System Benefits of Industrial Battery Storage: A Comparison of Grid and Facility Control and Dispatch

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Abstract

Customer-owned, distributed battery installations are being incentivized by utilities to increase installed battery capacity. In many of these incentive agreements, the battery owner relinquishes battery control to the utility in exchange for incentive money. The industrial sector has lagged in storage installation when compared to the residential and commercial sectors. This study compares the economic advantages to utilities and industrial facilities in different dispatch control situations. The study presents a novel framework for the optimization of multiple systems using load profiles from the industrial, residential, and commercial sectors. Case studies are presented to illustrate different dispatch scenarios. The simulations showed more fiscal benefit for the industrial facilities to dispatch the battery for electrical demand reduction than utility dispatch. In the case studies, facility dispatch control resulted in an increase of facility savings by a factor of about 8.7 when compared to utility dispatch. Battery size plays a significant factor on the impact of the grid's generating costs, showing that larger batteries can provide significant benefit even if dispatched by the facility. Future policies concerning industrial battery installations should consider overall economic benefits to utility and facility in the form of rate structures and incentive participation based on battery size.

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1. Introduction

Utilities across the United States utilize different structures for their customers to incentivize behaviors that benefit the utility and grid. Utility customers in the industrial sector typically are charged for the amount of total energy they use as well as a charge for their peak power usage during the billing period. This second charge, which is typically seen less in the residential and commercial sectors, provides a financial incentive for industrial customers to actively work to reduce these demand charges to reduce overall utility bill expenditures. Methods for achieving this include practices such as load shifting and peak shaving. Battery storage is a growing solution in helping large facilities to take advantage of peak shaving and reduce demand charges. Though conceptually the method works, the benefits of battery installation are closely associated with current demand rates and monetary incentives designed to increase battery installation.

In the industrial sector, battery installations have lagged compared to residential and commercial deployment. Utility companies have introduced generous monetary incentives to increase the number of battery installations. Those contracts include stipulations on letting the utility dispatch the battery to ensure benefit to the grid. If an industrial customer were to install battery storage under these stipulations, they would have to choose whether to discharge the battery themselves, utilizing the capacity for peak shaving, or let the utility discharge the battery and receive the incentive payments.

1.1. Literature Review

Industrial facilities' decisions to implement large projects are overwhelmingly driven by financial benefit, typically measured in payback or net present value. Considering battery storage installation to be a large project, most industrial users seek utility incentives to improve the financial benefit. Studies have found that though the deployment of battery storage provides fiscal benefit, most do not provide enough value to be worth the investment [1], and many still require incentives to be profitable for the facility [2]. This is especially true compared to more conventional energy efficiency measures [3]. Policy and incentives continue to have significant impacts on the economic performance of energy storage profitability and continuing investment, which in some places favors a recent growth in private investment in battery storage [4]. As private investment in battery storage grows, the industrial sector cannot continue to fall behind in battery deployment, necessitating a focus on the effects of dispatch from industrial battery storage.

Energy storage in the industrial sector has mainly been studied to analyze the financial benefit to the end-use customer. The financial benefit is typically seen in the form of utility cost-savings. A case study out of Malaysia used a cost-benefit analysis of industrial customers to determine the profitability of different types of batteries [5]. The study concluded that the industrial battery installations could decrease the overall levelized cost of energy, dependent on battery type. One other study concerning the economic profitability of solar and battery projects in the industrial sector in South-East Asia found that coupling batteries with solar reduces the profitability of the system when compared to just installing solar [6]. Recent studies have analyzed the fiscal benefits of other types of process storage in the industrial sector while also acknowledging the contributions to flexibility in a smart grid environment [7]. These contributions are compounded in time-varying processes that can be shifted or automated to provide flexibility while still providing financial benefit [8, 9]. In the commercial and residential sectors, demand charge savings to the customer are most directly augmented by the presence of battery storage when coupled with solar. However, these savings depend strongly on peak coincidence between solar availability and time-of-use rate schedules [10, 11, 12, 13]. Without the presence of batteries, peaks outside the solar production period cannot provide demand charge savings. Even with batteries, the savings are often not enough to justify a battery storage installation [14].

Economic viability of energy storage is highly dependent on local market designs and policies [15, 16, 17]. Scheduling of storage dispatch should be heavily dependent on the local utility rate structure [18], focusing on the availability of time-of-use and net-metering rate schedules [19] as well as the utility demand rates [20]. The rise of real-time electricity markets complicates the problem even more for any end-use entity hoping to utilize low prices in scheduling battery use [21]. A case study of commercial and industrial facilities in Hawaii analyzed the revenue streams of facilities participating in utility demand response services to receive incentive payments and demand charge reduction from battery use, coupled with solar. The study concluded that though the net benefits were positive, the magnitude of the demand rate and availability of utility demand response incentives had a significant impact on the net benefit of the system for the customers [22]. A similar case study in Georgia noted that storage systems could provide benefit when the goal is to minimize customer utility bills. The study even quantified the impacts of the utility rates on economic and system benefits [23]. The study mentioned the overall effects this objective could have on the grid but noted that the study of aggregation and analysis of grid effects is an area of future research. Though the optimal dispatch of storage systems, with or without solar, has proven effective and sometimes economically viable for customers in various sectors, it outlines the need for techniques to optimize the economic value to both the utility and the customer [24]. Appropriate compensation levels between utilities and customers for distributed energy sources, such as batteries, are hard to optimize and even harder to put into practice [25]. This highlights the importance of rate design in bringing overall benefit to the energy system. Even if an end-use consumer were to decrease their overall demand charges, this does not necessarily equate to a decrease in avoided generation system cost [26]. Utilities need to review the fiscal effects of distributed battery storage on the grid and reevaluate the current rate structures to control and incentivize storage installations that benefit the grid [27].

Researchers at the National Renewable Energy Laboratory have outlined broad solutions to behind-the-meter storage problems. They include well-designed battery interconnection processes when entities apply for grid connection, well-designed compensation mechanisms and other policies to ensure synergy of customer and utility goals, and specified interconnection requirements to ensure system compatibility with the existing grid [28]. Case studies have outlined similar problems with behind-the-meter storage, recommending that all barriers related to grid interconnection and participation with the utility in the energy market must be addressed with policy to ensure storage viability [29]. As energy consumers become energy prosumers, utility rates and incentives must be optimized to maximize system efficiency in both operation and economics [30]. These utility rates and incentives are direct results of legislation and policy in all types of utility structures. This optimization becomes more complicated when considering different energy consumers across residential, commercial, and industrial sectors. There exists a need to understand the effects of current policies on the effectiveness of battery storage across sectors, locations, and sizes of storage.

Location and aggregation of loads and storage capacities significantly impact the effective use of these assets. One Australian case study found that shared localized storage provides more benefit to the grid system than individual distributed storage in the residential sector [31]. The study analyzed interactions of the batteries with the grid to optimize the dispatch and charging for overall fiscal benefit. A similar study in the United Kingdom found that though most home and community storage systems are not currently economically feasible, utilizing larger installations to share loads and seeking other revenue opportunities would help make these installations economically feasible [32]. Locations of distributed storage become more challenging to optimize as the grid changes and as generating sources change. Though this is the case, studies have shown that optimal placement of battery storage within the grid must be considered in economic dispatch and cost-efficient generation [33, 34]. Stanford University researchers identified three different business model types for battery storage applications: co-located front-of-the-meter, behind-the-meter, and aggregated behind-the-meter [29]. The study noted that of the three types, conventional behind-the-meter storage requires less intervention from policymakers than the other two business models, as aggregation has not been as extensively explored in terms of effects and economics.

Distribution system effects and benefits of residential battery installations have been previously explored [35, 36, 37]. One notable study compared the power production costs between residential dispatch of storage and solar installations and the utility-controlled dispatch of those same systems [38]. This study assessed the use of residential batteries by the total reduction of electricity generation cost. A similar study noted the need for regulators to analyze residential objectives by utilizing storage installations and encouraging the use of residential batteries to increase overall system flexibility rather than just the benefits of battery prosumage [39]. Some studies have treated personal electric vehicles as forms of residential battery storage. These, as well as regular behind-the-meter storage, have the potential to provide more than just peak-shaving benefits to the overall grid. Other services such as local voltage management, reactive power supply, and over-voltage absorption are all ways batteries can contribute to the overall security and reliability of the distribution system without directly decreasing utility costs [40].

Grid modeling of distribution and transmission systems to include large amounts of battery storage is an ongoing area of research as the grid seeks more resilience and flexibility while integrating large amounts of renewable energy sources [41, 42, 43, 44, 45, 46, 47]. Short-term modeling of day-ahead markets and the interaction of demand-side management systems, including storage capacity, and long-term power system modeling, including power flow analysis, have been previously studied with various computational programs and considerations of different types of storage [5, 48, 49]. Optimization of economic dispatch problems assuming flexible demand-side energy use has shown promise in maximizing the overall benefits of demand management technologies like battery storage [50]. The IEEE 13-bus and the IEEE 123-bus systems have previously been used to analyze the locations of demand-side battery storage systems for maximizing economic benefit to battery owners [34]. A notable study sought to minimize operational costs of distributed energy sources using time-of-use rate schedules and utilized the IEEE 123-bus distribution network to analyze system effects [51]. Competing objectives in grid modeling can also become a problem as more storage is integrated into the grid system. Qin et al. [52] conducted a study analyzing the competing objectives of economic dispatch and demand response with a grid utilizing battery storage and sought to reconcile them by maximizing the total social welfare of the system. The study utilized a 14-generator model to test the solving algorithm and then verified the algorithm using the IEEE 162-bus benchmark system. Though these systems give glimpses into how storage can affect power flow and the economic dispatch of energy sources, there is no "one-size fits all" solution to all situations [53].

1.2. Contributions of this work

With the prevalence of economic profit as a focus of the industrial sector, the implications of battery installation and operation at industrial facilities need to be more thoroughly investigated to provide the most benefit possible to the end-user. As battery storage grows across all sectors, dispatch of those batteries needs to be considered to maximize benefit. Benefit in this sense is hard to define, being closely associated with the ownership of the batteries and the fiscal viability of installation. Utility rate schedules and incentive programs, especially in regulated utilities, should benefit the customer and help the utility achieve specified aims for power generation and transmission. This work aims to outline some of the industrial sector's hurdles when trying to participate in battery incentive programs and obtain fiscal benefits.

The major contributions of this work include the following:

- The problem is scaled up from a basic 3-bus system using two larger systems to illustrate the effects of the different dispatch schemes. Assumptions were made to categorize loads by type so industrial loads could be modified to include battery storage. The method treats loads at locations as aggregate loads to allow a more manageable solution of the optimizer.

- This method utilizes a power flow formulation with a simplified plant-scale optimization in tandem to model the dispatch of batteries by two different entities. These entities have similar goals of reducing costs but do so at different scales. Since the manufacturing facilities are large end-users, they can significantly impact the overall dispatch of grid-scale generating systems. This method compares these two dispatch schemes with multiple optimization problems together. Though similar grid formulations have been used in previous work [54, 55], the coupling of the formulation with industrial load optimization has not been addressed before.

- The methods and formulations found in this study are to be a framework for utilities to look at economic effects of battery installations at industrial manufacturing installations. National security prohibits published studies involving actual grid data so this study seeks to show some effects on different sized systems to provide examples for studies involving the actual grid.

- The findings of this study demonstrate a hole in policy concerning industrial battery storage. The last two cases in this study show an increase in facility savings by a factor of about 8.7 when the facility is left to discharge the storage. In case two, the social welfare savings essentially stay the same between the two dispatch configurations. In case three, the social welfare savings only increase by a factor if 4.6 when the utility retains dispatch control. This implies that current rate structures and incentive programs may not be conducive to maximizing economic benefit between utilities and facilities using battery storage.

2. Methods

This research utilizes power flow analysis and three different optimization problems to analyze the potential savings of three different case studies. The formulations of the power flow analysis, the three different optimizations of the system, and the optimization used to find the industrial load profile with battery power are outlined below. The three case study systems are then introduced from simplest to the most complex.

2.1. DCOPF Model

The unit commitment model used in this study is a DC optimal power flow (DCOPF) model. Pyomo is used to optimize the unit commitment model using a CPLEX solver, with a MIP gap of 0.001. The mathematical description of the model is presented below. This formulation is similar to the previous formulations like the one presented by Preskill et al. [54].

The objective function:

$$\min \sum_{t} \sum_{g} (C_g P_{gt} + u_{gt} NL_g + v_{gt} SU_g + w_{gt} SD_g) \tag{1}$$

The objective of the optimization model is to minimize the total system cost over all the generation units for a period of 24 hours. System costs include the generation cost of each generator g at different time t ($C_g P_{gt}$), as well as the no load cost (NL_g), start up cost (SU_g), and shut down cost (SD_g) of each generator.

The objective function is subject to certain constraints. Constraint 1 is the minimum and maximum capacity of each generator (P_g^{min} and P_g^{max} respectively) if turned on. 2 is the maximum amount of power allowed to be transmitted on each line (F_k^{max}). 3 is the DC power flow equation, and 4 is the node balance constraint. 5 and 6 are the minimum up time and minimum down time constraints of each generator, respectively. 7 and 8 are startup and shut down constraints. 9 and 10 are ramping up and down constraints. Lastly, 11 is battery constraints.

Constraints:

1. Minimum and Maximum generator capacity constraints

$$u_{gt} P_g^{\min} \leq P_{gt} \leq P_g^{\max} u_{gt}$$

where u_{gt} is the binary commitment variable, where 0 means off and 1 means on. g is the generator, and t is the time interval. P_{gt} is the power generated at generator g at time t. $P_g^{\min}$ and $P_g^{\max}$ are the minimum and the maximum power capacity of generator g respectively.

2. Transmission constraints

$$-F_k^{\max} \leq F_{kt} \leq F_k^{\max}$$

where F_{kt} is the flow on line k at time t, and $F_k^{\max}$ is the maximum power on line k.

3. DC Power flow equation

$$F_{kt} = b_k \left(\theta_{kt,to} - \theta_{kt,\text{ from }}\right)$$

where b_k is the b element in the Y-bus matrix corresponding to line k, $\theta_{kt,to}$ is the voltage angle of the bus line k is going to, and $\theta_{kt,\text{from}}$ is the voltage angle of the bus line k is coming from.

4. Node balance constraints

$$\sum_{\forall k \in \delta(i)^+} F_{kt} - \sum_{\forall k \in \delta(i)^-} F_{kt} + \sum_{\forall g @ i} P_{gt} + \sum_{\forall b @ i} P_{bt} = d_{it}$$

where $\delta(i)^+$ are the set of lines going to bus i, $\delta(i)^-$ are the set of lines coming from bus i. $P_{b,t}$ is the amount of power from battery b for time t, and d_{it} is the demand at bus i at time t.

5. Minimum up time constraints

$$u_{g,s} \geq u_{g,t} - u_{g,t-1}, \forall g, s \in \{t+1, ..t + UT_g - 1\}$$

where UT_g is the minimum up time of generator g.

6. Minimum down time constraints

$$1 - u_{g,s} \geq u_{g,t-1} - u_{g,t}, \forall g, s \in \{t+1, ..t + DT_g - 1\}$$

where DT_g is the minimum down time of generator g.

7. Start up constraints

$$v_{gt} \geq u_{g,t} - u_{g,t-1}$$
$$0 \leq v_{gt} \leq 1$$

8. Shut down constraints

$$w_{gt} \geq u_{g,t-1} - u_{g,t}$$
$$0 \leq w_{gt} \leq 1$$

9. Ramp up constraints

$$P_{g,t} - P_{g,t-1} \leq R_g^+ \quad \forall g, t$$

where R_g^+ is the maximum ramp up rate for generator g.

10. Ramp down constraints

$$P_{g,t-1} - P_{g,t} \leq R_g^- \quad \forall g, t$$

where R_g^- is the maximum ramp up rate for generator g.

11. Battery constraints

$$\sum_t P_{b,t} \leq P_b^{max} \quad \forall b$$

where P_b^{max} is the maximum amount of power stored in battery b, available for discharge.

The battery constraint in 11 and the $P_{b,t}$ term in 4 are only used in the formulation when the batteries are controlled by the utility. For the facility-controlled case, the batteries are utilized and dispatched in the facility load curve optimization as explained in Section 2.2. The batteries are already taken into account when the DCOPF is used to find system costs.

The batteries are modeled as no-cost generators at their respective nodes. This can be done as it is assumed that the industrial facilities have already installed the batteries, and thus no capital cost has to be taken into account. It is assumed that the charging process of the batteries does not lead to significant additional system cost. This effectively assumes that the energy storage element of the system acts as a price-taking resource. This assumption can be made when the storage element plays a minor role in the overall system operation: the total capacity of the batteries is only 3% and 2.4% of the total capacity of the system in the 118 bus system and the 500 bus system respectively. The total impact of the batteries on the economics of the system also is negligible and will be shown in Section 3. It is also assumed that the battery recharging cost would be the same or inconsequentially similar for both the utility-controlled and the facility-controlled cases, and thus the difference in the social welfare savings and the facility savings between the two cases would be the same whether the recharging cost is factored into the formulation of the study.

It is noted that energy storage efficiency of the batteries is not taken into account in the dispatch formulation. As noted above, charging costs of the battery are not taken into account. These costs would include charges on the amount of energy needed to recharge the batteries, which would be larger than battery output due to the energy storage efficiency. Thus, the output of the batteries in this formulation is the usable output of the batteries after storage losses. All batteries are modeled as 4-hour batteries. This means that each battery can be discharged at maximum power output for a total of four hours before the stored energy is exhausted. A 4-hour battery duration was chosen for ease as well as to comply with the "4-hour rule" established by the California Public Utilities Commission. The rule states that storage must have "the ability to operate for at least four consecutive hours at maximum power output" [56]. This same 4-hour simplification has been used by other government agencies in battery storage applications [57, 58].

2.2. Industrial battery discharge optimization

An optimization was formulated to reduce the peak of the industrial nodes using the battery discharges during high peaks. The objective of the optimization is formulated as following:

$$\min \int_0^{96} \left(\frac{d_{net,t}}{d_{it}^{max}} \right)^{60} dt \qquad (2)$$

The objective includes the minimization of the integral of the net demand across ninety-six time increments. In this problem, each time increment represents a fifteen-minute interval resulting in the whole simulation being the integral over the entire day. The net demand of the system ($d_{net,t}$) is normalized by the maximum demand of the profile without batteries (d_{it}^{max}) and then raised to a large power. This large power leads the optimizer to flatten the profile as much as possible to minimize the overall impact of higher numbers on the final value of the objective function.

The optimization is subject to certain constraints. The first is the system energy balance constraint, seen in 1. The battery size constraint can be seen in 2. The limits on battery discharge rates are seen in 3.

Constraints:

1. System energy balance

   $$d_{it} - P_{b,t} = d_{net,t} \quad \forall t, \forall b$$

   where d_{it} is the demand of the industrial facility at node i and $P_{b,t}$ is the power produced by the battery, b, all at time t.

2. Battery size constraint

$$\int_0^{96} \frac{1}{4} P_{b,t} dt \leq E_b^{max} \quad \forall b$$

where E_b^{max} is the maximum energy capacity of the battery in kWh.

3. Battery maximum discharge

$$0 \leq P_{b,t} \leq S_{bat,b} \quad \forall t, \forall b$$

where $S_{bat,b}$ is the size of the battery in kW.

Battery recharging was not included in any of the optimization models. This is because it was assumed that the battery charging would not occur during the same time periods when the battery needed to be discharged to reduce costs. The recharging of the batteries would result in the same amount of increased costs in the utility and facility dispatch scenarios, given that the batteries would be the same size. It is assumed that the utility and the facilities would be able to recharge the batteries without adding cost during peak times.

2.3. Case Studies

Three case studies were used to compare the savings of an industrial facility using a utility-controlled battery discharge and a facility-controlled battery discharge. A 3-bus system was developed to act as a simplified benchmark to understand and monitor system behavior before adding complexity. The IEEE 118-bus test system is used as a standardized test case in research, and was used as such in this study. A large 500-bus synthetic system was used to evaluate the system in a real-world scenario.

2.3.1. 3-bus system

Small 3-bus systems have previously been used in literature to show basic grid interactions and establish baselines [48]. The 3-bus system in this study was constructed with three buses, three generators, one battery, and three lines connecting the 3 buses with the DCOPF formulation. Three different generators with differing cost functions were connected to each node. The commercial and residential loads were connected to the same bus. The industrial load was connected to its own bus. The line diagram of the system can be seen in Figure 1.

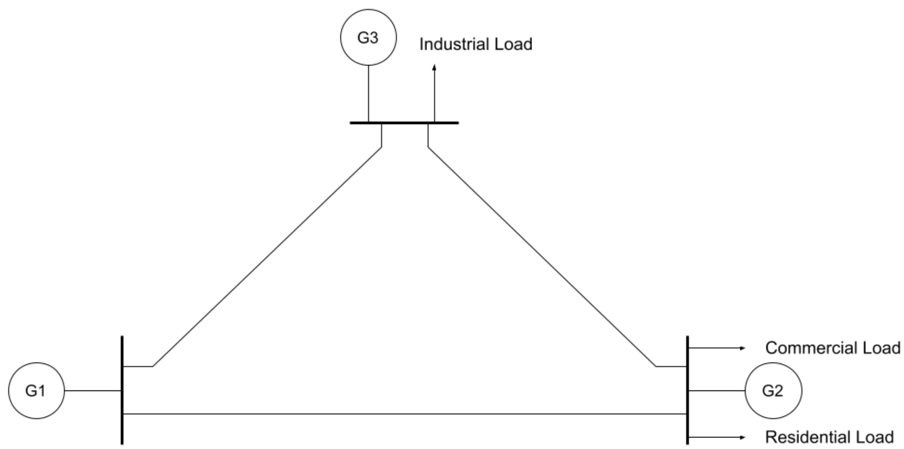

Figure 1: Line diagram for the simplified 3-bus system.

The peak value of each load was set to the same value and then scaled accordingly based on the type of load. The shape and values of the load profiles for the residential and commercial loads were taken from the U.S. Department of Energy Open Data Catalog [59]. The industrial load profile was taken from an actual industrial load profile from an industrial energy assessment performed by the Intermountain Industrial Assessment Center at the University of Utah. These load profiles can be seen in Figure 2.

The aggregate of these profiles is the overall load profile for the entire 24-hour period for the whole system. This aggregate load profile can be seen in Figure 2d.

First, the system was run as a simple DCOPF model without any batteries to establish a baseline for comparison. The two control schemes were then tested

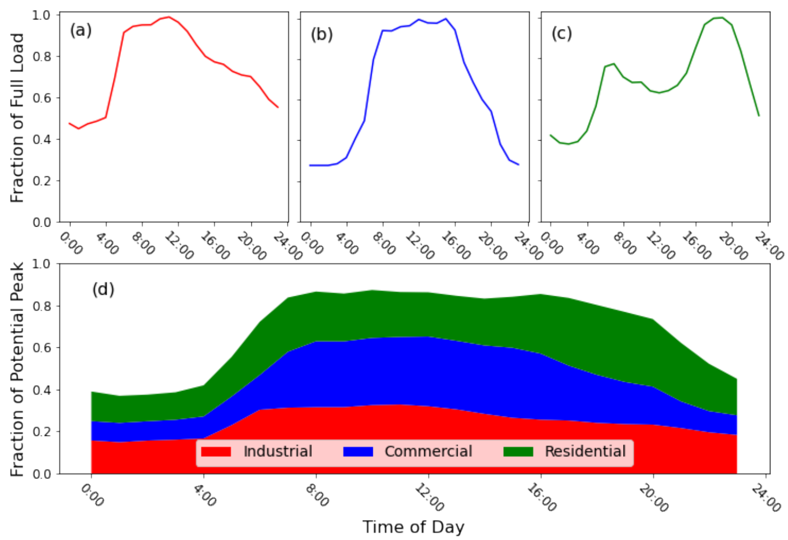

Figure 2: 24-hour load profiles used in the 3-bus case for industrial (a), commercial (b) and residential (c). The aggregate of these three profiles is seen in (d) as a fraction of the total potential peak. The potential peak is calculated as the amount maximum if all three peaks were to coincide at the same moment.

using the same sized battery at the industrial facility. For the grid-scale control, a cost-free generation source was added at the same node as the industrial load. The battery constraint was added to limit the output of that source to only the total power of the battery. This control would reduce the overall load when the optimization determined the need to reduce the cost of other units in the objective function. The overall load curve would look similar to the example in Figure 3.

For the facility-scale control, an optimization was formulated to reduce the overall peak of the facility while maintaining that only the amount of energy in the battery was discharged. The limits on the battery discharge rate and the total energy capacity of the battery were kept the same as the grid-scale control problem. The optimization then found the best dispatch to minimize

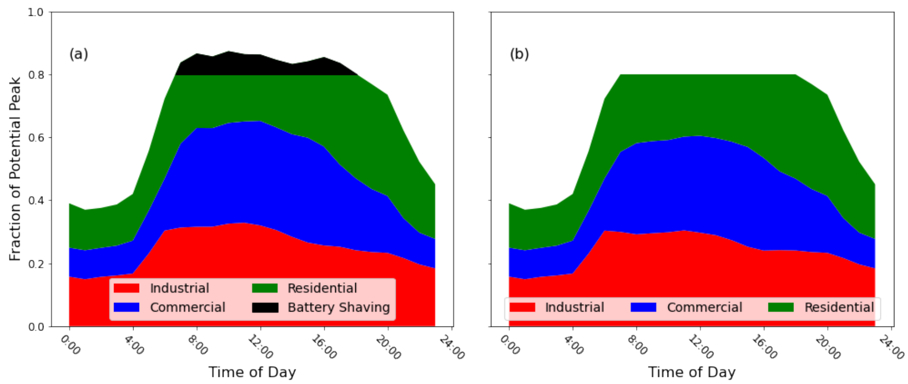

Figure 3: Example load profile with grid-scale battery control. The total profile with the indication of the power taken from the battery is shown in (a). The aggregate without the power from the battery is shown in (b).

the peak of the entire 24-hour period. This formed a new demand profile for the facility after reducing the original demand profile. The overall load curve for this control scenario would look similar to the example in Figure 4.

This new aggregate load profile was then run through the same DCOPF formulation without the extra battery, as the battery would have already been taken into account in the industrial load.

2.3.2. IEEE 118-bus system test case

The IEEE 118-bus system test case has been used as a standardized case study for research [60], [61]. The test case represents a simplified grid system of the mid-western United States. It consists of 118 buses, 54 generators, 99 loads, and 186 lines. The buses, generators, and load data were taken from [62]. The line data were taken from [63]. The line diagram of the system is shown in Figure 5.

The loads were divided into three different categories: industrial, residential, and commercial. In total, there were 33 industrial loads, 33 residential loads, and 33 commercial loads, each with varying magnitudes. The load data taken from [62] were used as peak loads of each respective node and then scaled accordingly

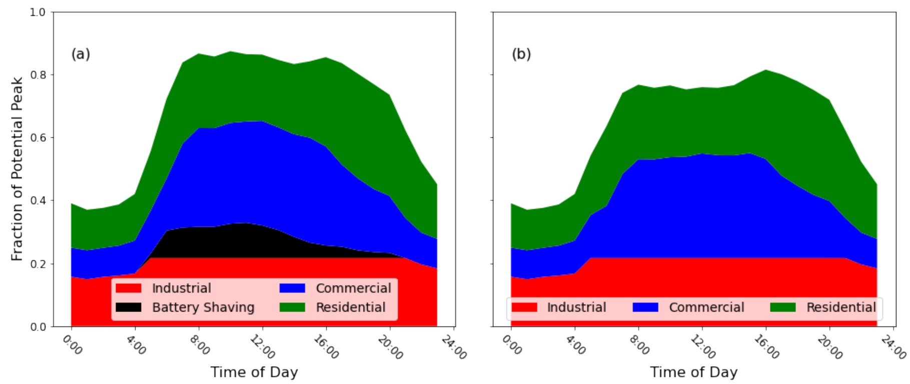

Figure 4: Example load profile with facility-scale battery control. The total profile with the indication of the power taken from the battery is shown in (a). This battery power draw is taken during the peak draws of the industrial profile. The aggregate without the power from the battery is shown in (b).

based on the type of load, as discussed in 2.3.1.

A no-battery control scheme was run in a 24-hour simulation to act as the baseline of the case study, using the DCOPF formulation discussed in 2.1. The industrial battery discharge optimization discussed in 2.2 was run to reduce the industrial peak nodes using battery discharges. A new industrial demand profile was calculated for the facility-scale control scheme. Batteries were added to all the industrial loads of the test case, and the grid-scale control scheme was run. The results of these two test cases were compared to the no-battery control results.

2.3.3. South Carolina 500-bus synthetic system

A 24-hour simulation was done on a 500 bus synthetic system to evaluate the benefits of the proposed system in a real-world setting. The data for the case study was taken from [64]. The system was created to model the northwestern part of South Carolina, as shown in the dashed area in Figure 6.

The case study was built from public information and statistical analysis of the real power system. To accomplish this, substations were synthesized from

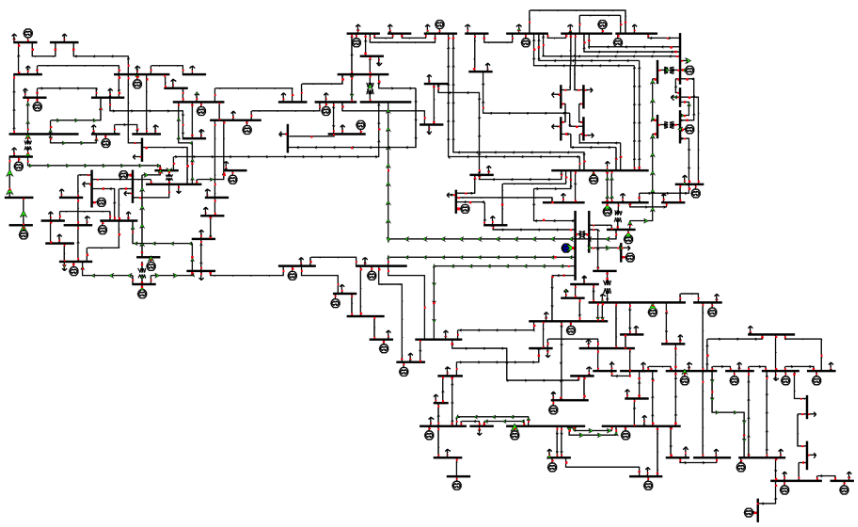

Figure 5: IEEE 118 bus test case [62]

public information of the population and the power plants in the location. Then, employing clustering techniques, the synthesized substations were modeled to meet the realistic constraints, such as the proportions of loads and generations. Next, a transmission network was modeled to link the synthesized nodes and their corresponding demand and generators. Multiple techniques and criteria were used to characterize real power system networks, such as connectivity, Delaunay triangulation overlap, DC power flow analysis, and line intersection rate. An in-depth discussion on the methodology of building the case study is presented in [64]. This case study has 500 buses, 75 generators, and 597 transmission lines. The buses, generators and transmission lines are illustrated in Figure 7.

Each bus had a peak real demand and a peak reactive demand data. Each generator had a no load cost, minimum up and down time, and its minimum and maximum generation constraint. The cost of each generator was given in the form of a quadratic function of the amount of power generated:

Figure 6: Northwestern part of South Carolina modeled for the case study.

$$C_g = A_g P_g^2 + B_g P_g + C_g \quad \forall g$$

with C_g is the cost of the generator g, A_g, B_g, C_g are the cost coefficients, and P_g is the amount of power generated by generator g.

Transmission data included from and to bus, resistance and reactance (p.u), and maximum capacity of each line. Batteries were added at 15 highest industrial loads. The batteries were modeled as generators at industrial nodes, with no cost for generating electricity. However, the batteries could only discharge up to 80 MWh in a day, as the batteries were modeled as 4-hour batteries with 20 MW capacity. This synthetic system was also run in 3 simulations: a no-battery baseline simulation, a utility-controlled battery discharge simulation, and a facility-controlled battery discharge simulation.

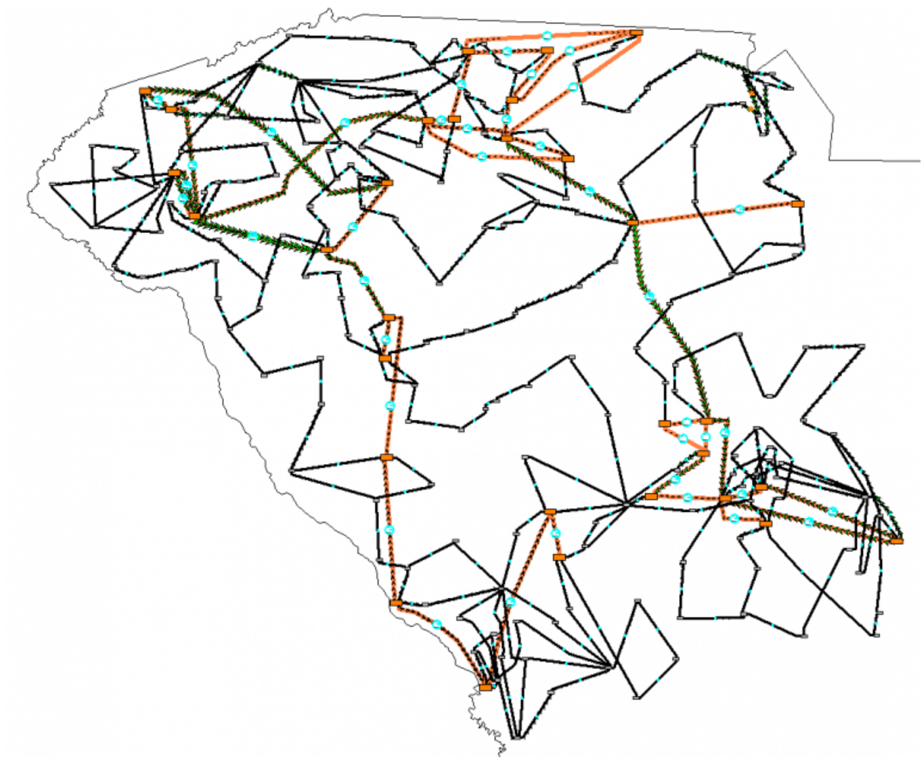

Figure 7: The interconnection between the buses in the South Carolina case study.

3. Results

The results in this section are presented for each of the three case studies. The resulting costs and savings are presented in current U.S. dollars ($). A few different metrics are used to compare the different scenarios and are defined below.

- Baseline cost - the final objective function value of the DCOPF formulation without any batteries.
- Utility dispatch cost - the final objective function value of DCOPF formulation with the utility-controlled battery discharge scenario.
- Utility dispatch savings - the baseline cost minus the utility dispatch cost.

- Incentive payment - the battery size (kW) times the incentive rate ($/kW) divided by 365 for an approximate incentive payment per day.
- Facility dispatch cost - the final objective function value of DCOPF formulation with the facility-controlled battery discharge scenario.
- Facility dispatch savings - the baseline cost minus the facility dispatch cost.
- Facility demand savings - the difference between the original maximum of the load profile and the new maximum of the load profile times the demand rate divided by 30 days per month for an approximate demand savings per day.

3.1. 3-bus system

The 3-bus system was simulated across the three different scenarios with a sensitivity analysis on various simulation parameters to compare the effects of these parameters. The analyzed parameters include battery size, utility demand rate, load size at each node, and transmission limit on each line. In each analysis group, the battery size was changed in each scenario along with one other parameter. The utility dispatch savings, facility dispatch savings, and facility demand savings were all recorded for comparison in each simulation.

The simulation results from changing the battery size and demand rate are seen in Figure 8. This simulation varied the utility demand rate between 10 and 20 $/kW in increments of 2.5 $/kW at each battery size of 20, 40, and 60 MW. All other variables were kept constant. The results from changing battery size and load size at each node are seen in Figure 9. This simulation then varied the load at buses 1, 2, and 3, in that order, between 180 and 220 MW in increments of 20 MW at each battery size of 20, 40, and 60 MW. All other variables were again kept constant. The plot utilizes shading to show the changes for the three different types of savings with each combination of the three changing load sizes. The first column of plots shows that the utility dispatch savings tended to be higher with lower loads at buses 1 and 2. The second column shows that the facility dispatch savings tend not to have much variation when the loads are not at the limits simulated. Even then, the variation is small. The right column shows that the facility demand savings tend to be highest with high loads at bus 1 and low loads at bus 2. This was true across all battery sizes. Lastly, the results from changing battery size and transmission limit on each line are seen in Figure 10. This simulation varied the maximum line limit of lines 1, 2, and 3, in that order, between 150 and 450 MW in increments of 100 MW at each battery size of 20, 40, and 60 MW. All other variables were again kept constant. The resulting plot was constructed similar to the plot for changing load size. The left and middle columns of plots show that both utility dispatch savings and facility dispatch savings become maximized at lower limits on lines 2 and 3. Line 1 does not seem to contribute at all to the maximization of those savings. The right column of plots show that the facility demand savings are minimally dependent on a low limit on line 2 over limits on any other line. The variations of all variables were then analyzed to determine Pearson correlation coefficients for each of the three types of savings.

Pearson correlation coefficients are commonly used to measure simple linear correlation between a pair of variables. The value of the Pearson correlation coefficient only determines if some linear relationship exists between two variables and not the nature or cause of the relationship. In the case of the 3-bus system, this value was used to quantitatively and simply determine the presence of relationships between the different variables. The values were calculated for each of the changing variables in the simulations with respect to each of the three different types of savings in the simulations. The Pearson correlation coefficient values can be seen in Figure 11. In the figure, hotter colors, like orange and yellow indicate a positive correlation, or that as the value of the variable increases, the resulting output increases as well. A strong positive correlation was seen between the three different types of savings and the battery size, with correlation values between 0.7 and 1.0. Facility demand savings showed a positive correlation between utility demand rate and the facility demand savings. This is expected as a large contributor to the value of utility demand savings would be the demand rate. Load sizes at each of the nodes showed low values of positive correlation with facility dispatch savings. The cooler colors in the figure, like dark purple and blue, indicate a negative correlation between the variable and the output, being that as the value of the variable increases, the output tends to decrease. Small negative correlation values were seen between all bus loads and the utility dispatch savings. The lowest negative correlation, which only had a value of 0.44 was seen between the facility dispatch savings and the capacity limit on line 3. This indicates a low-level negative correlation trend between these two values.

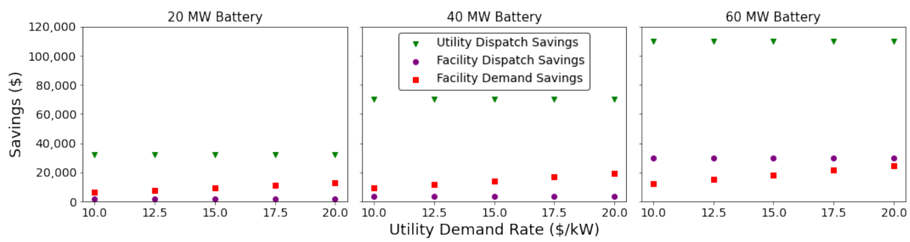

Figure 8: The 3-bus system results for changing battery size and utility demand rate.

The simulation results show that as the battery gets larger and can have more impact on the overall load of the system, the facility dispatch savings begin to overtake the facility demand savings. Regardless of what parameters were being changed, as the battery size increased, the resulting runs with the facility dispatch savings above the facility demand savings increased. As expected, the greatest amount of savings in any scenario would occur from the utility dispatch. This is true across all cases tested, though there were a few cases in changing the battery and load size where the savings were almost equal between the utility dispatch and the facility dispatch. The greatest utility dispatch savings were realized in the changing battery size and load size scenarios with the largest batteries. Intuitively, as the battery size increases, the amount of energy the grid can use at distributed times increases, so the total savings increases.

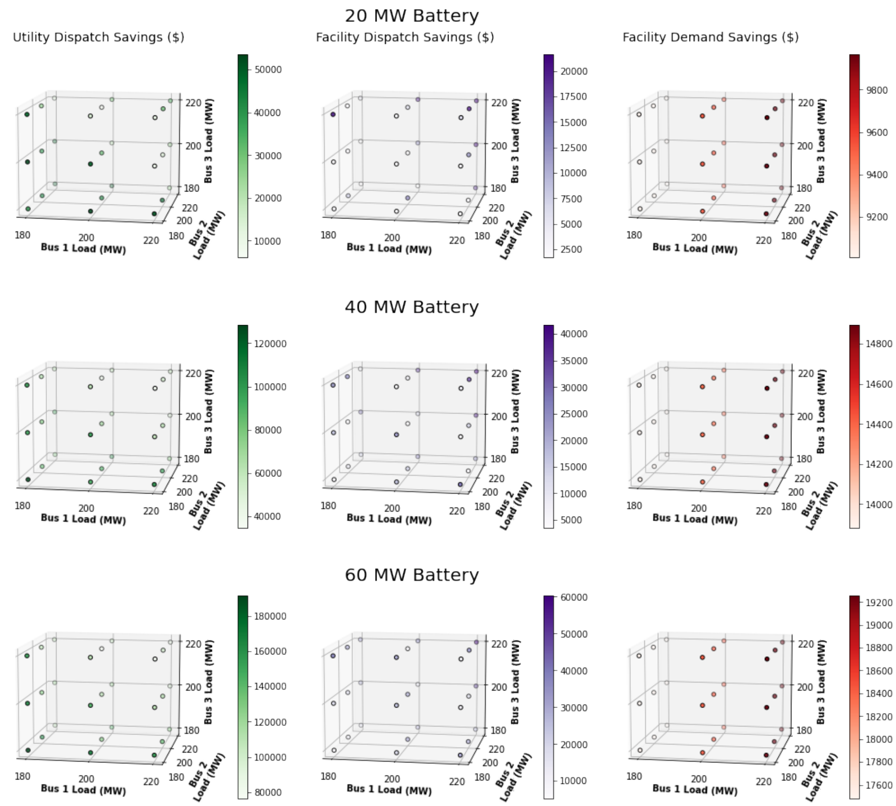

Figure 9: The 3-bus system results for changing battery size and load size at each node.

3.2. IEEE 118 bus system

The IEEE 118 bus system was simulated in: the no-battery baseline scenario, utility-controlled battery discharge scenario, and facility-controlled battery discharge scenario. All three were run using the DCOPF formulation.

The simulation results for the generators' output for the 24-hour interval for all three cases are shown in Figure 12. Since the generators' data taken from [62] have the same cost efficiencies for all generators, the generation was spread out evenly for each generator. Therefore, each case study was presented with one generation curve representative of each case study's simulation results. The baseline cost for the system was calculated to be $2,969,690.

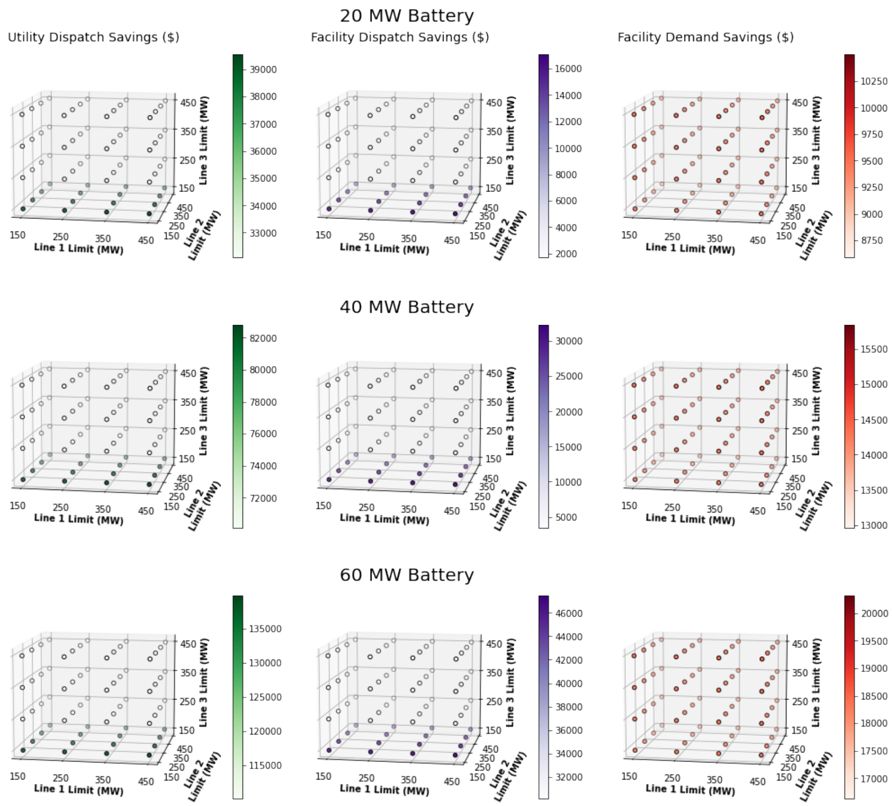

Figure 10: The 3-bus system results for changing battery size and transmission limit on each line.

In the utility-controlled case, batteries were added at each industrial node, and modeled as a zero-cost generator with a maximum capacity of 20% of the load of the industrial node where it is stationed. The resulting generation for each generator (without the batteries) is shown in Figure 12. The batteries discharge at each industrial node is presented in Figure 13 (a). As seen in Figure 13 (a), the battery was discharged from hour 7 to 17, with the majority of the discharges from hour 7 to hour 14. This flattened the generation curves at this time interval as shown in Figure 12. This is because with the addition of the batteries' usage at the utility's discretion, the utility was capable of spreading

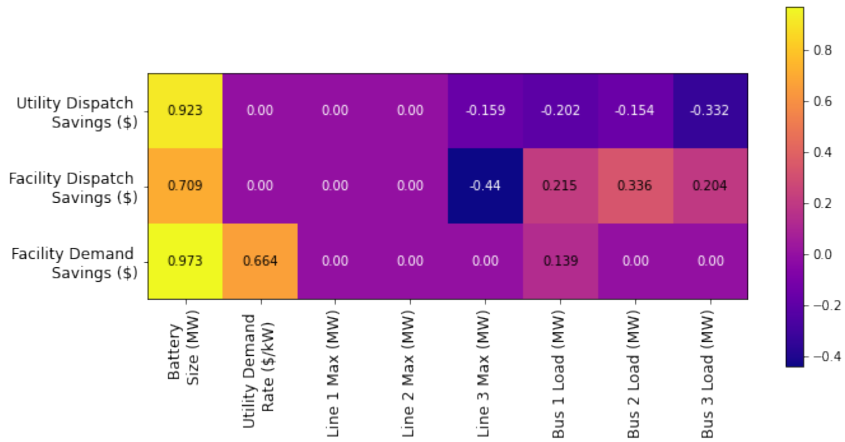

Figure 11: Pearson correlation coefficients of the three different types of savings for each of the different variables that were tested in the 3-bus system.

out the batteries' discharges to meet the peak demands at all three types of nodes: industrial, commercial, and residential. As a result, the total demand curve was shaved at the peak, and the generation cost was evenly distributed across all the generators.

The addition of the batteries at each industrial node resulted in a decrease in the objective function value, with the utility dispatch cost of $2,914,130, and a value of $55,560 for the utility dispatch savings. The incentive payment the industrial facilities received, as defined in Section 3, was $12,590. This amount is calculated with an incentive rate of 15 $/kW. This represents a saving for the utility company, as the incentive payment to the industrial facilities is less than the utility dispatch savings.

In the facility-controlled case, batteries were also added at each industrial node as in the utility-control case. The optimizer optimized the battery dispatch to peak shave the demand curve at the industrial nodes. The battery discharge is shown in Figure 13 (b). As shown in Figure 13 (b), the batteries were discharged during the peak hours of the industrial loads, from hours 6 to 15. This flattened the demand curves at the industrial nodes at this time in-

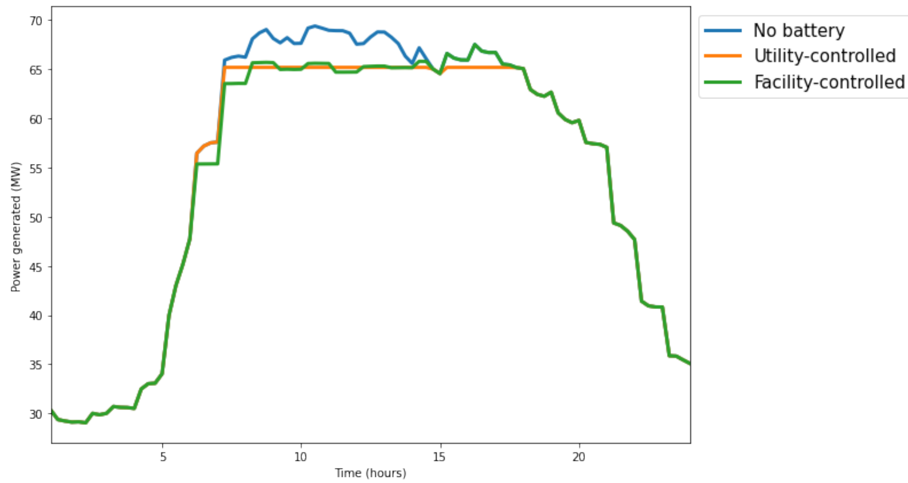

Figure 12: IEEE 118 bus three cases' generation profile

terval, as shown in Figure 14. Even though the industrial demand curves were flattened, the commercial and residential curves remained the same. This led to an arched total demand curve, unlike the utility-controlled scenario. The generators' output in the facility-controlled case is shown in Figure 12. Unlike the utility-controlled case, where the total demand curve was flattened, leading to the flattening of the generator's output, the total demand curve in the facility-controlled case was still arched. This led to the arching of the generators' output in this case, which can be seen in Figure 12. However, the total outputs of the generators in the two scenarios were the same, as shown in Figure 12 where the areas under the generation curves for each scenarios are the same.

Because the total demand was reduced compared to the baseline scenario, the objective function value was lower than the baseline results. The facility dispatch cost was $2,914,220, resulting in a $55,470 facility dispatch savings. This was less than the utility dispatch saving, albeit only by $90. This was expected because when the utility has control over the battery discharge, the utility can spread the savings to the commercial and residential nodes as well as the industrial nodes. Whereas when industrial facilities control the batteries, the savings are solely applied towards the facilities. The facilities also saved more from the facility demand savings. The facility demand savings was \$110,730 from demand shaving.

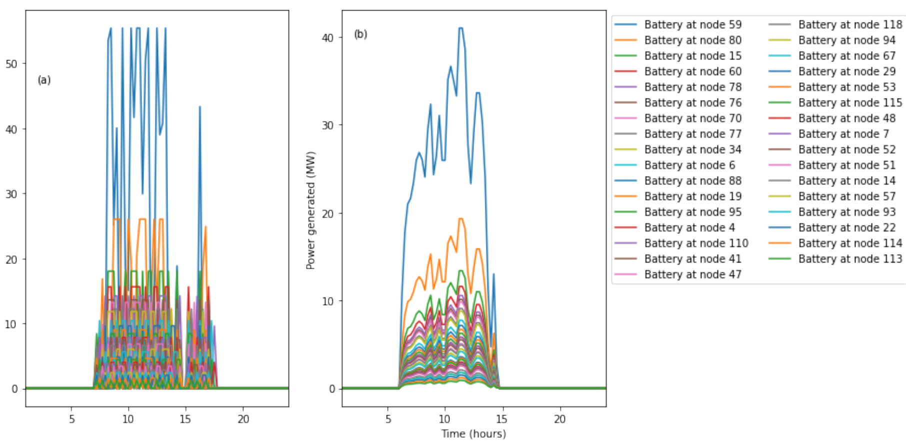

Figure 13: IEEE 118 bus battery generation profile in (a) utility-controlled case scenario, and (b) facility-controlled case scenario

The values of the objective functions for all three scenarios are summarized in Table 1. It can be seen that with the addition of the batteries at the industrial nodes, both the utility and the facility saved money compared to the baseline scenario. The savings to the utility was almost identical between the utility-controlled and the facility-controlled scenario, with savings of \$55,560 and \$55,470 respectively, a 0.16% difference in savings. However, table 1 also shows that in the IEEE 118 bus scenario, the facility-controlled case scenario brought the most savings to the industrial facilities of \$110,730, which came from peak shaving, compared to just \$12,590 from the incentive payments. This represents an increase of 880% in savings to the industrial facilities.

The addition of the battery in both the utility-controlled and the facility-controlled case only reduces the objective function value marginally, as shown in Table 1: \$ 55,550 and \$ 55,470, respectively. This is only a small fraction of the overall objective function: 1.87%, and thus justifies the assumption that

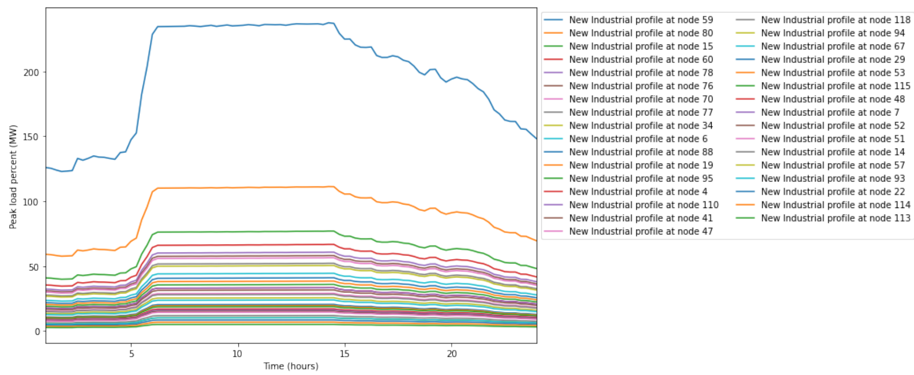

Figure 14: Industrial nodes' new demand profile in 118 facility-controlled case scenario

the battery recharge does not lead to significant system loss.

Table 1: IEEE 118 bus objective function values

Scenario	Objective function value	Social welfare savings ($)	Facility savings ($)
No-battery	2,969,690	0	0
Utility-controlled	2,914,130	55,550	12,590
Facility-controlled	2,914,220	55,470	110,730

3.3. South Carolina 500 bus system

The South Carolina 500 bus system was also simulated in three different scenarios like the IEEE 118 bus system, using the DCOPF formulation: no-battery, utility-controlled, and facility-controlled. The results are presented and discussed in this section in the following order: the baseline scenario, the utility-controlled scenario, and the facility-controlled scenario. The savings between the utility-controlled scenario and the facility-controlled scenario are then compared.

Unlike the IEEE 118 bus system, only the fifteen industrial nodes with the highest demand were assigned to represent the loads with batteries in this case study. The batteries were not scaled according to the load demand but were set at 20 MW capacity. The batteries were modeled to be 4-hour batteries. This presented a different approach to see the different interactions of battery installation's effect on industrial savings.

The resulting generation for each generator in the 24-hour interval in the no-battery baseline scenario is shown in Figure 15. Unlike the IEEE 118 bus system, the South Carolina bus system was created to synthesize a real system based on a real power system. Thus, the generators' cost coefficient, the minimum up and down time, ramping rate, and other generators' characteristics, were not identical. Thus the generators' profiles were different from each other, and the generation curves were different from one another, as shown in Figure 15. The baseline cost was calculated to be $4,578,980.

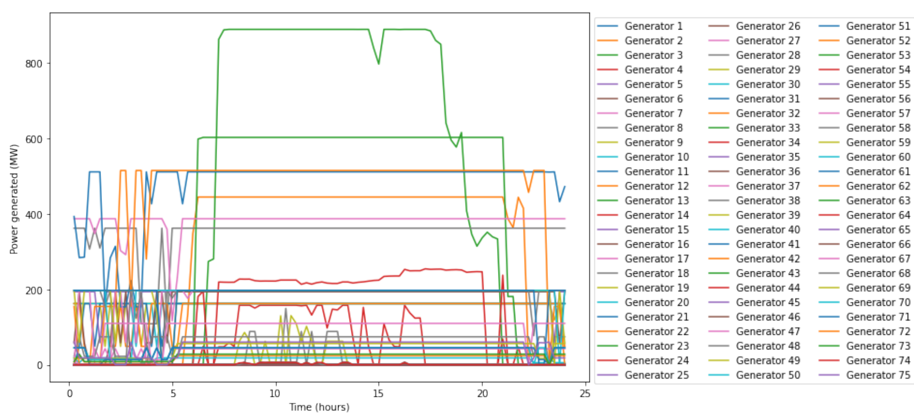

Figure 15: Generators' output in no-battery South Carolina scenario.

The batteries were added to the fifteen industrial nodes for the utility-controlled case as discussed above. The utility managed their discharge to minimize the cost of the whole system. The batteries' discharge schedule was thus spread out to minimize the peaks of the overall total demand curve. The utility-controlled battery discharge is presented in Figure 16. As shown in Figure 16, the batteries mainly were discharged at the peak hours, from hour 7 to hour 13. These discharges helped decrease the overall cost for the system, with a resulting utility dispatch cost of $4,555,300, a $22,680 value for the utility dispatch savings. The incentive payment the industrial facilities received was $12,330, using the same incentive rate as the IEEE 118-bus system. Like the IEEE 118 bus system, this represented savings for the utility company, albeit smaller savings.

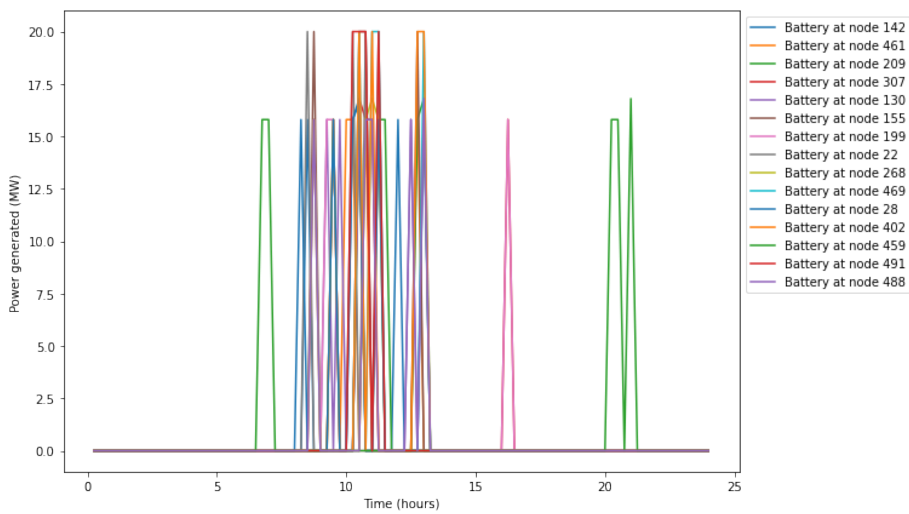

Figure 16: Batteries' discharge in utility-controlled South Carolina scenario.

For the facility-controlled case, the batteries were also added to the fifteen industrial nodes. The optimizer was used to optimize the battery discharge at the industrial nodes, creating a new demand curve for each of the fifteen industrial nodes with batteries. The industrial nodes without the batteries added had the same demand curve. The batteries' discharge is shown in Figure 17. The batteries were discharged during the peak industrial hours, from hour 6 to hour fifteen. The demand curves at these fifteen industrial nodes were flattened at these hours, as shown in Figure 18.

Because the total demand was reduced compared to the baseline scenario, the objective function value was lower than the baseline results. The facility dispatch cost was $4,574,250, a $4,730 facility dispatch savings. This savings was less than the utility dispatch savings by $17,950. This was expected because when the utility had control over the battery discharge, the utility could spread the savings to the commercial and residential nodes as well as the industrial nodes. Whereas when the industrial facilities controlled the batteries, the savings were solely applied towards the facilities. The facilities also saved more from the facility demand savings. The resulting facility demand savings was $107,290.

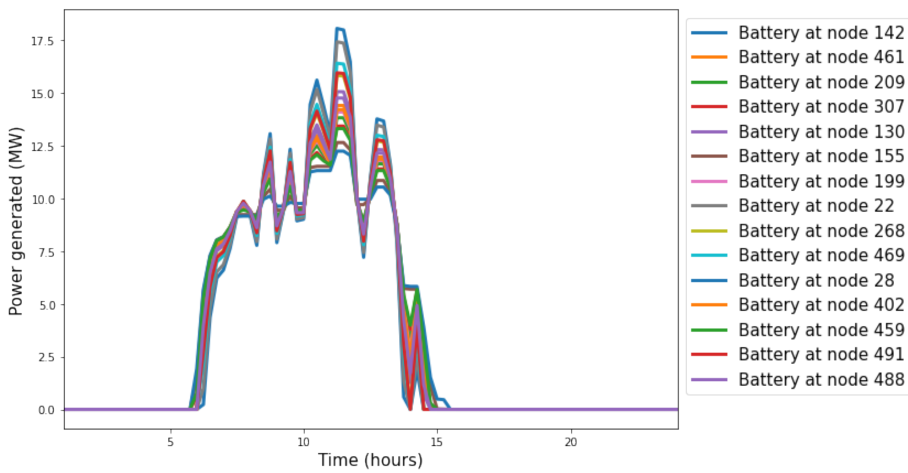

Figure 17: Batteries' discharge in facility-controlled South Carolina scenario.

The value of the objective function for all three scenarios are summarized in Table 2. It can be seen that with the addition of the batteries at the industrial nodes, both the utility and the facility saved money compared to the baseline scenario. However, unlike the IEEE 118 bus case, the savings to the utility company was very different between the utility-controlled and the facility-controlled scenarios, with savings of $22,680 and $4,730, respectively, a 379% difference in savings.

Like the IEEE 118 bus results, the results summarized in Table 2 also show that in the South Carolina case scenario, the facility-controlled case scenario

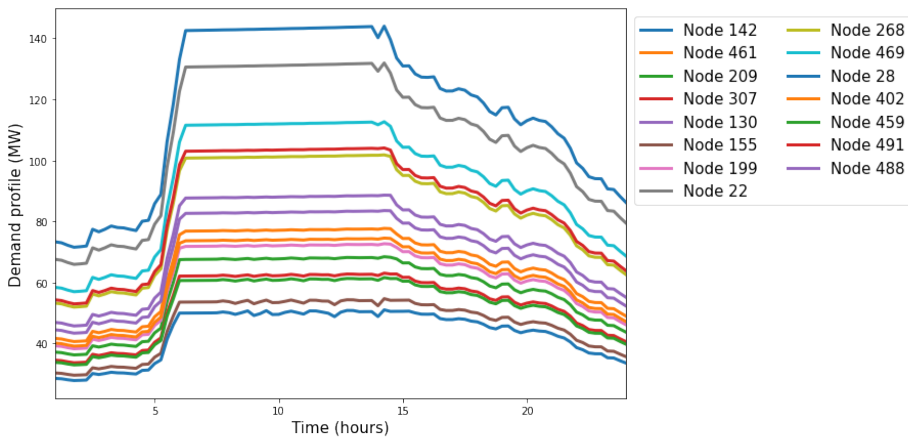

Figure 18: New demand curve at 15 industrial nodes in South Carolina system

brought the most savings to the industrial facilities of $107,290, which comes from peak shaving, compared to just $12,330 from the incentive payments. This represented an increase of 870% in savings to the industrial facilities.

Table 2: IEEE 118 bus objective function values.

Scenario	Objective function value	Social welfare savings ($)	Facility savings ($)
No-battery	4,578,979.70	0	0
Utility-controlled	4,555,300.64	22,075.04	12,328.77
Facility-controlled	4,574,250.70	4,729.00	107,288.19

It is also noted in the 500-bus case study that the addition of the battery leads to a marginal reduction in the objective function: $22,680 and $4,730, or 0.50% and 0.10% for the utility-controlled case study and the facility-controlled case study respectively. This justifies the assumption that the cost of battery storage recharge is negligible in overall system cost.

4. Discussion

This study was meant to provide a framework and case studies to illustrate the different effects of changing distribution control on the benefits of battery storage at industrial facilities. The formulations are intended to be used as examples for intended battery storage applications at industrial sites on the actual grid.

The results of the 3-bus system showed a positive correlation between battery size and the three savings types across the changes of all other variables. This would indicate the utility would be making a net gain with larger batteries by letting the facilities dispatch their own batteries. The decreased demand payments from the facilities would be less than the increase in savings from the battery being dispatched by the facility. In this case, the utility would not be paying incentive money to the facilities for grid benefit because the facilities would be dispatching the batteries. This could indicate that the utilities should incentivize the installation of new batteries. As those installations increase, the utility would not need to provide ongoing dispatch incentives. This hints at an optimal position in a system where the industrial battery installations are large enough to provide significant benefit to both the utility and the industrial facilities.

The main contribution of the 3-bus systems is to perform a simple sensitivity analysis and to test the formulation before applying it to larger systems. This approach, though simple, and seen previously in other studies [48], allows for small correlations to be noticed between changing variables in the system without having to solve a computationally expensive system. The 3-bus system has not been applied previously in looking at grid benefits of industrial battery dispatch, probably due to its simplicity. Though not a necessary component of every study concerning industrial battery dispatch, the 3-bus system provides insight into some trends that could be present with the application of a sensitivity analysis on a larger, more realistic system. Future work should consider these trends when analyzing the sensitivities of different variables in larger systems.

The 118-bus and South Carolina scenarios indicate that if industrial facilities possess battery installations, the overall benefit to the facility is much greater when the facility can dispatch its own batteries. The incentives to the facilities from the utility are not enough to let the facilities get the most benefit out of their battery installations. In both scenarios, the financial benefits to the customer from decreased facility demand charges were greater than the social welfare savings. The value of facility demand savings is directly related to the facility demand rate set by the utility within the billing structure. As the amount of industrial battery installations increases, it may be appropriate for utilities to change their billing structures to be more conducive to providing the benefits that the utility deems the most important to the entire grid.

The trends found while performing analysis of the 3-bus system help constitute the future work explored with the 118-bus and South Carolina scenarios. Future work is needed to explore the effects of the variables tested in the 3-bus system, especially those that showed high levels of correlation with the measured savings in the 3-bus scenario. With a higher number of lines and buses, testing of line capacities and bus load levels may not be as feasible as testing differences in utility demand rates and battery size. Battery size saw larger correlations with the different types of savings and would be important to be included in future work. Exploration of battery size would demonstrate the economic plausibility of these battery installations to industrial facilities when explored in the scheme of the entire grid system.

One future area of research could include taking into account capital investment costs of battery installation. For most industrial applications, the decision to install batteries would be based on a net present value (NPV) analysis determined in part by the savings and incentives that could be accumulated from battery usage. For simplicity, this model only included a 24-hour simulation. Future considerations could include a longer time horizon to look at facility demand savings and incentive payments over time to see if the installation would be profitable.

Aggregation of loads in grid modeling could also introduce error into these simulations. Some previous studies have shown that there is a benefit to aggregation of residential loads for energy storage applications [31]. Industrial loads tend to be larger than residential loads, but consideration must be taken to ensure that same benefits apply to the industrial sector. Geographical location and profile type and shape must be taken into account for proper aggregation. Future studies could consider these limitations. Aggregation also introduces whether it would be more beneficial for utilities to encourage industrial battery installations or seek industrial investment into grid-scale storage entirely controlled by the grid. Both are options to provide overall dispatch benefit to generating units but need to be analyzed for fiscal viability.

Aggregation is a tool that utilities and load-balancing agencies use to aid in system load forecasting. Forecasting at a higher level of aggregation typically leads to a more accurate forecast overall. This opens the discussion to a limitation of this study. Though these systems seek to be structured as real systems, the approach is deterministic with perfect foresight into the 24-hour load profile. The real application of battery storage requires forecasting and accounting for uncertainty in the load. This study assumes that if a facility has taken the effort to install batteries for peak shaving at their facility, then the facility has made significant effort and investment into the proper forecasting and control of that asset. Though forecasting has historically been done more commonly and successfully at the utility scale, future innovations concerning the integration of smart manufacturing with the smart grid are pushing facility-scale forecasting to be a more common practice. Despite current innovations, future work should consider the uncertainty of load and forecasting error in industrial battery dispatch scenarios.

This study assumes similar load profile shapes for all manufacturers, though realistically, the industrial sector includes a wide spectrum of manufacturing types. Future work should consider load leveling at different types of manufacturers or provide a more comprehensive aggregation of load profiles from facilities in various manufacturing sectors. Another limitation of this study is conventional utility rates. The study assumes a rate schedule but does not consider existing dynamic rate schedules such as time-of-use schedules and real-time pricing. These different schedules should be considered in future work as the rate schedule will directly affect the profitability of battery dispatch for industrial customers. As this study could not use real grid data or grid structure, limitations arise from direct applicability to realistic grid situations. In reality, battery installations at industrial facilities are low, and large amounts of load flexibility in the industrial sector are attributed to process flexibility. Even assuming that a facility has storage capacity that can directly be used in bringing down electrical power usage limits storage to types that can easily be converted to electrical power. Though this shows a limitation of this study, it also opens a wide field of future work in helping industrial facilities utilize different types of storage to benefit the overall social welfare of the grid. These become even more important as battery storage and other intermittent energy sources grow in the overall energy generation portfolio.

The findings of this study provide useful insight when considering the future of policies concerning industrial battery storage. One is the reevaluation of industrial utility demand rates to incentivize the installation of battery storage. Real-time electricity markets are becoming more common, especially in the United States. These markets could help the utility bring down demand at peak times and provide a significant incentive for facilities to reduce demand when prices are high. In the broad scheme, this would have the potential to help reduce ramping at generating sites and provide cheaper energy when renewable sources are prevalent. Another policy insight is the existence of size stipulations and requirements to receive incentives for battery storage installations. As illustrated in the 3-bus system, larger batteries have the potential to decrease overall grid costs even when dispatched by the facility. However, smaller installations do not have the same degree of benefit. Utilities should seek to find size thresholds to maximize overall benefits to social welfare. Extra considerations should be made when applying incentive structures to the industrial sector, even though they may be effective in residential and commercial sectors.

5. Conclusion

This research focused on the rising trend of utility dispatch of distributed battery storage, specifically in the industrial sector. The methods used in this paper provide a preliminary framework comparing the of dispatch of industrial battery storage by the utility or facilities that own the batteries. The use of a simple DCOPF formulation with the optimization of the grid system and the facility-controlled battery dispatch profile seeks to address an emerging issue that has not been explored previously. The study analyzed three separate cases to compare trends in dispatch economics. The study found that utility control will result in the highest grid cost savings, albeit only by small margins compared to the facility control in the IEEE 118-bus case. However, utility control does not always provide enough benefit to convince facilities to relinquish control of their battery installations. In both larger cases, the facility savings increased by a factor of about 8.7 when battery dispatch control was given to the facility. Battery size plays a significant factor in the decision of dispatch control for small experimental systems, but future work should study the effects of battery size on real, large, integrated grid systems. This study seeks to provide a framework to find optimal dispatch levels to maximize economic benefits for individual facilities and overall social welfare, as illustrated by different sizes of case studies. As industrial battery storage continues to grow, policy concerning installations at industrial facilities may require changes in rate structure and size qualifications for incentive participation to maximize the economic benefit to both the utility and the facility.

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