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Robert Gaffney rpg3435@rit.edu

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Robert Gaffney

A Thesis Submitted in partial fulfillment of the requirements for the degree of

Master of Science in Science, Technology, and Public Policy

Department of Public Policy

College of Liberal Arts

Rochester Institute of Technology

Rochester, NY

May 15, 2019

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> *College of Liberal Arts/Public Policy Program at ROCHESTER INSTITUTE OF TECHNOLOGY Rochester, New York*

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Abstract

In June 2018, the New York State Energy and Research Development Authority (NYSERDA) released the Energy Storage Roadmap (ESR). The ESR detailed a plan to increase the capacity of Battery Energy Storage (BES) across the state by 2025 to reach goals for improving the electric grid. A model was created to find how the operation of a residential solar + storage system could achieve the goals in the ESR. The model used linear optimization to maximize the residential homeowner's profit under different rate structures. Further analysis of the resulting system operation provided information on metrics directly related to the ESR goals; the cost reductions for the prosumer and utility, the $CO₂$ emission reduction, limiting exported energy, decreasing energy peaks for the system, and increasing the self-consumption of renewable solar energy. Final comparisons showed that the rate structures could be grouped into two types based on their resulting battery operation; 'Energy Arbitrage' when the battery was used to buy and sell energy to/from the grid, and 'Self-Consumption' when the battery was used to store excess solar energy and discharge to meet household demand. Energy Arbitrage rates resulted in greater decreased costs, and better emission reduction is Costs of Carbon were considered. Self-Consumption rates resulted in increased self-consumption of renewable solar energy and decreased exporting of energy. Compared to a home with only solar under Net Energy Metering, neither Energy Arbitrage nor Self-Consumption rates reduced CO₂ emissions for the region, or the peak demands of the residential system. Policy makers considering new rates structures will need to decide which ESR goals are more desirable for residential consumers before implementation.

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Definitions

Battery Energy Storage (BES(S)): Energy Storage that uses a large-scale Battery

Day Ahead Pricing (DAP): An electricity rate based on the forecasted cost of energy

Energy Arbitrage (EA): Buying/Selling power from/to the macrogrid

- **Energy Storage Roadmap (ESR):** A NYS governmental publication advocating the widespread adoption of energy storage
- **Feed-in-Tariff (FiT):** A crediting method for consumers that produced energy, based on a flat rate

Macrogrid: The whole electric grid, including utilities, generators, consumers, etc.

Microgrid: A system that usually operates within the macrogrid, but has the capability to become 'islanded', where the system can be fully functional without connection to the macrogrid thanks to energy generation and/or storage

Net Energy Metering (NEM): A volumetric system of crediting the production of energy by Consumers

Net Energy Pricing (NEP): A system of crediting the production of energy at an equal rate to the cost of energy

New York State (NYS): The Government and/or population of the state of New York

New York State Energy Research and Development Authority (NYSERDA): The governmental body of NYS responsible for researching and developing policies relating to the

Energy industry

NY-Sun: The governmental body of NY responsible for solar policy

Prosumer: A consumer of energy that also produces energy

Real Time Pricing (RTP): An electricity rate based on the real-time cost of energy

Reforming the Energy Vision (REV): A governmental publication advocating the reform of the electricity industry in NY

Self-Consumption (SC): Storing energy produced on site for future consumption

Smart Export (SE): An electricity rate in use by Hawaii, designed for BESS

Stacked: Features or values that can be used or operated concurrently

Time-of-Use (TOU): A electricity rate based on the time-of-day the electricity is used

Value of Distributed Energy Resources (VDER): Alternative Rate Structure created by

NYSERDA

1. Introduction

In 2018, the New York State Energy Research and Development Authority (NYSERDA), and the New York State Department of Public Service (NYSDPS) released the Energy Storage Roadmap (ESR) (NYSERDA, & NYSDPS, 2018), with the goal of improving the electricity grid by deploying energy storage. However, if residential solar customers were to adopt battery energy storage technology, what effects would changing rate structures for these consumers have on the goals of the Energy Storage Roadmap? Adopting Battery Energy Storage (BES) has been concluded by most research that it is beneficial to the system (Agnew & Dargusch, 2015), but usually for specific criteria. However, the ESR lacks details about the deployment of the battery energy storage, particularly for residential solar prosumers (a consumer of energy that also produces energy). This research seeks a method to compare rate structures that could be used for such residential solar + storage projects to help meet the goals of the ESR.

Overall, the ESR has a variety of goals for the deployment of energy storage. The ESR lists the following as general desired outcomes; reduced peak demand effects, reduced emissions, and reduced costs. The ESR also lists the following as customer-sited storage goals; residential solar + storage management, management of PV system output, providing cost savings via investment tax credits, limiting exported energy, managing an EV charging load, limiting impacts on demand bills, and potentially operating microgrids leading to other varied benefits (NYSERDA, & NYSDPS, 2018). Some of these goals can be 'stacked', having concurrent effects or value. For example, managing PV system output could also limit exported energy. Other goals may conflict with each other, such as using energy to manage EV charging as opposed to operating a microgrid. If such goals do conflict, NYS would have to determine which goal has priority, and find how to incentivize the consumer to act in ways that help the higher

priority goals. The ESR focuses on larger scale BES projects, for bulk systems, distribution systems, and larger customer cited storage such as businesses. However, as battery costs decrease, residential storage projects may also increase, and understanding how residential rate structures affect the homeowner's interactions with the grid becomes necessary. Especially for policy makers that wish to encourage customers to operate their battery in ways that help meet the ESR goals.

One such method of incentivizing consumers is based on the existing rate structure 'Capacity Alternative Option 2' for the Value of Distributed Energy Resources (VDER), listed in the Value Stack Calculator Overview (NY-Sun, 2019). VDER, or Value of Distributed Energy Resources, uses value-stacking, assigns the energy generated different levels of value based on certain criteria. Specifically, the hourly Location Based Marginal Price (LBMP) of electricity, the Installed Capacity (ICAP) credit, the Environmental Benefits (E) or Renewable Energy Credits (REC), the Avoided Demand (D), the Locational System Relief Value (LSRV), and the Market Transition Credit (MTC). The 'Capacity Alternative Option 2' gives a higher value to energy later in the day, to encourage storing energy in batteries for later discharge. This alternative rate structure was created to be attractive to customers with storage but may not be the best option for residential customers based on the ESR goals and available technology.

However, VDER is not yet the current standard rate structure for residential prosumers. The current standard residential rate structure involving solar energy injection is Net Energy Metering (NEM). This is a volumetric method of credit; the prosumer gets credit for the energy they produce for the same volume of energy they consume (Abdin & Noussan, 2018). This is a slightly different than Net Energy Pricing, or Monetary Metering (NYSERDA, 2017), where the monetary value of the energy produced is credited to the prosumer. VDER is a different crediting

system intended for larger-scale solar producers, which was adopted in 2017 (NY-Sun, 2019). While VDER is a good change for Utilities, as it credits the solar production of consumers at a more accurate value (due to the value-stacking), it does not yet consider BES specifically, and is currently optional for residential prosumers who wish to transfer. However, VDER is generally valued at a lower rate than NEM, so few customers would opt in. And until January 2020, residential consumers may apply for NEM under a 20-year contract. Policy makers may want to reconsider this length of contract as the BES market/technology improves. There is not currently rate structure in use in NYS that is designed to encourage residential BES operation that reflects NYS ESR goals for residential prosumers with energy storage. Nor is it likely that residential prosumers will install BES systems under NEM, as the efficiency losses from charging the batteries would lower the energy credited to the prosumer (Fisher & Apt, 2017). One goal of this research to find or create such a rate structures (hourly and/or seasonal) that incentivizes specific battery operation to meet ESR goals.

There are a variety of rate structures currently in use across the world, and all provide a variety of benefits and costs. Even in NYS, VDER and NEM offer two different valuations based on the consumer and utility criteria. The goal of this research is to determine how different rate structures would affect the patterns of BES operation for a residential prosumer from Western NY, who uses storage to maximize their own profit under the different rate structures. Further analysis of the optimization help find which rate structure best matches the desired behaviors of the ESR goals. These goals may require similar or conflicting operation patterns (Appen & Braun, 2018). Additional analysis would identify which rate structures best meet which goals to what extent, however it does not consider which goal(s) has priority. Such a decision would need to be made by policy makers considering or implementing new rate structures.

2. Literature Review

In attempting to find how different rate structures for residential solar prosumers affect their battery energy storage operation, three key themes emerge from the research; the physical Solar + Storage system capabilities and costs, the Rate Structures utilized, and the Effects of both the storage and rate structure, usually economical. Using information found on these topics revealed the needed capabilities of the storage system, the types of rate structures to be analyzed, and common goals desired from battery energy storage. It also informed the development of the model, including the linear optimization function.

2.1 Background

In the initial stages of the search for relevant information, certain criteria needed to be met. The research from the past few years (since 2015) would be the most applicable due to the increases in performance, decreases in cost, and boosts to capacity for large-scale Lithium-Ion Batteries (Ahmadi, Young, Fowler, Fraser, & Achachlouei, 2015). This time period also follows the rise of new solar installations in the US from 2013-2016 (SEIA, 2019), which instilled a growing fear of the 'Utility Death Spiral'. This would be a situation where solar prosumers would defect from the macrogrid, thus increasing prices on other customers and causing a desire to defect, a loop that would lead to the 'death' of conventional electric utilities (Laws et al., 2017)(Hledik, Zahniser-Word, & Cohen, 2018). While this has not happened, it did lead to increased research into alternative rate structures that would better disseminate the benefits of residential solar (and storage) across the macrogrid (Hledik et al., 2018).

The rates structures used throughout the relevant literature are varied, with a few specific formats standing out. These include Net Energy Metering/Pricing, Time-of-Use Pricing, Real-Time Pricing, and Day-Ahead Pricing (See Table 2.1.1). Demand rates were commonly studied

rate structures but not used in this model. Demand rates usually charge a certain price based on the highest amount of electricity delivered within a time frame. Due to the non-linear nature of the demand rate, it was unable to be solved with the linear optimization model used for this thesis. Demand rates are also frequently used by electricity consumers with much higher peak demands than the residential consumers studied here. Demand response programs, which are based on feeding energy in as requested by a $3rd$ party (usually a utility or demand response aggregator), were also not tested. Demand response programs involve larger scaled batteries, with more than one decision maker and/or energy contributor. It was the goal of this research to create a model where the only operator is the residential consumer, who seeks to maximize their own profit. Demand response may be a more feasible option as an increasing number of people adopt storage and the systems for operating smaller and more distributed storage improves.

	<i>rales and the variations made to them for this model can be found in Section 5.5.</i>	
Rate Structure	Description	
Net Energy Metering (NEM)	A Volumetric rate, where the total amount of energy	
	produced (in kWh), is credited toward the total amount of	
	energy used (in kWh).	
Net Energy Pricing (NEP)	Like NEM, but where the total value of energy sent to the	
	grid (in \$) is credited toward the billing cycle. May be used	
	in other rate structures.	
Time-of-Use Pricing (TOU)	Electricity is credited based on the time it is sent to the grid,	
	usually in a 24-hour structure. It also may be seasonal, and	
	an increase or decrease from the standard cost of electricity.	

Table 2.1.1: These were the most common rate structures used in the relevant literature, apart from a demand rate/charge. A more in-depth explanation into the rates and the variations made to them for this model can be found in Section 3.5.

Additionally, much research on BES and rate structures focused on countries outside the US, largely seeking relief from higher electricity prices or emissions (Khalilpour, Vassallo, & Chapman, 2017). While providing useful information on the models used or background information, these countries have different rate structures, electric grid structures, solar capacity, economics, etc.. Therefore, for results applicable to the economic situation, solar generation capabilities, and policy/rate structures, research from the US was prioritized.

2.2 Prior Research Results

The two resulting effects of battery energy storage that are discussed most in the current literature are the electricity cost reductions and emission reductions. Most cost reduction analyses focus on specific consumers or rates to determine the cost effectiveness of operating or purchasing BES. Generally, the larger consumers that operate under demand rates have the greatest cost savings for BES. For reducing emissions, the consensus among researchers seems to be that unless designed specifically to lower emissions, BES will lead to increases in emissions. Fisher $\&$ Apt (2017) specify that the increased emissions are caused by efficiency losses in the battery, and emission reduction by shifting times of charging/discharging only helps in certain regions. And in most cases, the cost to reduce emissions via battery energy storage, if possible, is simply prohibitively expensive compared to alternative means (Babacan et al., 2018).

Fisher & Apt (2017) and Griffiths (2019), modeled commercial and industrial customers that used BES across the country, to find the impacts on costs, emissions, and energy loads. The commercial and industrial customers did not have electricity generation on site for their energy profile, rather the model used for Griffiths (2019) used the battery solely for the building demand, while Fisher & Apt (2017) used energy arbitrage and demand reduction as the battery functions. Both models used a battery scaled to the power needs of the customers, which resulted in a much larger capacity than a residential sized battery. They found that in specific regions BES can mitigate emissions if a well-designed rate structure is implemented. Both recognize the rate structure needed involves a time-component based on the emissions of the region. They also recognize that a rate structure designed to reduce emissions is not necessarily the type of rate structure that provides the most revenue.

Results often indicated that positive effects like emission reduction were likely diminished by higher costs. Emissions reductions were often found in rates that cost significantly more than the reduction would be worth (Babacan et al., 2018). However, much research openly acknowledges that the grid makeup is shifting, and other regions or the future grid may have different outcomes. Other research focused on the costs and effects of using a BES system to completely defect from the macrogrid, but these often are too cost prohibitive to be feasible options due to the cost of the larger system needed for grid defection (Hittinger $\&$ Siddiqui, 2017) (Ren, Grozev, & Higgins, 2016). And due to intermittent renewable generation, defection may end up being 'dirtier' than staying on the grid, especially in areas with low grid generation emissions.

2.3 Models of Battery Operation

Perhaps the most frequent problem with the research on battery energy storage, and microgrids in general, is that the battery operates in a very specific way for nearly all models. The battery either will not feed energy into the grid and only cover the local demand (such as in Griffith (2019)), or does not charge from local renewable energy, only from the grid (such as in Fisher & Apt (2017)). This poses a problem, as the goals of the Energy Storage Roadmap, timeshifting the residential renewable energy and managing the PV system, may require feeding energy from the residential solar system into the grid at a later time.

In Ren, Grozev, & Higgins (2016) model (Figure 2.3.1), the battery only discharges to provide power to the home and does not discharge energy back into the electrical grid. Their model studied the cost impact of different sized solar + storage systems on residential locations with varying demand and a few electricity rates. They found that the solar + storage systems were most attractive in conjunction with TOU rates. They also found that due to battery efficiency and the format of some TOU rate structures, the battery would charge from the grid during low cost periods. It would then discharge to cover the household demand while solar is being produced, feeding the solar directly into the grid and thus avoiding efficiency losses. This method of operation could negatively affect the emissions of the system, but Ren, Grozev, & Higgins do not study the effects on emissions.

Figure 2.3.1: (Ren, Grozev, & Higgins, 2016). While the flowchart shows the battery charging from solar (and references charging from the grid in the text), it *does not discharge the battery to sell energy to the grid, only discharges to cover household demand.*

Nojavan et al. (2017), had the ambitious goal of creating a multi-objective model to optimize microgrid operation for reductions of emissions and cost. They used a demand response program for their system containing a battery, fuel cell, and PV system. Nojavan et al. (2017) does find that the specific demand response program helps reduce both cost and emissions in their case study. However, the modeled system (shown in Figure 2.3.2) does not discharge energy back into the 'Upstream Grid', or even the macrogrid, it simply uses the battery storage, along with other mechanisms, to provide energy for the overall electrical load.

Figure 2.3.2: (Nojavan, Majidi, Najafi-Ghaleloum Ghahramani, & Zare, 2017). As seen in the grey circle, the battery storage only takes from the grid (or fuel cell/PV), and does not discharge back to the grid, only discharges to cover household demand.

Babacan et al. (2018) has a similar situation in Figure 2.3.3, specifically the scenario b, where the solar PV, Battery Energy Storage, and macrogrid are used to meet the household demand, and the battery is generally used for self-consumption of the generated PV Energy. However, Babacan (2018) also shows that in Figure 2.3.3 scenario c, the battery buying *and* selling energy from/to the grid and calls the model 'Energy Arbitrage'. This refers to the market interactions between the system and the macrogrid, and they later explain that emission reduction was possible with energy arbitrage but come at very high costs, between \$180-\$5160 per ton. To put that in perspective, New York State estimates the Social Cost of Carbon to be around \$40 per ton (NYISO, 2018).

Fig. 2.3.3: (Babacan et al., 2018). Of the three models discussed in this research, the only one that uses solar PV (PV Self-Consumption) does not sell energy to the grid, however the model that does sell energy to the grid (Energy Arbitrage) uses standalone storage.

Yet even the model used in Figure 2.3.3 only partially captures the capabilities of the battery energy storage + solar PV system, because Babacan et al. (2018) does not combine energy arbitrage and solar generation. In the model used here (Figure 2.3.4), the battery is capable of charging from the PV system and the grid, and can discharge to the grid and for the household demand. While features that are desired from a battery energy storage system can be realized without this function, the battery being able to feed energy into the grid is a key feature that is utilized by larger storage systems and should be considered for residential systems as well.

Figure 2.3.4: Model of the System Used. Upon investigation into the models of the systems used in much of the research, one of two areas were found missing compared to the model used here. For the most part, smaller sized (residential) PV + Storage systems did not allow the battery to feed into the grid, or larger sized (standalone storage, usually for commercial, industrial, or distribution) did not have PV systems, but operated based on their demand charges from the grid and battery. This figure represents the 4 hubs of electricity usage/production within a home, and the 6 actions available to the homeowner, which are further *explained in Table 3.2. The key aspect which is better illustrated in this figure is how the flow of energy between certain hubs is limited in one direction, specifically, energy must flow from the PV or into the Demand, you cannot send energy into a PV system or take energy from the demand. However, you may take or send energy into the battery and macrogrid.*

2.4 Research Question

This thesis seeks to find the effects of new/different rate structures on the goals of New York State's Energy Storage Roadmap when used with a residential solar system and battery energy storage system. This research was not provided in the ESR, despite referencing the potential for residential solar + storage. The goals of the ESR are reducing costs and emissions, managing solar production, limiting exported energy, time-shifting renewable energy, operating microgrids, and mitigating peak energy effects. Cost and emission reductions for battery energy storage have been researched but did not operate the battery in the same manner that this model does. By being able to charge and discharge from the macrogrid, charge from home's solar, and discharge to cover household demand, this provides a different model than recent relevant literature (See Figure 2.3.4). The connections between the some goals of the ESR and changing rate structures are not well examined in current literature and are expanded upon here. In this model, the homeowner has a solar + storage system and will operate it to obtain the most profit for their monthly bills. A linear optimization model will determine the residential prosumer's most profitable battery operation under a variety of rates. The annual results will be analyzed based on a series of metrics created from the goals of the ESR.

3. Methods

The goal of this system is to provide the most profit to the Solar + Storage prosumer. The subject in this method has a PV Solar Array and a Battery Energy Storage System and wants to operate it in the ways that are most profitable. Trying various rate structures will yield different ways to operate their BES, and the results can be compared with other rate structures. These results include the factors related to the goals laid out in the Energy Storage Roadmap. The model represents a single residential solar system with battery energy storage and runs a linear optimization to determine the battery charge/discharge operation, and energy taken from/sent to the grid. Using a variety of rate structures, it can determine how the residential solar customer would operate a BESS within their home to maximize their own profit with the different rate structures. The output from that optimization was then used to see how well the customer's behavior matched the goals of the Energy Storage Roadmap based on the metrics mentioned in Table 3.3.1.

The process starts with optimizing for customer profit (Babacan et al., 2018) (Maleki, Rosen, & Pourfayaz, 2017). The monetary value to credit demand and production was based on different rate structures, run for each month, then summed over a year to simulate a customer's annual electricity bill. Linear optimization was used to determine what actions the prosumer would make in order to maximize their profit with the battery. The outcomes or actions resulting from the optimization were then used to determine how well the new rate structures matched the goals of the Energy Storage Roadmap. This was determined by analyzing the use patterns and metrics based on ESR goals; the difference in $CO₂$ emissions compared to a home with solar, change in utility electricity cost, change in consumer bills, and change in demand, demand profiles, and peak demand of the prosumer.

3.1 What actions the homeowner can take

There are essentially four different bodies within the model; the macrogrid/meter, the PV system, the battery, and the household demand. The homeowner has two inflexible conditions, the amount of energy that is produced by their solar array aka the PV System, and the energy needed for their home, aka the Household Demand. For these two bodies however, the energy may be sent/received to/from various places. The PV System may send energy to cover the Household Demand, to charge the battery, or send excess energy to the grid. The Household Demand may be covered by the PV System, the Battery, or from the grid. The homeowner has control over the battery operation, and any demand not covered by the battery or PV system must be taken from the grid.

It is important to note that the grid should not be receiving and delivering energy within the same hour. For example, when the PV system is producing energy the household demand must be met first, as the grid could not send energy and receive it. A single wire cannot allow flow in opposite directions at the same point in time. This is also true for the battery's charging/discharging. To use Figure 2.3.4 to explain, arrows A/C cannot be used at the same time as arrows B/F. Nor can arrows A/E be used at the same time as arrows B/G. While performing linear optimization, this type of constraint is difficult to process, as it is seemingly non-linear. To account for this difficulty, the model uses the 'Big M' method, explained with equations 5-15.

3.2 The Model

The model created for the battery operation requires well defined variables and constraints for the battery operation, a method that allows for discharging/charging to/from the

macrogrid, a way to balance the energy flowing in/out of the system, and the linear optimization equation to get the prosumer the maximum profit.

Variables

Battery Physical Constraints

The constraints for the battery were taken from the Tesla Powerwall functionality (Tesla, 2019). A Tesla Powerwall was chosen for a variety of reasons; the popularity of Tesla, the comparable cost, and the use of Lithium-Ion rather than Lead-Acid. Batteries of similar capability are also used in much of the current research (Fridgen, Kahlen, Ketter, Rieger, & Thimmel, 2018) (Babacan et al., 2018). The Battery has a maximum charge/discharge (*Bc*/i) rate of 5 kW (Equations 1-2), and a maximum Capacity of 13.5 kWh (Equation 3).

$$
0 \le Bc \le 5 [1] 0 \le Bd \le 5 [2] 0 \le Bt \le 13.5 [3]
$$

The Battery Total (*Bt*) for each hour (Equation 4) is calculated based on the amount the battery charges or discharges, with efficiency reducing the charge to the total and increasing the discharge from the total, as well as the battery total from the previous hour.

$$
Bt_h = Bt_{h-1} + Bc_h * Ed - Bd_h * Ei [4]
$$

Big M Method

The model uses the 'Big M' method for constraining the battery charging/discharging and grid energy flowing in/out of the house. The 'Big M' method is used in linear programming to create constraints on variables within the optimization that wouldn't normally be viable for linear programming. Specifically, in this case some variables need to be 0 if a paired variable is greater than 0. To use the 'Big M' method, a new set of binary variables are created and paired with the original variables (Equations 6-9). These binary variables are summed, and the sum must be less than or equal to 1 (Equations 10-11). These paired binary variables are then multiplied with a number larger than they could theoretically be (Equation 5), to become the upper limit for the paired non-binary variables (Equations 12-15). This way, whichever variable is required to be 0 cannot exceed the zero value of the binary variable.

For this model, the 'Big M' method involves the Battery Charge (*Bc*)/Battery Discharge (*Bd*), and the Grid Energy Into House (*Gi*)/Energy Sent out to Grid (*Go*) for the two sets of paired binary variables (*Xbin*). This is to ensure the Battery cannot charge and discharge at the same time and the Grid cannot both send and receive energy

Balanced Energy Equation

The total energy flowing into and out of the house must be balanced. There shouldn't be an excess of energy sent into the house that isn't used, and there cannot be energy sent to the grid if the household needs aren't met. To ensure this, the model uses the Energy Balance Equation

(Equation 16), where any energy flow needed for the system (Household Demand, Battery Charging, Energy into Grid) is taken from the energy flow into the system (PV solar, Battery Discharge, Grid into House).

$$
(Pv + Bd * Ed + Gi) - (Hd + Bc * Ei + Go) = 0
$$
 [16]

Unlike the Battery Total (Equation 4), the Battery Discharge (*Bd*) Efficiency is decreased (*Ed*), and the Battery Charge (*Bc*) Efficiency is increased (*Ei*). This is done to ensure the efficiency losses are correctly compensated for by the grid/solar/demand.

Optimization Equation

After all the constraints, the optimization equation is relatively simple. Maximize the sum of the consumer's bill from the initial to the final hour (Equation 17). To get the consumer's bill, multiply the Grid Into House Energy by the demand credit and subtracted from the Energy Sent To Grid multiplied by the injection credit.

$$
\max \sum_{h}^{n_f} (Fo_h * Go_h - Fi_h * Gi_h) [17]
$$

 \overline{a}

3.3. Metrics:

After performing the linear optimization with Equation 17, the model now needs to determine the effects of the battery operation. This is done with various metrics, values based on the goals set forth in the Energy Storage Roadmap. These goals, seen in Table 3.3.1 below, are calculated from the data gathered after the optimization.

Table 3.3.1: A basic description of the goals of storage from the Energy Storage Roadmap. 'What the battery would do' is a general description of the way the battery would need to function to match ESR Goals. Energy from discharging the battery could be used to cover the household demand or also to be sent into the grid.

ESR Goals	What it means	What the Battery would do
Cost Reduction	to the consumer and/or the utility	Reduce Electricity delivery costs Discharge while electricity costs are high, charge while costs are low

Cost Reduction

The cost to the prosumer (Equation 18) is important to consider for any rate structure design. The Consumer Cost metric is the cost of buying/selling electricity to the utility and is dependent on each rate structure. The cost is determined by taking the grid energy in/out result of the monthly optimizations for each hour, multiplying each by their respective financial credits, and summing the hourly totals for the year. Thus, the consumer cost is the cost of buying/selling electricity from/to the grid for the year (\$/yr.). The battery is used to minimize that cost (maximize the profit). Thanks to the linear optimization, all that requires is the same optimization equation, but negative to account for the metric being a cost rather than a bill credit as it was defined as in the model.

$$
\text{-}\Sigma_{hi}^{hf}(Fo_h * Go_h - Fi_h * Gi_h) \text{ [18]}
$$

The Utility Cost (Equation 19) is more complicated than the consumer cost. The utility is both buying energy from the macrogrid generators (at the Real-Time Price of Energy) and the prosumer (at the injection credit cost), as well as selling energy to the prosumer (demand cost). This means that in order to find the net cost to the utility, the metric needs to calculate the

difference between the Real-Time Price of energy and the Financial charges the prosumer pays or gets credit for.

$$
\sum_{h}^{hf} \{ (Gi_h * (RTP_h - Fi_h) + Go_h * (Fo_h - RTP_h) \} [19]
$$

As seen in Equation 19, the prosumer pays the utility for Grid Energy into the Home (*Gi*), so the difference in price between the Real-Time Price (*RTP*) and the Financial Charge (*Fi*) is profit, whereas the prosumer gets credit for Energy Sent to the Grid (*Go*), so the difference between the Financial Credit (*Fo*) and the Real-Time Price (*RTP*) costs the utility. This equation provides the cost per hour for providing/buying energy to/from the home, and the metric is summed for the year $(\frac{f}{y})$.

The consumer and utility costs used only considers the cost of buying/selling the energy delivered to/from the home, i.e. the 'delivery charge' for electricity. It does not take minimum or fixed costs that would be present on a typical consumer bill into account. One such cost, a demand change, in not used in the model optimization. Demand charges are based on the highest electricity demand for the consumer, and apply a charge based on the amount used for that peak demand. This is a non-linear cost that was not included in the linear optimization model. Other fixed costs, minimum costs, or subsidies/credits would be independent of the optimization and applied to a consumer bill per month. These types of additional costs could be used to equalize differences in costs between rate structures that may otherwise have preferable operation patterns. Such changes in fixed costs should be considered by policy makers that wish to implement rate structures while mitigating costs to different entities.

CO² Emission Changes

CO² emissions for the modeled system are based on the Marginal Emission Factors for Upstate New York. These factors provide an hourly emission rate (kg/kW) for 3 seasons, Winter (November - March), Summer (May - September), and 'Transient' (April & October). These hourly emission factors (*Me*) are multiplied by the hourly difference between Grid Energy into the Home (*Gi*); which is 'dirty' energy taken from the grid, and Energy Sent to Grid (*Go*); which is 'clean' energy from the battery or solar, thus reducing overall emissions. Summing this annually gives a net value of marginal $CO₂$ emissions (kg/yr.). Subtracting the annual marginal emissions of a similar home with only a solar system shows the change in $CO₂$ emissions generated from the battery operation, where a positive value is an increase in emissions over a solar-only home, and a negative value is a decrease in emissions from a solar-only home.

$$
\sum_{hi}^{hf} (Me_h * \{Gi_h - Go_h\}) - SolarCO_2 \ [20]
$$

While the energy sent to the grid from the battery may not have been 'clean' originally, if it was charged from the grid, that is compensated by the increase in emissions from when it did charge. Theoretically, the battery could be charged during periods of low emissions and discharged during high emissions in order to reduce overall emissions. This is explored later with the 'Marginal Emission' rate structure and the 'Real-Time Price/Day-Ahead Price + Cost of Carbon' rate structure.

Operate Microgrids (Increased Resiliency), Manage PV System, Limiting Exported Energy, Time Shift Renewable Energy (Grid Average Daily Use Patterns)

Operating Microgrids/Increasing Resiliency can be measured by taking the average battery capacity (Equation 21) and the total energy taken from the grid (Equation 22). The average amount of energy stored in the battery is a good indicator of how readily the household can 'island' itself from the grid in the event of an outage.

$$
\frac{\sum_{hi}^{hf}(Bt_h)}{hf}[21]
$$

However, the battery average capacity is not the only factor when determining microgrid operation or increases in resiliency. When determining how effective the BES is at managing the PV output and how it limits exported energy, the model compares the amount of energy taken from/ sent into the grid across different rate structures (Equation 22). As the prosumer charges the battery from the solar and discharges to meet the demand, the amount of energy taken from/sent to the grid decreases (kWh/yr.). However, if the prosumer charges from the grid (when prices are low) or sends the energy to the grid (when prices are high), the Grid In/Out totals will increase.

$$
\sum_{hi}^{hf} Gi_h, \ \sum_{hi}^{hf}Go_h [22]
$$

The average daily use patterns for the battery and grid also provide a clearer understanding of how the battery operates in conjunction with the grid. These patterns are found by taking the average battery use (Equation 23) or grid use (Equation 24) for a 24 hour day.

$$
Averageif (hi - hf, hx, Bch - Bdh) [23]
$$

Averageif (hi - hf, hx, Gi_h - Go_h) [24]

The average daily use patterns are important when considering other metrics. For example, the average battery state of charge may be low for some rate structures because it uses the energy stored to meet the household demand through the day. This could lead to lower average battery state of charge, but still relatively high resiliency since it operates mostly independently of the grid. This would also be reflected in the total Grid In Energy (Equation 22]

Peak Demand/Injection

The peak demand for the average consumer usually occurs during the peak demand for the macrogrid, which can lead to negative effects. Increased peak demands for the macrogrid can lead to increases in electricity costs and use of high-emitting peaker plants. When comparing the peak demand/injection for different rate structures, the time and amount of energy taken from the grid (or sent out to the grid if the rate incentivizes discharging during to the grid) at the highest points, provides valuable information on changes to the prosumer's peak demand/injection. A lower peak demand/injection is more desirable, as it indicates more stable consumption. The time at which the demand/injection peaks is not a metric itself but provides insight to the underlying motivation/optimization that results in such battery behavior. Such information can also be seen by comparing the average daily use patterns. The peak demand/injection was found with Equation 25.

$$
Peak\,Demand = \max(Gi), Peak\,Injection = \max(Go)\, [25]
$$

3.4 Data Sources

The model created was of a residential prosumer with an average demand profile and average solar production for the region of Rochester, NY. The demand and PV production profiles for the home were needed to create such a model, as well as the relative size for a base case home. In this case, the average residential solar system installation size in NY is about 7.5 kW according to NYERDA NY-Sun Data and Trends residential data (NY-Sun, 2019). Inputting the average size and location (7.5 kW and Rochester, NY) into the PVWatts Calculator from NREL, gets the PV AC System Output (W) data column, as well as the hourly time and date for the year (NREL, 2016). At this point it is best to convert the AC system output to kW, as using kilowatts rather than watts will be beneficial in keeping a standard unit between the production, household demand, battery operation, and cost of electricity.

The next set of data gathered was the household demand data. This was taken from OpenEI's dataset of the "NREL Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States" using a base case load for a home in Rochester, New York (OpenEI, 2018). In this case, the column for the annual hour and date and the Electricity: Facility [kW](Hourly) is needed. Combining the annual data of the solar PV production and household demand required too much memory for the model and solver used in the analysis (OpenSolver, 2019) so the year was segmented into months. To create the annual rate structure, two columns for pricing were needed, one for the electricity consumed by the household from the grid and one for the electricity produced by the household sent to the grid. These changed with different modeled rate structures.

The Real-Time Price of Electricity is needed to calculate the utility costs, as well as for the Real-Time Price rate structures. This was found with LCG Consulting (2019) and NYISO Industry Data, using the Genese region for 2016 to correspond with our PV production data. The real time price of electricity gives a good indicator of the cost to utilities in providing, selling, and buying the electricity going to and coming from the residence. To calculate the $CO₂$ emission reduction that the battery provides, the Marginal Emission Factors for Upstate NY were used. They have averaged hourly (0-23) $CO₂$ emissions in kg/kW for 3 different seasons, Winter (November-March), Summer (May-September), and Transition Seasons (April & October). By making any energy the home provides to the grid have negative emission factors (PV & discharging the battery), and energy taken from the grid have positive emission factors (meeting demand & charging the battery), the model will then sum the annual results and determine the total emissions avoided by the residential system (See Equation 20).

The PV data, Household Demand Data, Real Time Price, and $CO₂$ Emissions give the data needed for the average homeowner's hourly electricity profile for a year's time. The data was then used to create the model of the homeowner's optimal battery operation based on different rate structures for crediting the feed-in energy to the macrogrid and electricity demand rate structures.

3.5 Rate Structures

There are a variety of rate structures chosen for use in the model with various purposes. For residential homeowners in NYS, the most common rate structure is Net Energy Metering (NEM). This is a volumetric rate, where the total amount of energy produced (in kWh), is credited toward the total amount of energy used (in kWh). NEM thus does not encourage the use of a BES, as the total amount of solar injected would be credited, and the efficiency losses of the battery would always result in less energy being credited. NEM is used frequently to encourage residential solar adoption, as an average home may greatly reduce their electricity bills with an average sized solar system. However, NEM may not fully capture the effects that the operation of residential solar has. Residential homes with solar often stop producing energy as demand for their homes and the macrogrid is spiking (later in the evening), leading to a drastic increase in demand from the grid. Despite this increase in overall demand from the macrogrid, there would not be an increase in pricing for NEM rate structures. As more and more homes install solar and are put on NEM rate structures, this may exacerbate the problem.

New York State permits residential homeowners to use NEM for a 20-year period after a solar installation. This provision is in place until 2020, but any change afterwards has not yet been announced. One potential change is to simply reduce the value of NEM by reducing the injection credit. This changes the rate from a volumetric rate to a monetary rate. This was modeled by changing the injection credit to varying percentages of the demand cost. It was found that for changes between 82-100%, there was no change to consumer behavior. This was due to the efficiency losses incurred by the battery charge/discharge. Changing the injection value to 81% or lower resulted in the consumer charging the battery during solar production and discharging to cover household demand.

A potential alternative to traditional NEM proposed by NYS is the Value of Distributed Energy Resources (VDER) rate structure. There are many different 'stacked' variables that VDER uses to more accurately value the distributed generation of electricity. VDER has a Timeof-Use rate structure mentioned specifically in the Value Stack Calculator (VSC) to be used with BESS called the Capacity Alternative 2. This TOU rate would increase the value of energy between the hours of 2 PM – 7 PM during the months of June, July, and August. For use in the model, this rate was designed based on Net Energy Pricing (NEP), where the injection credit and demand costs are equal at any given point in time. Between the hours of $2 PM - 7 PM$, this Capacity Alternative rate structure gave a 25% increase for both the injection credit and demand cost (Equations 26-28). This was done both for the originally defined summer months as well as annually.

> VDER Capacity Alternative 2 $0 \le hx \le 13$, $Fo = Fi = 0.11 [26] $14 \leq hx \leq 19$, $Fo = Fi = 0.13 [27] $19 < hx < 23$, $Fo = Fi = 0.11 [28]

VDER was originally designed for use during the summer season, but an annual alternative could be created based on the marginal emission factors for the region, as well as the limits the battery would have. The rate structure created was called Marginal Emissions (ME), and used the 25% increase like VDER, but over different and shorter time periods for each season. These were 10 PM – 2 AM during the winter season (Equations 29-31), 12 PM – 4 PM during the summer season (Equations 32-34), and 11 AM – 3 PM during the transient months (Equations 35-37). These seasonal TOU rates can also be used with NEM during the off months, like the VDER Capacity Alternative operation in the summer.

> ME Winter $0 \le hx \le 1$, $Fo = Fi = 0.13 [29] $2 \le hx \le 21$, $Fo = Fi = 0.11 [30]

 $22 \le hx \le 23$, $Fo = Fi = 0.13 [31]

ME Summer

 $0 \le hx \le 11$, $Fo = Fi = 0.11 [32] $12 \leq hx \leq 15$, $Fo = Fi = 0.13 [33] $16 < hx \leq 23$, $Fo = Fi = 0.11 [34]

ME Transient

 $0 \le hx \le 10$, $Fo = Fi = 0.11 [35] $11 \leq hx \leq 14$, $Fo = Fi = 0.13 [36] $15 < hx \leq 23$, $Fo = Fi = 0.11 [37]

Another Time-of-Use rate designed for BESS is the Smart Export rate structure, currently in use in Hawaii. This rate does not credit any injection of energy into the grid between the hours of 9 AM - 3 PM and otherwise uses net pricing at the standard rate (Equations 38-40). This drastically increases consumer costs and reduces utility costs, and the battery chosen does not have the capacity to store all solar electricity produced during this time. However, based on the previous testing with the NEM percentage alternatives, the rate structure would have similar performance if the credit between 9 AM – 3 PM was simply reduced to 81% of the standard rate rather than no credit at all (Equations 41-43). This rate structure could also be changed by altering the hours or seasons that it would be in use, which was done with the Smart Export 81% 11-1, June-August rate structure (Equations 44-46).

> Smart Export $0 \le hx \le 8$, $Fo = Fi = 0.11 [38] $9 \leq hx \leq 3$, $Fo = 0$, $Fi = 0.11 [39] $4 \leq hx \leq 23$, $Fo = Fi = 0.11 [40]

Smart Export 81% $0 \le hx \le 8$, $Fo = Fi = 0.11 [41] $9 \leq hx \leq 3$, $Fo = 0.08 , $Fi = 0.11 [42] $4 \leq hx \leq 23$, $Fo = Fi = 0.11 [43]

SE 81% 11-1 J-A $0 \le hx \le 8$, $Fo = Fi = 0.11 [44] $11 \leq hx \leq 1$, $Fo = 0.08 , $Fi = 0.11 [45] $2 \le hx \le 23$, $Fo = Fi = 0.11 [46]

Real-Time Pricing (RTP) is a rate structure created using the actual energy price from the NYISO data, which is the price that the utilities pay for the energy they deliver (Equation 47). Day-Ahead Pricing (DAP) operates in much the same way, but the price is forecasted ahead of time (Equation 48). This leads to real-time pricing having more instability due to events that are not forecasted. The original RTP/DAP rates used net pricing, where the injection credit and demand costs were equal. An alternative was also tested with the model, using RTP/DAP for the injection credit and a standard flat rate for the demand costs (Equations 49-50). RTP/DAP prices are generally lower than the consumer demand cost, and if the prices are higher it is because the grid demand is much higher than normal. The RTP/DAP rates did not reduce emissions well, so another rate structure was created using both the RTP/DAP prices while adding on a cost of carbon. Using the marginal emissions (kg/kW) multiplied by the cost of carbon $(\frac{C}{k}g)$ and added to the RTP/DAP rates created the RTP/DAP + Cost of Carbon rate structures (Equations 51-52).

> Real-Time Price $Fo = Fi = RTP [47]$

Day-Ahead Price $Fo = Fi = DAP$ [48]

RTP Flat Demand $Fo = RTP, Fi = $0.11 [49]$

DAP Flat Demand $Fo = DAP, Fi = 0.11 [50]

RTP + Cost of Carbon $Fo = Fi = RTP + Cost of Carbon * Marginal Emissions [51]$

DAP + Cost of Carbon $Fo = Fi = DAP + Cost of Carbon * Marginal Emissions [52]$

At this point, every part of the model is in place. The demand profile for the household,

the solar energy production, the battery capabilities, the constraints the prosumer must adhere to,

the linear optimization equation, the cost of electricity delivery for utilities, the marginal emission factors, and the different rate structures. The next step is to run the optimization and compare the metrics between the different rate structures.
4. Results

4.1 Time-Shift & Annual Daily Averages

When analyzing the results of the optimization for each rate structure, the first metric to be observed is the average daily use patterns (Figure 4.1). These patterns help give a general idea of the effects the rate structures have on the interactions between the battery, grid, solar system, and household demand. Particularly, these daily use patterns (seen for each rate structure in Figure 4.1) are useful in identifying how well the optimization time-shifts the solar energy, PV management, and potential microgrid operation. As seen in the standard Net Energy Metering, the solar production would normally be sent to the grid between 8 AM and 4 PM. If the battery charges during this time period (as seen in Figures 4.1.2-3,5,8,10-12), then it successfully timeshifts the renewable energy while managing PV output. Another goal that can be observed in the average daily use patterns is the peak demand/injection. The peak demand/injection can cause stress on the grid connections, especially if used frequently at high power . The sharper the difference between the peaks, the more problems that may arise. Generally, smoother and flatter curves are desired for demand/production profiles. Looking at Figure 4.1, VDER & the Marginal Emissions rates may not be desirable considering the goal of reducing peaks/peak shaving.

Figure 4.1: Shown here are the annual (except for Marginal Emissions, which varied by season) Average Daily Use Patterns for the rate structures analyzed, along with some of their adjusted/changed rates that provided interesting/useful results. For each graph, the green solid line represents the battery operation, positive being charged, negative being discharged, and the red dashed line represents energy from the grid, positive energy fed into the house, negative being sent out to the grid. The x-axis is the time of day (0-23), and the y axis is the kW being used by the battery/grid.

Discussion of Rates based on Average Daily Use (Figure 4.1)

For Net Energy Metering (NEM, Figure 4.1.1), the model found that if NEM credits the production of energy above 81% of what it charged, then the model did not operate the battery. Thus, as energy is produced by the solar it is sent to the grid. However, if the value of the credit for production fell to or below 81%, the desired behavior shifted, as we see in 81% Net Metering (Figure 4.1.2). The same concept was also applied to the VDER rate structure, to find at which point above 100% the changes in behavior take place, and it was found that an increase of 23% or more would change the optimization result. Thus, any rate structure proposed will need to take the efficiency of the battery, given that a 90 % efficiency means rate changes between 82-122% will not change behavior. As battery technology improves, this range should decrease. At the 81% injection credit for NEM, the battery is used to charge during solar production as much as possible, with excess production being sent to the grid. The battery is then discharged later to cover some of the household demand. This is a great example of microgrid operation and managing the PV system output, which can also be seen later in Table 4.2.1.

The next rate structure, VDER (Figure 4.1.3), increases the credit/charge for energy between 2 PM – 7 PM. A noteworthy consequence of this is that immediately at 2 PM there is a sharp spike in energy sent to the grid, a combination from both the battery and the PV system, as there is still solar production at that time. This also has the side effect of causing the battery to

drain and take energy from the grid immediately after 7 PM. These sharp peaks are not desired behavior, as discussed with the peak effects.

The next set of rate structures in Figure 4.1 are the Real-Time Price (RTP) rates, which are more unstable than NEM. The first RTP (Figure 4.1.4) rate used a Net Energy Pricing (NEP) structure, where both the credit for production and cost for energy were the same. This led to a scenario where the battery didn't charge from the solar as much, but rather from the grid when the energy was less expensive during the morning. The RTP Flat Demand rate changes the rate to only credit injected energy at the Real-Time Price and instead charge the normal price of energy for energy from the grid (Figure 4.1.5). RTP Flat Demand functions almost the same as 81% NEM, charging during solar production then discharging later to cover some of the household demand, with a small difference around 11 AM. Given the battery charges less at this point on average, it can be assumed that the price of energy at 11 AM may be high enough occasionally to be worth inserting energy into the grid. Finally, the last of the Real-Time Price rates is the RTP + Cost of Carbon (Figure 4.1.6). This rate structure is created by combining the Real-Time Price of Energy with the Cost of Carbon (Zeng et al., 2018). This rate structure seems to follow the same general pattern as the normal RTP but is slightly more unstable. This increased instability may be due to the seasonal changes in the marginal emission factors affecting the cost of carbon. Because these are annual averages, the seasonal changes may affect the annual average stability.

Day Ahead Pricing (DAP) (Figure 4.1.7), is like RTP, both in the structure and resulting patterns of behavior. DAP is forecasted by utilities to estimate electricity prices, generally leading to smoother transitions/curves, and less instability. These aren't very apparent when comparing Figure 4.1.4 and 4.1.7, as the instability in RTP is smoothed by the annual average.

However, when comparing RTP to DAP, we notice some irregularities. One example is at 8 PM the RTP rate encourages battery discharge, indicating higher prices, while the DAP does not. While this could be chalked up to the instability inherent in RTP, these patterns are averaged over a year, which means it is more likely that the DAP forecast is missing a peak demand at 8 PM, causing spikes in the RTP. A similar trend occurs at 5 AM. Like the normal DAP and RTP, the overall pattern for the flat demand rates (Figure 4.1.8) are similar, but again with slight differences. The slight peak at 11 AM from the RTP still there, but the battery has a smoother transition over that point. The differences between the DAP/RTP + Cost of Carbon (Figure 4.1.9) are hard to discern due to the more chaotic patterns but seem to be comparable to the differences between the regular RTP/DAP, with shifts at 5 AM and 8 PM.

The rate structure is Smart Export (Figure 4.1.10), used in Hawaii and developed for battery energy storage. The structure credits the production of energy at \$0 from 9 $AM - 4 PM$, and equal to the demand between $4 PM - 9 AM$, while demand remains consistent through the day. For this rate, the model shows an increase in battery charging from the solar during the day, and overall decreases in energy taken from the grid. Like the NEM analysis (4.1.1), the Smart Export 81% (Figure 4.1.11) shows that changing the production value from 0% of the demand to 81% does not change the pattern of behavior. Changing the time period (Figure 4.1.12) from 9 AM- 4 PM to 11 AM $-$ 2 PM has a very significant effect. While the beginning and end of the day have similar grid use, if slightly increased due to less BES charging, the sharp peaks between sending energy to the grid and charging the battery are very pronounced.

The Marginal Emission (ME) rate structure was designed to be like the VDER rate, where for a period during the day, production and demand are 25% higher. The difference is VDER was originally designed for the summer, while the ME rate is designed for each season of the marginal emission factors. In the winter (Figure 4.4.13), this is between 10 PM- 2 AM, the summer (Figure 4.1.14) 12 PM – 4 PM, and the transient season (Figure 4.1.15) 11 AM – 3 PM. With each season there are different battery and grid trends to accommodate this. In the winter, there is increased demand at night, as the battery charges during the day to discharge later. In summer, the battery charges in the morning, and later has very high discharge rates during the afternoon. The transient season is very similar to the summer due to the similar time frames.

4.2 Rate Variations

The six main rate structures, Net Energy Metering (NEM), Value of Distributed Energy

Resources (VDER), Marginal Emissions (ME), Smart Export (SE), Real-Time Price (RTP), and

Day-Ahead Price (DAP), all had various variations used to either compare to another rate or

achieve a better metric of an ESR goal. The tables and charts in this section explain the

reasonings behind the variations to the base rate structures, and how they ended up comparing to

the original.

Net Energy Metering

Table 4.2.1: Metrics for Net Energy Metering (NEM) rate structures. Rates highlighted in blue have injection credit above 81%, rates highlighted in orange have injection credit 81% or below. The blue rates do not operate the BES, while the orange rates all operate in the same manner. The Net Energy Metering rate, due to the battery efficiency losses, would not cause the battery to be used unless injection credit fell below 81% of the demand charge, and the battery starts at 0 kWh for the model. Therefore, NEM rates above 81%, the battery capacity is 0 kWh. Once the price was low enough, the battery operated by charging from the solar and discharging later to cover the household demand (See also: Figure 4.1.2). Once the NEM credit was below 81%, the battery was operating in the most profitable way, as the credit did not change over time, hence the consistent values between rates aside from the Consumer/Utility Cost. This differs from the other rates, which are based on a Time-of-Use rate structure.

Based on the Consumer and Utility Cost of the NEM rate structures, the battery operation can provide a significant consumer savings if the injection value decreases. Between 82-100%, every 1% decrease in injection value causes about a \$6 increase in consumer cost, but when the battery operates below 81% injection credit, each 1% decrease only increases consumer cost by \$2. These increases in Consumer Cost are the same decrease in Utility Costs, but once the injection credit is low enough that battery begins to operate, the Utility's Costs increase slightly. The battery usage does not significantly change within the 25%-81% group, as between 25%- 81% the credit is low enough that the battery efficiency losses don't matter, meaning the battery is already operating at maximum profit by increasing the homeowner's self-consumption of electricity. Between 81%-100% credit, the battery is not used as the efficiency losses incurred would lower the profit compared to simply feeding in any excess solar.

A significant change between the NEM and NEM 81% likely due to efficiency losses is the change in emissions. Because standard NEM sends nearly as much energy out to the grid

(from the solar) as it requires from the grid, the emissions are very low. This makes sense, as the marginal emission factors can be higher during the day when the solar is producing and lower at night when the house draws energy from the grid, thus reducing the systems net emissions. However, when the battery operates, the Grid In energy is decreased by 3,736 kWh/yr., while the Grid Out energy is decreased by only 3,042 kWh/yr., meaning a difference of 694 kWh/yr. energy is lost due to the battery efficiency. This energy lost leads to an increase in emissions roughly equal to the difference between the $CO₂$ Emissions for the two rates.

Despite the increased cost and emissions, the NEM 81% was a great example of the ESR goals of microgrid operation, PV management, and limiting exported energy. The Grid In/Out energy is greatly reduced from standard NEM, from charging the battery from the solar and using that energy to meet the household demand. The Average Battery Capacity is above zero, making it better for microgrid operation. And while the Peak Grid In/Out for the NEM rates do not change significantly, with only a minor reduction in the Peak Grid Out, they do not increase as seen in later rates.

Table 4.2.2: Metrics for the Value of Distributed Energy Resources (VDER) rate structures. The Value of Distributed Energy Resources rates were based on the VDER Alternate Capacity Option Two, where between 2 PM – 7 PM energy for both injection and demand have increased value, for 25% above the standard rate, and 50% for VDER Annual (50%). This rate was proposed to occur between June-August, using NEM the rest of the year, but was also extended throughout the year for the VDER Annual rate structure.

Rates	Consumer Cost (\$/yr.)	Actual Utility Cost $(\frac{\sqrt{3}}{3})$	$CO2$ Emission Changes (kg/yr.)	Average Battery Capacity (kWh)	
VDER J-A	4.43	-20.52	448.13	$4.20*$	
VDER Annual	10.51	-26.64	124.14	4.86	
VDER Annual (50%)	-89.14	73.01	124.14	4.86	

**VDER J-A Average Battery Capacity is measured during June-August, the rest of the year it is 'zero'.*

VDER June-August and VDER Annual had comparable Consumer and Utility Costs, where the \$6.08 increase in Consumer Cost is the same decrease in Utility Cost. Testing was done on the increases of the percent change for the TOU rate (seen with VDER Annual (50%)), but a greater percentage had higher Utility Costs, making the rates less competitive with the standard NEM rate. The example shown above used a 50% rate instead of the 25%, which gave a \$4 cost decrease to consumers and increase to utilities per 1% increase. Also, prices were only effective after a 23% increase due to battery efficiency, like the 81% decrease tested with NEM. The Peak Grid In/Out times shifted from NEM's due to the time period of the rate structure; at 8 PM when costs went down, the battery charged from the grid, and at 2 PM when injection credit was high, the battery and solar both injected into the grid.

However, beyond the Consumer/Utility Costs and Peak Grid times, the differences for VDER June-August and VDER Annual are very significant. The Grid In/Out energy is increased for the annual rate, as is the Peak Grid In/Out energy. The $CO₂$ emissions are greatly increased for the VDER annual rate, likely due to the increased Grid Energy In. This highlights an important factor for the battery that was not seen with NEM rates. If the rate structure values injection higher at some points than the demand cost at other points, it is possible the battery will charge from the grid when demand costs are lower. While this is a feature for some types of storage, it is a detriment to some of the goals of the ESR for residential solar + storage systems.

Increased charging from the grid as opposed to the solar system means increased emissions, increased peak demand, increased exported energy, poor microgrid operation (requiring energy from the grid), and poor PV management. This can be seen comparing the VDER rate structure effects with the NEM's. There is an increase in VDER's grid in/out energy, increases for the Peak Grid In/Out energy, and increases in emissions. In this regard, VDER June-August seems to be the better rate of the two, with better metric results for meeting the goals of the ESR.

Marginal Emissions

Table 4.2.3: Metrics for the Marginal Emissions (ME) rate structures. The Marginal Emissions rate structures were created for use in the model and based on the VDER rate. As reducing emissions is a key goal of the Energy Storage Roadmap, and the VDER rates used were originally intended to be used only in summer, the annual VDER rate structure did not do a great job reducing emissions. Therefore, using the same concept, a 25% increase over a set period of hours, a new TOU rate structure was created. This rate structure used the three seasons that were used for the marginal emission factors, Winter, Summer, and Transient. It was also used to create TOU rates for each season individually that used NEM for the rest of the year, again like VDER.

ME						
Summer						
$(M-S)$	6732.28	6170.86	7.18	8:00 PM	9.47	12:00 PM
ME						
Summer						
$(J-A)$	6394.88	6002.85	7.18	9:00 PM	9.44	1:00 PM
ME						
Transient	6511.47	6205.66	7.11	8:00 PM	9.63	12:00 PM

^{}ME Winter, Summer (M-S & J-A), and Transient Average Battery Capacity is measured seasonally, the rest of the year they are 'zero'.*

The Marginal Emissions rate structures are difficult to compare to one another. Unlike NEM or VDER, there does not seem to be one rate structure superior to the others. Like VDER, the ME rates suffer from charging the battery from the grid, with higher Grid In/Out and Peak Grid In/Out energy than NEM, as well as increased $CO₂$ emissions. Looking at Figure 4.2.4 below can help narrow down the better rates. The ME Summer June-August and ME Transient rates seem to be the 'best' of the ME rates used, as both have negative Consumer and Utility Costs, as well as lower emissions. However, the much greater emissions of the ME Transient rate structure seem to give it the edge between the two. Going back to table 4.2.3 shows that the Grid In/Out energy is slightly higher for the ME Transient, which may make the ME Summer June-August rate the more desirable. The close comparison between these two rates is a good example of one of the problems with the ESR; it doesn't specify which goals have priority for residential prosumers with storage. However, for the purposes of future comparison, the ME transient is possibly the best of the Marginal Emissions rate structures, due largely to the lower $CO₂$ emissions. With a moderate social cost of Carbon, this change emissions may make the rate more desirable than others.

Figure 4.2.4: Costs and Emissions Metrics for the Marginal Emissions (ME) rate structures. Negative Costs and Emissions signify a better rate. Consumer/Utility Costs and CO² Emission Changes are the displayed metrics.

Smart Export

Table 4.2.5: Metrics for the Smart Export (SE) rate structures. The Smart Export Rate Structure is used in Hawaii for consumers with Energy Storage, and values energy injected between 9 AM – 3 PM at \$0. The SE 81% uses the principle from the NEM 81% and increases the injection value to 81% of the demand, which causes very little change to the consumer behavior, but gives a much fairer value to the consumer. The SE 81% (11-1) (J-A) shortens the length of time energy is credited to 11 AM – 1 PM and only applies the rate between June-August, using NEM the other months.

Smart						
Export	4232.11	3391.55	2.36	7:00 PM	7.33	8:00 AM
SE 81%	4219.43	3378.87	2.41	7:00 PM	7.29	8:00 AM
SE 81%						
$(11-1)$ $(J-A)$	5649.29	5352.32	2.41	7:00 PM	9.08	$2:00$ PM

^{}SE 81% (11-1) (J-A) Average Battery Capacity is measured during June-August, the rest of the year it is 'zero'.*

The Smart Export 81% rate is better than the Smart Export rate, but mostly due to the decreased consumer cost. And this benefit is negated if utility costs are of higher priority. This shouldn't be surprising, as the pattern of behavior for the two is nearly identical, but the Smart Export essentially gives the utility free energy from excess solar produced. Smart Export 11 AM – 1 PM June-August was used to see how shortening the time period and months applied would affect the rate, like the VDER and ME rates. There are a few key differences between the metrics of the Smart Export rates that provide interesting insight into the optimization. For example, the peak grid out time is 8 AM for the Smart Export and SE 81%. This happens because 8 AM is the hour before injection credit is reduced, which means having the battery discharge at this point. The slight difference in Average Battery Capacity occurs because the Smart Export discharges some excess energy during the day, as that energy is valued at zero anyway, making the Average Battery Capacity slightly lower. It is also lower in the SE 81% (11-1) (J-A) because of the shorter period it would charge in.

Real-Time Price

Table 4.2.6: Metrics for the Real-Time Price (RTP) rate structures. The Real-Time Pricing uses the Actual Energy Price for the injection and demand charges, while the RTP flat demand uses the Actual Energy Price for injection credit only. The RTP + Cost of Carbon rate adds a social cost of carbon (\$40/kg) using the marginal emission factors to the Actual Energy Price for the injection and demand charges.

The Real-Time Pricing rate structure had a huge decrease in the Consumer Cost, due to the many opportunities the battery had to make a profit buying and selling energy solely from the grid. This can be seen not only in Figure 4.1.4, but also the Grid In/Out energy in Table 4.2.5. As with the VDER and Marginal Emissions rates, charging the battery from the grid lead to poor metrics compared to NEM. The significant difference between Real-Time Pricing and NEM led to the rate RTP Flat Demand, which would operate like NEM 81% but discharge the battery into the grid when electricity is valued significantly high enough. However, this did not occur often enough to be profitable for the consumer (although like Smart Export, the consumer's loss is the utilities gain). While attempting to bring down the huge increase in $CO₂$ emissions from the Real-Time Pricing rate, the rate was combined with a social cost of carbon based on the marginal emission factors. Interestingly, this drastically reduced $CO₂$ emissions, while affecting the other metrics only slightly.

Day-Ahead Price

Table 4.2.7: Metrics for the Day-Ahead Price (DAP) rate structures. The Day-Ahead Pricing uses the Day-Ahead Energy Price for the injection and demand charges, while the DAP flat demand uses the Day-Ahead Energy Price for

injection credit only. The DAP + Cost of Carbon rate adds a social cost of carbon (\$40/kg) using the marginal emission factors to the Day-Ahead Energy Price for the injection and demand charges.

Rates	Consumer $Cost$ (\$/yr.)	Actual Utility Cost $(\frac{\sqrt{3}}{yr})$	CO₂ Emission Changes (kg/yr.)		Average Battery Capacity (kWh)	
Day Ahead						
Pricing	-58.38	37.25	338.12		6.71	
DAP Flat						
Demand	260.36	-247.97	337.78		5.92	
$DAP +$						
Cost of						
Carbon	-57.06	31.53	88.35		7.26	
	Grid In (kWh/yr.)	Grid Out (kWh/yr.)	Peak Grid In (kW)	Peak Grid In Time	Peak Grid Out (kW)	Peak Grid Out Time
Day Ahead						
Pricing	9842.80	8738.20	7.19	10:00PM	9.44	11:00 AM
DAP Flat						
Demand	2926.96	2089.93	2.41	7:00 PM	7.18	10:00 AM
$DAP +$						
Cost of						
Carbon	9609.28	8637.77	7.29	7:00 PM	9.60	11:00 AM

The Day-Ahead Price is more modest than the Real-Time Pricing rate, but with similar effects. Compared to NEM, it has lower Consumer Costs, higher Utility Costs, increased CO² emissions, and increased Grid/Peak Grid In/Out energy. It does shift the Peak Grid In Time but considering the Peak Grid In energy increase that is less significant. Both the Real-Time Pricing and Day-Ahead Pricing have high Average Battery Capacity, but that could be because of frequent charging, meaning the Average Battery Capacity for these is not a good metric to measure the goals of microgrid operation or PV management. Like the RTP + Flat Demand, the DAP + Flat Demand acts like the NEM 81%, however it does not seem to discharge to the grid as frequently as the RTP + Flat Demand did, likely due to the Real-Time Pricing having high cost events not forecasted in the Day-Ahead Pricing.

4.3 Comparing Different Rate Structures

In Section 4.2, the rate structure variations were elaborated and compared to the originals. In this section, some of the variations and originals are compared to other rate structures based on the metric results and goals of the ESR. When comparing the rates, Net Energy Metering was chosen as a baseline rate structure, as it is the current standard for residential prosumers in NYS. However, some of these rate structures use the battery to reach certain goals of the ESR, while standard NEM doesn't use the battery. Not using the battery means there is no energy lost due to the battery efficiency, which affects the other metrics. It is also useful to also compare the rates to the NEM 81%, which uses the battery and meets many of the goals of the ESR. The other rates chosen to compare were based on how well they met the metrics/goals. The RTP Flat Demand, DAP Flat Demand, and Smart Export 81% were able to manage PV output, operate microgrids, and limit exported energy (Smart Export 81% 11-1 J-A was included as the Smart Export rate with the lowest consumer cost and $CO₂$ emissions). RTP + Cost of Carbon, DAP + Cost of Carbon, VDER J-A, VDER Annual, ME Summer (J-A), and ME Transient were able to lower consumer costs.

In a similar manner to Babacan et al. (2018) different scenarios, the effect that the rates have on the battery operation seem to fall into one of two categories, either 'Energy Arbitrage' (RTP/DAP, VDER, ME), where the battery buys/sells energy from/to the macrogrid, or 'Self-Consumption' (NEM 81%, RTP/DAP Flat Demand, SE), where the battery charges/discharges within the microgrid. These rates seem to function based on the way they are designed, with 'Energy Arbitrage' taking advantage of injection credits higher than demand costs, and 'Self-Consumption' charging from solar when injection costs are lower than demand. The 'Energy Arbitrage' group seems to have an advantage on the cost metrics, while the 'Self-Consumption' group has advantages with energy management. However, neither perform better regarding $CO₂$ emissions than NEM.

Consumer Costs

Figure 4.3.1: These are the Consumer Costs for the rates chosen to compare. The RTP/DAP + Cost of Carbon are the best of the rates chosen in terms of Consumer Costs, while the NEM 81% and RTP/DAP Flat Demand are the worst.

The Consumer Costs shown in Figure 4.3.1 reinforce the problem with many of these rates, where the rates that charge the battery from the solar, RTP/DAP Flat Demand and NEM/SE 81%, have higher consumer costs. This is largely due to the energy losses from the battery efficiency. Rates that allow for lower costs by increasing the value of injection credits end up charging from the grid during periods of low demand costs, as the energy lost from charging/discharging efficiency would be the same no matter the source. When comparing SE 81% and NEM 81%, which both have similar functions, it is shown that SE 81% has a slight edge over NEM 81% for consumer costs, since during the time that the SE rate isn't active, it

receives full value for any energy produced. However, as noted in Figure 4.3.1, the energy produced during higher injection value is not significant enough to show large changes in the annual values. It's also seen on Figure 4.3.2 and Figure 4.3.5 that this decrease in consumer cost is nearly directly proportional to the increase in utility costs.

Utility Costs

Figure 4.3.2: These are the Utility Costs for the rates chosen to compare. The RTP/DAP Flat Demand and NEM 81% are the best, while the RTP/DAP + Cost of Carbon and ME Transient are the worst.

The Utility Costs changes for most of the rate structures chosen are proportional to the changes in the consumer costs. However, a few rate structures, RTP + Cost of Carbon and ME transient have decreased costs for both the Consumer and Utility. Interestingly, the DAP + Cost of Carbon has increased the cost to the utility, significantly more than the RTP + Cost of Carbon, despite the Consumer Cost being lower for the RTP + Cost of Carbon than the DAP + Cost of Carbon. Looking back on Table's 4.2.6-7, this is also the case with the Standard RTP/DAP. This

is a good indicator that more accurate Real-Time Pricing/Day-Ahead Pricing could be key to ensuring the Utility and Consumer both get the full benefit of the battery energy storage systems.

CO² Emissions

The $CO₂$ Emission Changes shown in Figure 4.3.3 help illustrate the problem inherent in using battery energy storage to try and reduce emissions, energy lost due to battery efficiency make it extremely difficult to reduce emissions beyond what can be done by simply providing the clean energy (NEM). This is especially noted by the VDER, SE, and ME rates, as comparing the annual vs season rates shows that the less time that those rates are active, the lower the annual emissions. The closest to the NEM reduced emissions is the ME Transient rate, which is

only active in April & October. However, it is of note that including a Cost of Carbon to the RTP and DAP rates significantly lowered emissions, without being detrimental to the other metrics of those rates. Adding carbon costs to rate structures seems to be an effective way to reduce emissions within those rates, without overly affecting the other benefits.

Part of the reason that lowering emissions beyond a solar-only home is difficult for these rates is that Upstate NY (the region used in the model), has very low emissions compared to other areas. To prove this, the model was recreated using data from Long Island, NY (NYLI), which has higher $CO₂$ emissions. Using the lowest emitting annual rate structure (Day-Ahead Pricing plus Cost of Carbon), it was found that the new rate structure decreased emissions compared to the solar-only house by around 169 kg/yr., where in Upstate NY the emissions had been increased by 88.35 kg/yr. under the DAP+ Cost of Carbon rate structure. Two other rate structures, VDER J-A and RTP + Cost of Carbon, were also used in the NYLI location, and while they didn't decrease emissions beyond the solar-only home, they did decrease emissions more effectively than the Upstate NY rates.

Figure 4.3.4: These are the CO² Emission Changes for the rate structures in two different regions, Upstate NY and NYC (for selected rate structures). The changes in CO² Emissions are based on the difference between the marginal emissions generated from these rates compared to a home with only solar. Thus, the Upstate DAP + Cost of Carbon rate emitted 88.35 kg/yr. more than a home using only solar, while the NYLI DAP + Cost of Carbon rate emitted 168.95 kg/yr. less than a home using only solar.

Figure 4.3.5: These are the Consumer Costs, Utility Costs, and CO² Emission Changes for selected annual rate structures. The rates are sorted based on whether they encourage Self-Consumption (NEM 81%, RTP/DAP Flat Demand, SE 81%) or Energy Arbitrage (VDER Annual, RTP/DAP + Cost of Carbon, ME).It can be seen that the Self-Consumption rates decrease costs to the utility about as much as they increase the cost to the customer. Energy Arbitrage rates seem to be slightly more equitable, decreasing costs to the consumer slightly more than they increase costs to the utility. Energy Arbitrage rates also have the potential for lower CO² emissions than Self-Consumption rates, as seen with DAP + Cost of Carbon and ME. However, none of the rates succeed in getting below the emissions of a solar-only home for the region of Western NY..

Figure 4.3.5 shows the cost to the Consumer, costs to the Utility, and the Annual Carbon Emissions, and Figure 4.3.6 shows the combination of those three, using a social cost of carbon (\$40/Mg). This combination of costs in Figure 4.3.6 reduces to Equation 53, the Real-Time Cost of Electricity and the Carbon Cost of electricity times the energy sent from the grid to the house minus the energy sent from the house to the grid. This is the wholesale cost of electricity to/from the grid for each rate structure, plus the cost of carbon emissions.

$$
\sum_{h}^{hf} [(RTP_h + Me * CarbonCost_h) * (Gi_h - Go_h)]
$$
 [53]

Figure 4.3.5 shows that Self-Consumption rates generally have reduced utility costs, and Energy Arbitrage rates have lower consumer costs. Comparing to Figure 4.3.6, Energy Arbitrage rates also have lower wholesale + cost of carbon costs (except for the RTP Flat Demand rate).

Figure 4.3.6: The Combination of Utility Costs, Consumer Costs, and Carbon Costs, (aka the net cost of electricity to/from the grid for each rate structure, plus the cost of carbon emissions). This reduces to The Wholesale Cost of electricity plus the Carbon Cost of electricity (Using a social cost of carbon of \$40 per ton), for energy taken from the grid minus energy sent to the grid, to determine the overall cost of the different rate structures.

Limiting Exported Energy, Solar+ Storage Management, Microgrid Operation, & Peak Energy

Figure 4.3.7: This is the Grid Out Energy for the rates chosen to compare. NEM 81%, RTP/DAP Flat Demand, and SE 81% are all rate structures that have decreased energy sent to the grid compared to NEM, and this is due to the rates valuing injection credit less than demand costs.

The NEM 81%, RTP/DAP Flat Demand, and SE 81% all reduced the Grid Out energy, limiting the exported energy from the solar as seen in Figure 4.3.7. They also decreased the Grid In energy, as seen in Figure 4.3.8. These rates are focused on PV management and microgrid operation, also shown by Figure 4.3.9, where they generally have higher Average Battery Capacity. The $RTP/DAP + Cost$ of Carbon rates have higher, but that is due in part to the much

larger Grid In/Out energy they use, as they frequently charge and discharge the battery. NEM 81%, RTP/DAP Flat Demand, and SE 81% all slowly use the battery's stored energy to cover the household demand after charging from the residential solar system. This is further illustrated with Figure 4.1's Average Daily Use Patterns. The way NEM 81%, RTP/DAP Flat Demand, and SE 81% rates function also influences the Peak Grid In metric. Because the batteries do not charge from the grid, the peak demand stays as low as the standard NEM. However, the Peak Grid Out metric is changed for RTP/DAP Flat Demand and SE 81% because there are points where the value of injection is higher, making it worthwhile to discharge the battery before charging from the solar when injection credit is lower again.

Figure 4.3.8: This is the Grid In Energy for the rates chosen to compare. It is very similar to the Grid Out Energy, as the rates that focus on self-consumption choose to charge the battery from the solar and use it to cover demand rather than send it to the grid. They do not charge the battery from the grid, unlike the rates that discharge the battery to the grid to decrease the consumer costs.

Figure 4.3.10: This is the Average Battery Capacity, and Electricity In from the Grid/Out to the Grid for selected annual rates. The rates are sorted based on whether they encourage Self-Consumption (NEM 81%, RTP/DAP Flat Demand, SE 81%) or Energy Arbitrage (VDER Annual, RTP/DAP + Cost of Carbon, ME). The NEM (Solar) rate does not have a battery capacity because it represents a home with only solar, and if NEM is the rate use the profit maximization of the linear optimization model does not incentivize using the battery, as the efficiency loss would mean less profit.

The Average Battery Capacity and Energy In from/ Out to the Grid all relate to the ESR goal of Operating Microgrids. A higher average battery capacity can generally mean that the battery would have a larger capacity available should access to the grid be cut off. However, while the increased average battery capacity of the RTP/DAP + Cost of Carbon rates may seem beneficial, these rates buy/sell energy to/from the grid at much higher frequency and quantity than other rates, meaning the capacity my be low when grid access is cut. This issue can be further examined when comparing rates daily use patterns on Figure 4.1.1. The RTP/DAP + Cost of Carbon rates discharge most of the battery energy in the evening and charge the battery during early morning from the grid. Should power be cut during this time, the battery would likely have very low capacity, making it incapable of islanding (operating a microgrid). Also seen when comparing Figure 4.1.1 and Figure 4.3.10, the Self-Consumption rate structures (NEM 81%, RTP/DAP Flat Demand, and SE 81%) require much less energy from the grid, both in their daily use patterns and the annual energy taken from the grid. This shows they are more capable of operating a microgrid should the need arise.

Figure 4.3.11: This is the Peak Grid Energy In/Out for the rates chosen to compare. The Peak Grid In is the same value for rates that have higher demand costs than injection credits. Rates with higher Peak Grid In will use the grid to charge the battery when costs are low. Most rates have an increased Peak Grid Out because the battery will discharge while credits are higher to charge when credits/costs are lower. The exception to this is the NEM 81%, which is because there is no point where the injection credit is higher than any other point.

A compilation of the results for annual rate structures sorted between rates that are examples of Self-Consumption and Energy Arbitrage can be seen on Figure 4.3.12 below. Figure 4.3.12 shows an interesting connection between the consumer and utility for Self-Consumption rates. When the consumer buying/selling much less energy from the utility under Self-Consumption rates, the utilities cost is significantly reduced, and the consumer's cost is much higher, despite buying significantly less energy from the grid. Because the Utility is buying much less energy from the consumer (which while under NEM is normally valued much higher than the RTP), the utility ends up saving money while having less interaction with the consumer. This highlights how Self-Consumption rates disproportionately benefit the utility.

Figure 4.3.12: These are the Costs, Emissions, Capacity, and Annual/Peak Grid Energy In/Out for the annual rates, sorted between Self-Consumption rates to Energy Arbitrage rates. This chart really displays how Self-Consumption rates have much less interactions with the grid, with lower Grid In/Out energy, but still reduce utility costs drastically and the Energy Arbitrage rates take more energy but reduce consumer costs. However, Energy Arbitrage does not cost the utility as much as Self-Consumption costs the Consumer, likely due to the higher demand when discharging.

4.4 Sensitivity, Fixed Costs & Tax Credits

The sensitivity analysis chosen was adjusting the rates to match the standard NEM utility costs. Initial testing directly resulted in some of the seen rates, specifically the ME seasonal rates and Smart Export's 81% 11-1 June-August rates. These adjustments fundamentally changed the rate structure design, essentially creating new rate structures and not analyzing sensitivity to cost changes, but rather shifting times or months in operation. Another method could be changing the percent increase/decrease that rates like VDER, ME, and SE used for the injection/demand charges. However, as discussed with the NEM variations, limitations caused by battery efficiency meant rates between 82-122% of the demand cost did not operate the battery. And in cases above 122% or below 81%, changing the percentage did not result in behavior changes, as the most profitable patterns were already in place. However, by increasing or decreasing the whole rate (not just the TOU) by a certain percent, most models could show how matching utility costs would affect the consumer cost. Some rates (RTP Flat Demand, ME & ME Summer/Transient) were not able to come close to the utility cost no matter how drastic the change. The rates that were able to be changed are shown in Figure 4.4.1 where it can be seen that the Real-Time Price, RTP + Cost of Carbon, Day-Ahead Price, DAP + Cost of Carbon, VDER Annual and VDER June-August were the only rates that kept the utility cost the same, while decreasing the consumer cost.

Figure 4.4.1: Rates matching the Utility Cost of NEM, and their corresponding new Consumer Cost. The rates were made to match the Utility Cost (orange) of the standard NEM. The changes made in the rates caused changes in the Consumer Cost (blue). These rates had some of the lowest consumer costs before adjustment.

Fixed Costs/Tax Credits

As discussed in Section 3.3, fixed costs can be applied to rate structures after their implementation or operation to determine a what is essentially a 'cost of operation'. The State or Utility could determine that a rate structure leads to desired outcomes but would also lead to lost revenue or unequal distribution of benefits. They could then decide to increase the fixed costs of the electricity bills for consumer on that rate structure, thus solving the problem without affecting the use patterns. This would work with rates that cost the consumer less than NEM and can be seen below on Figure 4.4.2.

Figure 4.4.2: Increases to the monthly 'Fixed Costs' that would keep the consumer bill equal to that of the standard NEM. For rates that have lower consumer costs than NEM but with desirable behavior.

A goal mentioned in the ESR was to provide savings via investment tax credits. These could function in the same vein as the fixed costs, but rather than artificially increase consumer costs, the state could provide a subsidy or tax credit to consumers if their costs were higher than those of the NEM rate. This would be especially effective on rate structures that met the goals of limiting exported energy and managing the solar + storage, as those rates had higher costs due to losses from the battery efficiency. The tax credit amounts that would be needed can be seen below on Figure 4.4.3.

Figure 4.4.3: Annual 'Tax Credit' that would keep the consumer bill equal to that of the standard NEM. For rates that have higher consumer costs than NEM, but with desirable behavior.

5. Discussion

Findings

From the effects of the rate structures, there emerge two distinct modes of battery operation, 'Energy Arbitrage' (EA) and 'Self-Consumption' (SC). EA is where the battery finds it profitable to charge from the grid and discharge to the grid and/or household demand later. The rates that fall into this category (RTP, DAP, ME, VDER) are where the injection credit of one time period can be higher than the demand costs of other time periods. Energy Arbitrage can take advantage of the macrogrid electricity market with rate structures like Real-Time Pricing or Day-Ahead Pricing, or they can be encouraged to inject energy at specific times such as VDER or ME. The SC mode charges the battery almost solely from the solar system and discharges the battery usually to cover the household demand. These rates (SE, NEM 81%, RTP/DAP Flat Demand) have decreased the value of the injection credit compared to the cost of electricity (\$/kW). Self-Consumption can help encourage time-shifting excess renewable solar generation to help cover future demand. This can also lower the peak demand of the prosumer. In general, EA rates have lower costs, both to the consumer and utility, but SC rates better fit the ESR goals of limiting exported energy and managing the PV system.

Policy Implications for Goals of the ESR

The Energy Arbitrage and Self-Consumption modes of operation can affect goals of the Energy Storage Roadmap, and their differences can illustrate the difficulty in stacking those goals. The reduction in emissions for the RTP/DAP + Cost of Carbon rates show that the Energy Arbitrage rates could stack emission reduction and cost reduction more effectively if a social cost of carbon is added. The Self-Consumption rates stack goals like solar + storage management,
limiting exported energy, reducing demand, and time-shifting the renewable energy. However, due to battery efficiency and capacity, SC rates are not as successful at reducing emissions beyond a solar-only home, nor are EA rates as successful at limiting exported energy or reducing peak demand. Policy makers will ultimately need to consider which goals have higher priority for residential storage. A likely choice would be the SC rates, as the EA method could be handled more effectively with large-scale BES operation.

Cost Reduction

Reducing Consumer costs was done most effectively with EA rates, while reduced utility costs were more effective with SC rates. This is because the consumer could get greater values for stored energy with the EA rates, while the Utility payed less for the energy provided with SC rates. While increasing costs are not desirable, additional costs to one party could be offset by subsidies or changed fixed costs. Such subsidies or fixed cost changes should be considered when considering/implementing rate structures that are more effective at reaching other goals. Also, reductions in Wholesale Cost $+$ Cost of Carbon (Figure 4.3.6) were usually more effective with EA rates, apart from the RTP Flat Demand rate, which benefits from lower consumer and utility costs compared to the DAP Flat Demand rate. The benefits of Self-Consumption rates may be worth the additional cost and can be dependent on case-by-case based on the individual prosumer (different demand patterns, reliability, microgrid operation, utility subsidy, etc.). If policy makers wish to implement either EA or SC rates, they need to consider the increased costs they would have on the utility or consumer, and how likely they are to be adopted.

Emission Reduction

While reducing emissions beyond a solar-only home was not done with most rate structures, including a Cost of Carbon on either the RTP or DAP rates cut $CO₂$ emissions compared to the standard RTP/DAP. While this didn't get the emissions below a solar-only home in the region chosen, it did help reduce emissions in Long Island, NY for the DAP + Cost of Carbon rate. Such a factor will need to be a consideration in the implementation of local rate structures with the different electric utilities across the state. The differences in emissions for different regions will have an impact on the effectiveness of the rate structures ability to lower emissions. The capabilities of batteries may also change as the market grows, and emission reductions may become more feasible as battery efficiency improves. However, frequent use of the battery may also degrade efficiency as time progresses. Policy makers should pay attention to improvements in the technology, and both policy makers and consumers should be aware of the effect time may have on installed battery capabilities.

Solar + Storage Management, Limiting Exported Energy, Time-Shift Renewable Energy, & Operating Microgrids

It should be noted that Energy Arbitrage rates do not limit exported energy. EA rates involve selling energy to the grid when prices are higher, meaning this goal does not stack well within these rate structures. Self-Consumption rates on the other hand, store the solar energy produced and use it to cover future household demand. This is Solar + Storage management, Limiting Exported Energy, and Time-Shifting Renewable Energy. Like Emission Reduction, these goals could also benefit from improved battery technology. Unlike Emission Reduction, the most effective improvement in battery technology would be the capacity of the battery. By increasing the capacity of the battery, more of the solar energy could be stored and less would need to be exported to the grid. For future incentives, policy makers may want to consider having a per kWh credit, or requiring a minimum capacity to be eligible, in order to better meet these goals.

The battery used for this model was based on a Tesla Powerwall; a lithium-ion battery with a capacity of 13.5 kWh and charge/discharge rate of 5kW. As an alternative, lead-acid batteries could potentially provide more storage capacity for cheaper investment. However, leadacid battery systems also have less longevity and shorter lifespans, especially when frequently discharged. Their depth of discharge is also much lower than lithium-ion batteries. Lead-acid batteries could be more feasible for the goal of operating microgrids, as the battery would be mostly used when the connection to the grid is severed. However, not operating the battery frequently reduces the capability to meet ESR goals. Lead-acid batteries may be better for rate structures that require less battery use, such as NEM, where the battery is not used, or VDER J-A and SE 81% 11-1 J-A where the battery is used seasonally. If microgrid operation at lower costs is more desirable to the prosumer or policy makers than other ESR goals, higher capacity batteries should be incentivized.

Peak Demand

The ESR goal of peak demand reduction was not effective with the rate structures chosen, particularly for Energy Arbitrage rates. Because EA rates incentivize buying/selling energy to/from the grid, the battery would often charge from the electrical grid when costs were low. This leads to peak demands 5 kW greater than Self-Consumption rates, which do not charge the battery from the grid. Rates that may encourage peak demand reduction, like demand charge rates, were not considered in this model due to the linear optimization limitations. Injection peak reduction, like peak demand reduction, doesn't work well with most of the rate structures. Unlike peak demand reduction, this includes the SC rates. This is because many SC rates credit injection higher than when solar is not being produced, and if a battery has excess capacity at those times it may be beneficial to discharge before charging later (when solar is being produced). Therefore, SC rates peak injections are higher than the NEM rate. NEM 81% is the exception, because its injection credit is consistently 81% the flat demand cost. If peak demand/injection is an important goal for policy maker, they will need to consider either adopting different rate structures than the ones studied here or prevent residential batteries from charging/discharging from/to the grid.

Limitations of the Model

The model used was based on a home with a standard demand profile, average solar production profile, marginal emission factors, and electricity costs for Western New York. This was chosen because of New York State's Energy Storage Roadmap, but within other regions of New York the results could be different. Western New York as an excess of low emission energy thanks in part due to Niagara Falls (which provides clean hydroelectricity). New York City or Upstate New York has different real-time prices, marginal emission factors, solar production, demand profiles that change the results of the model, as seen in Figure 4.3.4. The marginal emission factors could be improved upon with increased granularity analysis of the macrogrid, a goal mentioned in the ESR.

Beyond these limitations, there are also aspects of the battery energy storage system that are not considered. For example, a common method in current research is a cost/benefit of the battery system, to determine how cost effective such a system would be for various purposes. This model did not take the initial cost of the battery into account, nor the lifespan of the battery. The model itself is only run over a single year, which may not be indicative of the full effect of the battery over its lifespan. For example, the Real-Time Price rate structure had the highest

consumer profit but used the battery nearly twice as much as any other rate structure. This could cause severe wear over a much shorter period compared to other rates. The battery chosen, a Tesla Powerwall, costs \$6,500 for the battery itself, and an additional \$3,600-\$4,600 for installation. Assuming the maximum reduced costs from the rate structures analyzed (\$200/yr., Real-Time Price), it would take 32.5 years to pay off the battery alone. Considering the expected lifespan of lithium-ion batteries is around 10 years, the monetary benefit-costs don't encourage this battery adoption. To make up the cost of the battery within the expected 10-year lifespan, the battery would need to cost only \$2,000, or have a cost reduction of \$650/yr.. As the maximum reduced cost was an Energy Arbitrage rate, this also means that non-monetary benefits, such as limiting exported energy or increasing self-consumption, would not contribute positively, as they did not stack well within EA rates. Thus, for current battery capabilities and prices, it would not be cost effective to use residential BES storage.

The Tesla Powerwall also has a capacity of 13.5 kWh and charge/discharge rates of 5 kW. While this is not an insignificant capacity or flow rate, there were points in the rate structures where the technical aspects of the battery ended up being the limiting factor to the systems capabilities. Battery Efficiency was even more of a factor considering the emission increases and energy lost. The system didn't even find the battery useful to run with injection credit between 81%-122% of the standard demand cost, due to the efficiency losses. Future improvements to the technology these factors may become less of an issue, but still worth consideration in rate design.

There is much potential for this model to be used to help develop rate structures, especially given the goals of the Energy Storage Roadmap. This model only considered residential homes, due to lack of consideration in the ESR, and the decreased red tape that comes

from a single decision-maker (the homeowner). However, if provided with additional data regarding the production/demand, there is no reason this model couldn't be used for projects of larger size. When choosing a larger system that has demand charges within its rate structure, the model would encounter problems. Demand charges affect the highest level of demand a customer has during a set time period and charges an increased rate for that specific level of demand. This rate becomes non-linear and would require a different type of optimization to calculate. A similar comparison could be made for the fixed costs of electricity bills that this model does not consider (the model uses optimization for the electricity delivery rate). However, fixed costs can change with different rate structures (as explored in Section 4.4) and could be a method used to make the benefits of BES more equitable.

The model used also does not consider consumer preferences, or other decisions made while using the battery. Consumers may desire keeping a minimum charge on the battery or different charging/discharging rates for emergency power consumption or improved battery life. The model uses only the profit maximization as it's linear optimization. This is especially apparent in the NEM rate, where the battery is constantly at zero charge, as there is no profit benefit to keep a charge on the battery. In addition, there are logical and mathematical limitations to the model, or certain assumptions built into the optimization. The rates were run monthly, then collated for the year to get the annual results. This provides a certain foresight that allows for perfect predictions that would not be true to life. This is especially the case for Real-Time Prices, solar production, and household demand, all of which can be affected by real-time events. Another type of real-time event, power outages, did not occur in the model, and depending on the severity could drastically change the battery performance (although likely only for a short

time that wouldn't drastically impact the annual values). Each month also started with a battery capacity of 0 kWh, which would likely not be true to life.

Other Goals of Residential Storage

There are other reasons to consider alternative rate structures with storage aside from profit maximization, which depends on the consumer's desires. Creating a microgrid system to be able to island the solar + storage system for household demand in case of macrogrid power outages can be very beneficial, and a feasible alternative to generators. This may be more applicable to customers with solar who are in areas with frequent grid outages or need continuous/stable power supplies. Customers who have electric vehicles would also be ideal candidates, in order to reduce the effects of charging a vehicle in the evening, when grid demand is at a peak. With the growing electric vehicle market, EV charging could have dramatic impacts on the macrogrid, impacts that could be limited by BES systems. Incentivizing the installation of a BES system with the purchase of an EV could be an interesting policy application, especially considering the EV tax credit is phasing out for some manufacturers leaving a policy gap in EV incentives.

However, applications of the battery system like these are not based on profit maximization and would require separate modeling than the method used here. these goals also depend on individual desires and would require a different optimization system/model. For example, if a prosumer is aware of an increased chance of macrogrid power failure (such as incoming severe weather), they would likely desire to retain a full charge on their battery for later microgrid use, until the chance of failure had passed, something that was not accounted for here.

The potential market that might value other goals above reduced costs should not be discounted. And while current trends indicate that NYS is focusing efforts on battery energy storage in New York City (NYC), this may result in a narrow residential consumer market. Other consumers across the state would need different considerations to encourage the adoption of BES. While this method focused on Western NY residential battery storage in relation to the goals of the ESR, it did not fully consider battery energy storage statewide. There are many factors that would need to be considered to increase the potential for battery energy storage adoption to a wider range of residential customers. Increasing the availability to more rural areas with worse quality grid connectivity would build up a wider market range and could also help provide more granularity of the macrogrid analysis. There are also many areas besides residential prosumers that could benefit from the adoption of BES systems, but may need policy makers to start incentivizing the adoption. Requiring a basic BES system for newly built homes could provide better cost effectiveness, since the installation of the BES system while the home is being built may be easier. A BES system would also benefit from more modern/efficient appliances, requiring less power for the household demand. Rural, remote areas could benefit from a stable, consistent, and clean power supply, like park police/ranger offices.

Current Trend/Goals

The New York State Energy and Research Development Authority currently uses the Value of Distributed Energy Resources to determine the more accurate cost that should be applied to distributed renewable generators like solar. A problem with the VDER rates is the cost difference from NEM. For community scale distributed generation, VDER is projected to have injection values between 90-95% the demand costs (comparable to NEM 90/95%). The example run in the model with NEM injection credit reduced to 95% led to higher to consumer costs and

utility profit but no other effects, this percent difference may be hurting customers. It also would not encourage battery use, due to efficiency losses. However, until January 2020 residential solar customers will be able to sign up for a net metering contract for a period of 20 years. Considering the benefits that NEM has over most of the other rates (lower emissions, lower exported energy than EA rates, lower costs, etc.), it may be more beneficial to the goals of the ESR for policy makers to not encourage residential battery adoption/operation via new rate structures.

Currently, residential battery operation in Western NY doesn't seem to have significant value beyond limiting exported energy or microgrid operation. Yet NYSERDA wants to be have 1.5 gigawatts of Battery Energy Storage by 2025. While most of this BES will be larger scale for bulk system and distribution system storage, some residential early adopters will likely take advantage of the improved large-scale battery market and install their own storage. The rates studied here show the different ways that a prosumer might operate their battery, and what effects those operation patterns may have. Given the increasing BES market, and the potential for residential installations, the contract period for NEM rates should probably be shorter than 20 years. Battery technology and economics may make deployment more feasible for a broader population, leading to the need for new rates that encourage different operation for different locations. Increasing the storage across the state and macrogrid should also increase the information granularity about emissions, demand spikes, renewable generation, etc.. This information will be invaluable in optimizing future policy and rate structures to better fit specific regions. Effects like these can already be seen in the changes to the Real-Time Price and Day-Ahead Price rate structures. After adding in a cost of carbon to the rates, the emissions dropped significantly with very little change otherwise.

6. Conclusion

The New York State Energy Research and Development Authority (NYSERDA) desires the installation and operation of battery energy storage (BES) to reach the goals of reduced peak demand effects, reduced emissions, reduced costs, residential solar + storage management, manage PV system output, limiting exported energy, limit impacts on demand bills, and potentially operating microgrids. However, the Energy Storage Roadmap (ESR) that outlines those goals does not specify how they should be met by residential prosumers with BES. Most research states that in order to use BES to reduce emissions, and be economically optimal for a system, a rate structure specific to the region and consumer is needed. Without a well-designed rate, emissions are likely to increase. None of the rate structures in this model were able to improve net CO² emissions for the system beyond the Net Energy Metering (NEM) rate for the Western NY region. This can be attributed partially to the energy lost from battery efficiency. However, other goals, such as reduced costs or limiting exported energy were improved from NEM with new rates. The effect that the rates have on the battery operation falls into one of two categories, either 'Energy Arbitrage', where the battery buys/sells energy from/to the macrogrid, or 'Self-Consumption', where the battery charges/discharges within the microgrid. These rates function based on the way they are designed, with 'Energy Arbitrage' taking advantage of injection credits higher than demand costs, and 'Self-Consumption' charging from solar when injection costs are lower than demand. When NYSERDA is considering future rate structures for residential solar + storage customers, they need to clearly define which goals have priority, and use that to inform their selection. Self-Consumption rates would be more effective for residential homeowners, while Energy Arbitrage effects would be better suited to large-scale bulk/distribution systems.

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