on BTM ESS system, Section III describes the optimization, system impact analysis and benefit/cost methodology. Section IV describes the development of the datasets needed for the simulation. Section V provides the simulation results, and section VI presents the conclusion of this work as well as directions for future efforts.

II. Literature Review

Historically, battery ESSs have often been used as a complement to photovoltaic systems (PV), in order to maximize the benefits derived from the solar panels [3]. However, current studies have shown that various optimization techniques can utilize standalone ESS to generate reliable revenue streams for BTM customers under both time-of-use (TOU) and demand charge (DC) tariffs [2]-[14]. Customer bill management and opportunities for energy arbitrage (EA) have been the primary drivers for standalone BTM research. Depending on the cost of the ESS, these revenue streams can result in reasonable payback periods that demonstrate the economic viability of ESS systems in certain conditions [2]-[5]. Under a TOU tariff, EA is the primary source of revenue, however [2], [5], and [6] demonstrate that when the tariff includes a DC, then peak shaving is significantly more profitable than EA. In fact, when optimizing for battery capacity and power under a DC tariff, the quickest pay back periods are seen with smaller batteries, because generally the revenue from DC cost reduction grows linearly while the cost of energy necessary for peak shaving experiences exponential growth [5], [7], and [8]. While most studies focus on existing battery technologies, [9] demonstrates that if the price of batteries drops in the future (as predicted), the payback period of larger batteries will continue to approach that of smaller capacity batteries.

Another benefit of utilizing ESS for peak shaving applications is that since the DC is calculated monthly, with proper optimization only the peak loads for the month need to be shifted, which can allow operators to avoid daily cycling and can extend the operational lifespan of their ESS [8]. One concern with ESS is that in order to generate revenue, the system must be optimally operated. However, [4] shows that even when forecasting errors are present in the model, there is a minimal impact on the overall revenue of the system and resulting payback period. The impact of BTM battery ESS deployment on CO_2 emissions is mixed, and not fully explored in selected regions. While some specific use cases of ESS can decrease net emissions, [7] determined that in specific regions the composition of the generation fleet results in a net increase in overall emissions when incorporating ESS, which means that tariff redesign may be necessary to reduce overall emissions. While previous studies have demonstrated the viability of ESS in a variety of use cases, this study provides a comprehensive view of how the varied rate structures currently used in the Southeast have an impact on both the payback period and optimal operation of BTM ESS to aid owner/operators in making informed decisions on the procurement and operation of ESS in today's market.

III. Proposed Methodology

In this Section, the methodologies and assumptions developed for the simulation of BTM ESS are presented. The simulation workflow is illustrated in Fig. 1. The analytical modules include:

- Optimization,
- System Impact Analysis, and
- Benefit Cost Analysis.

These modules are discussed in the next subsections. The input data required for this study is discussed more in detail in the next Section.

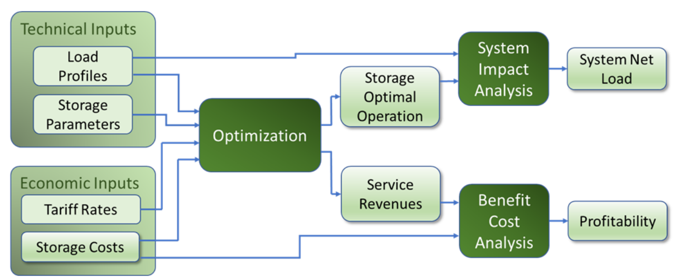


Figure 1. The simulation workflow.

A. *Optimization*

The core of the methodology developed is the temporal optimization module. Using this module, customers who own and operate ESS can evaluate the minimum monthly charge for their electricity bill. Equivalently, the optimization determines the optimal operation of ESS that minimizes the monthly electricity charge subject to ESS parameters, tariff rates, and customers' load profiles.

Regardless of the inputs, the optimization can be generically modeled as in (1)–(12). The objective function in (1) is the monthly electricity charge that consists of energy charge (the first two terms) and the DC (the second two terms). The energy charge can be calculated based on either a TOU tariff (with price π_t associated with each time period t) or an energy-tiered tariff (with energy price C_b associated with block b of a stepwise function). The DC can also be calculated similarly.

$$\min \sum_{t=1}^{T} \pi_t^{ene} P_t^{net} \Delta t + \sum_{b=1}^{B_e} C_b^{ene} E_b^{net} + \sum_{l=1}^{L} \pi_l^{dem} P_l^{dem} + \sum_{b=1}^{B_d} C_b^{dem} P_b^{dem} \tag{1}$$

s.t. $\forall t \in \mathcal{T}$

$$\{ P_t^{net} = P_t^{load} + P_t^{chg} - P_t^{dis} \tag{2}$$

$$-sP_{\max}^{dis} \le P_t^{net} \tag{3}$$

$$0 \le u_t^{dis} + u_t^{chg} \le 1 \tag{4}$$

$$0 \le P_t^{dis} \le P_{\max}^{dis} u_t^{dis} \tag{5}$$

$$0 \le P_t^{chg} \le P_{\max}^{chg} u_t^{chg} \tag{6}$$

$$E_t^s = \eta E_{t-1}^s + \left(\eta_{chg} P_t^{chg} - P_t^{dis} / \eta_{dis} \right) \Delta t \tag{7}$$

$$E_{\min}^s \le E_t^s \le E_{\max}^s \tag{8}$$

$$E_T^s = E_0^s \} \tag{9}$$

$$0 \le E_b^{net} \le E_b^{\max} u_b^{ene} \quad \forall b \in \mathcal{B}_e \tag{10}$$

$$u_b^{ene} \ge u_{b+1}^{ene} \quad \forall b \in \mathcal{B}_e \setminus \{B_e\} \tag{11}$$

$$u_{b+1}^{ene} \le \frac{E_b^{net} - E_b^{\max}}{E_b^{\max}} + \varepsilon \le 1 + u_{b+1}^{ene} \quad \forall b \in \mathcal{B}_e \setminus \{B_e\} \tag{12}$$

$$\sum_{b=1}^{B_e} E_b^{net} = \sum_{t=1}^{T} P_t^{net} \Delta t \tag{13}$$

$$P_t^{net} \le P_l^{dem} \quad \forall t \in \mathcal{T}_l, \forall l \in \mathcal{L} \tag{14}$$

$$0 \le P_b^{dem} \le P_b^{\max} u_b^{dem} \quad \forall b \in \mathcal{B}_d \tag{15}$$

$$u_b^{dem} \ge u_{b+1}^{dem} \quad \forall b \in \mathcal{B}_d \setminus \{B_d\} \tag{16}$$

$$u_{b+1}^{dem} \le \frac{P_b^{dem} - P_b^{\max}}{P_b^{\max}} + \varepsilon \le 1 + u_{b+1}^{dem} \quad \forall b \in \mathcal{B}_d \setminus \{B_d\} \tag{17}$$

$$\sum_{b=1}^{B_d} P_b^{dem} = P_l^{dem} \tag{18}$$

Constraint (2) defines the net load as the load plus ESS output where charging is considered as a positive load and discharging is a negative load. Constraint (3) limits the lower bound of the net load. If net metering does not apply (s=0), the negative net load is avoided. Conversely (s=1), the net load can be a negative value bound by the negative of the ESS maximum discharging power. Constraints (4)–(9) model ESS technology constraints [15]. Simultaneous charging and discharging operation is avoided by (4). Discharging and charging powers are limited by their maximum ESS ratings in (5) and (6), respectively. Constraint (7) models the ESS energy level evolution at each time step based on the previous time step and the current output powers. The limits on energy level are modeled in (8) where energy level should not exceed its minimum and maximum allowable energy levels to avoid over-discharging and overcharging, respectively. Constraint (9) enforces the energy level at the end of the last time step to be equal to the energy level at the beginning of the first step.

Constraints (10)–(13) define a stepwise function for the monthly energy consumption. As an example, some tariffs charge customers at C_1 \$/kWh for the first $E_1^{\max}$ kWh of their monthly consumption and at C_2 \$/kWh for their next $E_2^{\max}$ kWh. If TOU tariff is applicable, there is only one C_b that models overhead charges energy charge available in some tariffs, e.g. fuel cost recovery. Constraint (14) defines the demand for each demand level l, i.e. the maximum net load over all the time steps in period $\mathcal{T}_l$. We associate demand levels with the temporal variability of DCs, e.g. a two-level demand rate with level one being 5\$/kW during off-peak and level two being 10\$/kW during on peak hours. Moreover, if demand rates are variable based on the maximum demand, i.e. a stepwise function of demand, only one demand level is assumed and the set $\mathcal{T}_l$ is equal to $\mathcal{T}$. In this case, constraints (15)–(18) define the stepwise function for the monthly demand. Note that in both energy and DCs if C_b's are nondecreasing with b, the objective function is convex and integer variables u_b^{ene} and u_b^{dem} are relaxed as well as constraints (11), (12), (16), and (17). Otherwise, these constraints enforce the order of blocks in the optimization, i.e. the block b_1 is used first to include the energy/demand and only if b_1 has reached its maximum of $E_1^{\max}/P_1^{\max}$ then u_2^{ene}/ u_2^{dem} can become 1 and b_2 is used to include the rest of the energy/demand and so on.

B. System Impact Analysis

The system impact of BTM ESS shows how the system's total net load (NL) profile changes under various tariff rates and ESS penetration levels (PL: the proportion of total customers with BTM ESS). It is expected that customers seeking to minimize their bill operate their ESS as determined by the proposed optimization problem. Therefore, the system impact is calculated using the optimal ESS operation of the customers. If there are N customers under study, the system's net load at time t is found using (19). This calculation is useful for planning studies as well as rate design.

$$NL_t(PL) = \sum_{n=1}^{N} P_{t,n}^{load} + PL\left(P_{t,n}^{chg*} - P_{t,n}^{dis*} \right) \tag{19}$$

C. Economic Analysis

The profitability of BTM ESS is calculated using economic metrics such as net present value (NPV) and payback period (PP). The optimal revenues found by the optimization module are passed into the Benefit-Cost Analysis module where they are first subtracted by the storage costs. The metrics are then calculated using (20) and (21).

$$NPV(Y) = \sum_{y=1}^{Y} \frac{Revenue_y - Cost_y}{(1+r)^y} \tag{20}$$

$$PP = \min y \quad ; \quad NPV(y) \ge 0 \tag{21}$$

where Y is the expected storage life and r is the discount rate. As in (21), payback period is the first year whose NPV is nonnegative (if exists). The profitability results are helpful information for customers' investment decisions in managing their electricity bill.

IV. Data Collection

In order to simulate the impact of rate structures on optimal operation and payback period in realistic cases, the required input data was collected strategically to represent actual load data sets and battery parameters. Thus, the results better match real-life scenarios, which is critical for decision making.

A. Load Profiles

For residential customer load profiles, we use the Pecan Street Database [16], 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 sum of daily load profiles for summer (June through September) and winter months (October through May) are plotted with the system impact results in the Section V.A.

For commercial and industrial (C&I) load profiles, we use a publicly available data source supported by Department of Energy (DOE) [17]. 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. Fig. 2 shows the demands (maximum hourly load) and average hourly consumption of the diverse set of load profiles used which represent a realistic spread of actual commercial load variability to better visualize ESS impact. The average daily load profiles for summer and winter months summed up over all these customers are also plotted in Section V.B.

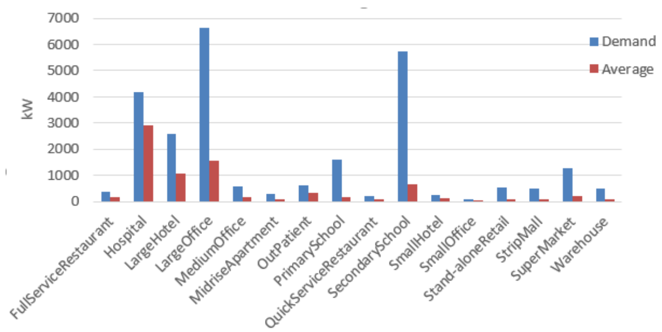


Figure 2. Maximum and average of C&I loads per each building type.

B. ESS Parameters

For residential customers, ESS parameters are selected based on Tesla Powerwall [18]: 7 kW maximum charging/discharging rates, 15 kWh total and 13.5 kWh usable capacity (90% depth of discharge), and 90.25% roundtrip efficiency (95% charging efficiency × 95% discharging efficiency). The cost of the Powerwall is 6700 $/module (equivalent to about $500 per usable kWh of storage). We use this number as fixed capital cost and assume no fixed or variable O&M costs. Based on the load profiles, one module is calculated to be enough for each customer.

For C&I customers, ESS power ratings ($P_{\max}^{dis/chg}$) are selected based on their load profiles. These ratings are assumed to be both equal to 20% of the customer's annual maximum load. The capacity rating is selected as 2 hours for all customers which based on the most common duration parameter for BTM application available at DOE, Energy Storage Database [19]. We assume the same ESS technology used for residential customers are used for C&I but in larger scale. Therefore, the depth of discharge and efficiencies are assumed similar to those of the residential ESS. The total cost (sum of capital and O&M costs) is assumed to be $400/kWh [20] and incurred in the Capex year.

C. Utility Tariffs

We used publicly available Georgia Power tariff schedules and rate structures [21] to create the tariff parameters. Strictly energy-tiered (net consumption) tariffs with no demand charges are not considered for the residential simulations since ESS cannot take advantage of this price structure to offset costs. Only residential TOU tariffs provide economic benefits. There are three of such rates: Nights & Weekends (N&W), Plug-In Electric Vehicle (PEV), and Smart Usage (SU). The SU rate includes DC and TOU energy charges. The C&I load profiles in this study are grouped into medium (demand≤500kW) and large (demand>500kW) subtypes based on Georgia Power definition. For each subtype, the most common two rates are used: energy-tiered with DC (Power and Light, PL), and TOU. Regardless of the customer type, the breakdown of a customer's bill is as follows:

$$\begin{aligned}&\textit{Total Monthly Bill Charge} = \textit{Base Rate} + \textit{Other}\\ &\textit{Schedules} + \textit{Municipal Franchise Fee} + \textit{Sales Taxes}\end{aligned} \tag{22}$$

where

$$\begin{aligned}&\textit{Base Rate} = \textit{Basic Service Charge} +\\ &\textit{Energy Charge} + \textit{Demand Charge}\end{aligned} \tag{23}$$

$$\textit{Basic Service Charge} = \textit{Fixed} \tag{24}$$

$$\textit{Energy Charge} = \textit{Energy*rate [c/kWh]} \tag{25}$$

$$\textit{Demand Charge} = \textit{Demand*rate [\$/kW]} \tag{26}$$

$$\begin{aligned}&\textit{Other Schedules} = \textit{25\% Base Rate} + \textit{Energy*Fuel}\\ &\textit{rate [c/kWh]}\end{aligned} \tag{27}$$

$$\begin{aligned}&\textit{Municipal Franchise Fee} = \textit{2.9989\% (Inside City}\\ &\textit{Limits) of sum of all above}\end{aligned} \tag{28}$$

$$\textit{Sales Taxes} = \textit{6\% of sum of all above} \tag{29}$$

As can be compared, the proposed optimization formulation (1)–(18) can model all of the above details. Using these tariff structures creates six test cases for residential: three cases of TOU where customers can sell back to the utility (net metering is applicable, s=1), and three cases where they cannot (s=0). The C&I tariff structures create six cases as well: two TOU rates and two energy-tiered with DC. For the two TOU rates, two cases where the customer can sell and cannot sell are analyzed. For each test case, the ESS annual revenues for each customer under a specific tariff type were calculated by solving the optimization problem. The results are provided in the next Section.

V. Simulation Results

The developed simulation was used to determine the profitability and system level impacts of BTM ESS in various test cases for both residential and C&I customers.

A. Residential Test Cases

Each of the three residential TOU tariff rates is simulated twice with either s=0 or s=1 for all residential customers. Table I shows economic results namely the customer's savings and payback periods for the six test cases. Due to the variability of customers' load profiles, a distribution of savings and payback periods is obtained. For the first four cases, most of the customer savings are close to the maximum value. Therefore, the reported median (Med) represents the savings for a typical customer. The maximum savings (Max) shows the best case, which is not much greater than the median. Thus, the customers' savings are very close to the maximum possible regardless of their load profiles. For test cases (2) and (4), since the only revenue is from energy time-shifting with no demand charge and the customers can sell energy, the optimization problem and its outputs are no longer dependent on the load profile. Moreover, since the rates are known with certainty in advance, all customers can obtain maximum revenue and minimum payback period in these two cases.

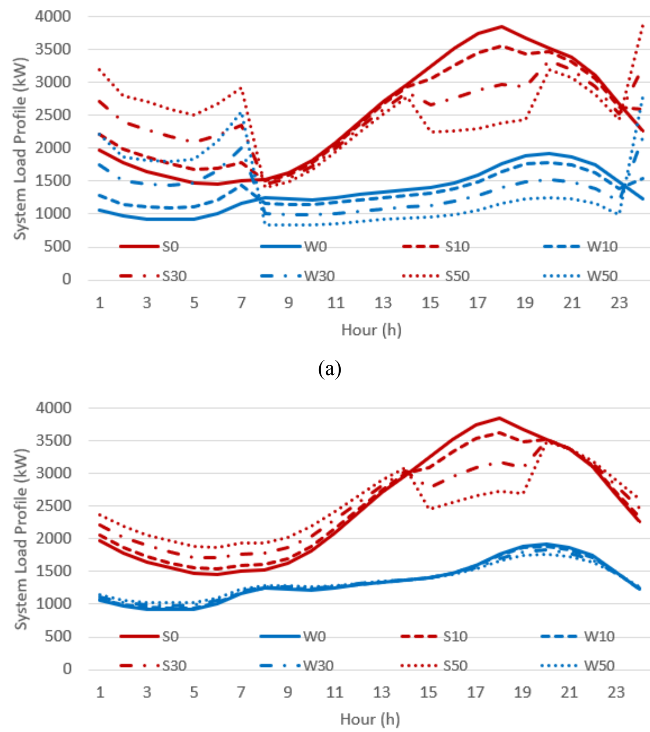
TABLE I. ECONOMIC RESULTS FOR RESIDENTIAL TARIFFS

Test Case #	Rate	Annual Cust Savings ($)		Payback Period (years)	
		Med	Max	Med	Min
1	N&W (*s*=0)	248	277	27.0	24.2
2	N&W (*s*=1)	277	277	24.2	24.2
3	PEV (*s*=0)	600	643	11.2	10.4
4	PEV (*s*=1)	643	643	10.4	10.4
5	SU (*s*=0)	289	635	23.2	10.5
6	SU (*s*=1)	305	688	21.9	9.7

The minimum payback period for the N&W rate is higher than the other rates since the energy rate is flat during winter months and ESS optimal dispatch is nonzero during the weekdays of four summer months where the energy rate is not flat. While test cases (3)-(6) each have a minimum payback period of less than 11 years, it is important to note that the median payback periods for test cases (5) and (6) are more than double their minimum payback periods, while in test cases (3) and (4) there is a minimal increase between the median and minimum payback periods. This demonstrates how the PEV tariff provides reliable revenue for the majority of residential ESS owners, while the potential revenue from the SU tariff is highly dependent on the individual load profile of the customer. This is driven by the DC in the SU rate that makes the optimization dependent on the load profile. In summary, while the SU rate with *s*=1 provides the lowest payback period, the risk associated with the savings from this rate is higher than that of the PEV rate. The PEV rate, however, can provide less risky savings with 10 to 11 years of payback period.

The system level impact is calculated from the optimal ESS dispatch of all the customers using (19). For brevity, the results for test cases (3) and (5) are presented in Figs 3(a) and 3(b), respectively. The first letter (S/W) shows the season and the number after that is the percentage of penetration level of ESS in the system ($PL\times100$). Summer and winter months are plotted separately to capture the impact of the seasonal changes in tariffs.

The high peak prices in both cases incentivize the customers to discharge their ESS during the afternoon hours of summer months and lower their bills. Therefore, peak prices in both these tariffs is a proper signal to shave the summer afternoon peak. However, in test case 3, the peak load is shifted to the super-off-peak hours (11pm to 7am). This can become challenging especially with the increasing penetration of BTM ESS resulting in new peak hours and increasing the generation ramping requirement around the hours that tariffs change their rate. Test case 5, on the other hand, results in a more desirable system impact with the peak load shifted almost evenly throughout the nonpeak hours. The above comparison holds for winter months as well. The more desirable system impact of case 5 is due to the DC in SU tariff that incentivizes the smooth total load that minimizes demand.



(a)

(b)

Figure 3. System level impact of BTM ESS for test cases a) 3 and b) 5.

B. *C&I Test Cases*

The four C&I test cases (two subtypes and two rates each) are simulated and results are presented here. The parameter *s* is unnecessary here since the net load does not become zero in any case for any of the customers. Table II shows the minimum, median and maximum payback periods for these cases. Since the ESS is different for each C&I customer, their total bill and also their savings cannot be compared directly and thus not reported in Table II.

TABLE II. ECONOMIC RESULTS FOR C&I TARIFFS

Test Case #	Rate	Payback Period (years)		
		Min	Med	Max
7	P&L-M	7.7	9.6	12.7
8	TOU-M	5.2	6.8	7.4
9	P&L-L	5.7	8.2	16.9
10	TOU-L	44.6	44.6	44.6

Results for test cases 7, 8, and 9 show promising payback periods. Especially, the TOU tariff for medium-sized loads (case 8) provides the best payback periods in less than 7.4 years regardless of the load profile. This indicates that many of such customers can considerably and reliably benefit from the installation of a BTM ESS at their sites. Also, for the large customers, the TOU tariff results in relatively low payback periods but with more risk compared to the TOU-M. In case 9, the median payback period is higher than that of case 8, which shows that the profitability of installing ESS is more dependent on the customer's peak demand and how much energy is needed to reduce the peak demand. The payback periods in the case 10, TOU tariff for the large customers, are all very large and nonprofitable since the rate is flat for 8 months and the ESS revenue in this case is restricted to the four summer months. The payback periods are also constant since again the optimization problem is independent of the load profile because there is no DC in this tariff.

The system level impact of these test cases is also calculated using (19). In almost all these cases, the system impact is negligible and therefore not reported. The most significant system impact is resulted by case 8 where only during the peak hours of summer months the system total net load is reduced up to 10% with PL = 50% as a result of ESS discharge operations as shown in Fig. 4. However, this is change still much less than that in residential test cases.

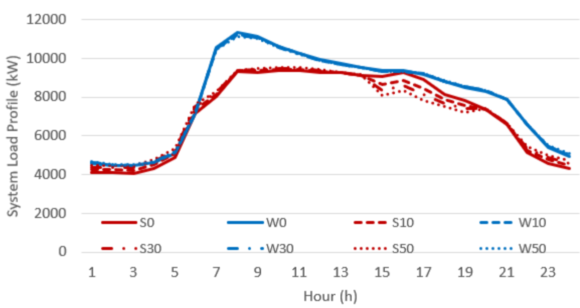


Figure 4. System level impact of BTM ESS for test case 8.

VI. Conclusion and Future Work

A generic optimization approach is proposed in order to analyze the economics and system impacts of behind-the-meter (BTM) energy storage in the state of Georgia. The proposed mixed-integer optimization formulation supports various tariff rates including energy charges, time-of-use, demand rates, and real-time pricing, making the methodology applicable to multiple regions. Georgia Power tariff rates and metered customers' load profiles are used to simulate realistic cases. The results reveal promising payback periods as low as five years for BTM energy storage projects under some tariff rates. It is shown that the time-of-use rates are usually less profitable for customers but more reliable since they are less dependent on uncertain data. On the other hand, tariffs with demand charges can provide more profit for the customers but with more uncertainty. The system impact assessment of BTM energy storage reveals that demand charge rates can result in smoother system net load profiles with high penetration of BTM energy storage. The results provide insights for BTM customers to invest in energy storage to reduce their bill, and for utilities to understand the impact of tariff rates on the adoption of BTM storage especially at high penetration levels. Future work will include incorporating the randomness of load profiles as well as battery degradation. It is also interesting to analyze scenarios where an aggregator can use BTM storage devices to participate in ancillary services market and increase the value of BTM storage.

References

[1] S. Vejdan and S. Grijalva, "Analysis of multiple revenue streams for privately-owned energy storage systems," in *IEEE Power and Energy Conf at Illinois (PECI)*, Champaign, IL, USA, Feb. 22-23, 2018.

[2] J. Eyer, J. Iannucci, G. Corey, "Energy storage benefits and markets analysis handbook," Sandia National Lab., Albuquerque, NM, USA, SAND2004-6177, Dec. 1, 2004.

[3] M. Narimani, B. Asghari, and R. Sharma, "Energy storage control methods for demand charge reduction and PV utilization improvement," in *Asia-Pacific Power and Energy Engineering Conf. (APPEEC)*, Bangalore, India, Nov. 8-10, 2017.

[4] W. Hu, P. Wang, and H. Gooi, "Assessing the economics of customer-sited multi-use energy storage," in *Proc. IEEE Region 10 Annual Int. Conf.*, Singapore, 2016, pp. 651–654.

[5] J. Neubauer, and M. Simpson, "Deployment of behind-the-meter energy storage for demand charge reduction," National Renewable Energy Lab., Golden, CO, USA, TP-5400-63162, Jan. 1, 2015.

[6] 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.

[7] M. Fisher, and J. Apt, "Emissions and economics of behind-the-meter electricity storage," *Environmental Science and Technology*, vol. 51, no. 3, pp. 1094–1101, Jan. 2017.

[8] R. Moslemi, A. Hooshmand, and R. Sharma, "A data-driven demand charge management solution for behind-the-meter storage applications," in *IEEE Power and Energy Society Innovative Smart Grid Technologies Conf. (ISGT)*, Washington, DC, USA, Apr. 2017.

[9] D. Wu, M. Kintner-Meyer, T. Yang, and P. Balducci, "Economic analysis and optimal sizing for behind-the-meter battery storage," in *IEEE Power and Energy Society General Meeting*, Boston, MA, USA, Nov. 2016.

[10] M. Gitizadeh, and H. Fakharzadegan, "Effects of electricity tariffs on optimal battery energy storage sizing in residential PV/storage systems," in *Int. Conf. on Energy Efficient Technologies for Sustainability (ICEETS)*, Nagercoil, India, 2013, pp. 1072–1077.

[11] J. Leadbetter, and L. Swan, "Battery storage system for residential electricity peak demand shaving," *Energy and Buildings*, vol. 55, pp. 685–692. Dec. 2012.

[12] T. Nguyen, and R. Byrne, "Maximizing the cost-savings for time-of-use and net-metering customers using behind-the-meter energy storage systems," *North American Power Symposium (NAPS)*, Morgantown, WV, USA, Sept. 17-19, 2017.

[13] A. Oudalov, R. Cherkaoui, and A. Beguin, "Sizing and optimal operation of battery energy storage system for peak shaving application," in *Proc. IEEE POWERTECH,* Lausanne, Switzerland, 2007, pp. 621–625.

[14] A. Zurfi, G. Albayati, and J. Zhang, "Economic feasibility of residential behind-the-meter battery energy storage under energy time of-use and demand charge rates," in *6th Int. Conf. on Renewable Energy Research and Apps. (ICRERA),* San Diego, CA, USA, 2017, pp. 842–849.

[15] S. Vejdan and S. Grijalva, "Maximizing the revenue of energy storage participants in day-ahead and real-time markets," in *Clemson University Power System Conf.*, Sept. 4-7, 2018, Charleston, SC, USA.

[16] [Online]. Available: https://pecanstreet.org/dataport/

[17] [Online]. Available: https://openei.org/datasets/files/961/pub/

[18] [Online]. Available: https://www.tesla.com/powerwall

[19] [Online]. Available: https://energystorageexchange.com

[20] "Lazard's levelized cost of storage—version 2.0," Lazard, Dec. 2016. [Online]. Available: https://www.lazard.com/media/438042/lazard-levelized-cost-of-storage-v20.pdf

[21] [Online]. Available: https://www.georgiapower.com/