BRIDGING THE GAPS FOR VALUING DISTRIBUTED ENERGY RESOURCES

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A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2017

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Abstract

Bridging the Gaps for Valuing Distributed Energy Resources

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Distributed Energy Resources (DERs) comprise of distributed generation (DG), energy storage (ES) and demand response (DR). DERs are different from other participants because of their distinctive characteristics: they are located on the demand side and they have some flexibility. DERs bring many streams of benefits for different system participants. Various methods have been proposed to capture and quantify the benefits DERs bring and distribute them to DERs. In general, these methods can be put into two categories: avoided-cost based methods and tariff based methods. Both categories have disadvantages: the avoided-cost methods calculate the benefits indirectly which makes it complicated for DERs to be rewarded. The tariff based methods fail to represent some benefits while mispresent some other benefits. The goal of this work is to bridge the gap for valuing distributed energy resources. We first evaluate on the tariff based methods: we study the financial impacts of DERs owned by commercial customers on

their load serving entity. The study shows the tariff should be modified in order to fairly represent the true values of DERs. Then we design value of DERs tariffs and conduct many case studies to show these tariffs provide DERs with higher savings at the same time reduce the amount of losses the load serving entity experiences. Secondly, we study the avoided-cost based methods. We propose a battery scheduling algorithm that simultaneously maximize multiple streams benefits calculated by avoided-cost methods. Next, we develop a battery aggregator model that combines the tariff based methods with the avoided-cost based methods. This model incorporates the advantages of both categories and bridges the gap for valuing DERs.

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ACKNOWLEDGEMENTS

I thank my parents for encouraging me to apply for PhD and continuous support during the last five years. I thank my wife Zhongming, for her loving support. Thanks to my family for encouraging me to pursue my academic interest. Without their support, I cannot imagine completing the PhD.

I gratefully acknowledge my advisor Daniel Kirschen, for his guidance, encouragement, humble character and mentoring. I appreciate his “hands-off” advising style, encouraging me to explore, learn, analyze and critique independently. Apart from the technical knowledge, one essential skill I gained is to navigate the unexplored topics/areas on my own. I also thank each of my committee members: Migual Ortega-Vazquez for his optimistic character, humor and efforts to teach oral Spanish; Kevin Schneider for his deep knowledge in distribution networks and insightful advice on my research; and Amy Kim for her kindly support.

I also thank the members of Renewable Energy Analysis Lab: Ahlmahz for her introduction to my PhD research topic and our weekly discussions that help me make great progress; Yishen for his expertise in forecasting and support during my first year in Seattle; Yushi for his knowledge on optimizations; Bolun for this expertise about battery degradation modeling; Yury, Mushfiqur, Remy, Ting, Jesus, Ahmad, Abeer, Ryan, Daniel, Kevin, Ryan, Yao, Nam, Agata Jinjiang, Leonardo, Hao, Pan, Chase, Atinuke, Yuanyuan, Yize, Chenghui, Jingkun, Yang, Yao, Yangwu, Weiling and Yunfeng.

I would like to express my gratitude to the companies I interned and the supervisors. The internship experiences shaped my research directions and provided me with many great ideas. Thanks to Paul Kuntz and Frank Wang for their kindly guidance on Alstom Grid’s DMS system and network analysis functions. They helped me to understand the scale and complexity of real distribution systems. Thanks to Jianhui Wang for introducing me to microgrid restoration and provide me with brilliant research ideas. I treasure the three months spend at Argonne. Thanks to Babak Asghari for his encouraging personality and great support during the three months at NEC Lab.

I would like to thank the EE department people for their kindness. I thank Brenda Larson for showing me the steps for PhD general and final exams. I thank Eric Eto for his answers to payroll related questions.

Thank you all.

DEDICATION

This thesis is dedicated to my parents and my wife.

Chapter 1. INTRODUCTION

Distributed Energy Resources (DERs) have attracted considerable attention as their penetration increases in recent years. In general, DERs comprise of distributed generation (DG), energy storage (ES) and demand response (DR). DERs are different from other participants because of their distinctive characteristics: they are located on the demand side and they have some flexibility. Traditionally the demand has been treated as a passive market player with little price elasticity. The current electricity markets, retail tariffs and distribution networks are designed based on this assumption. The presence of DERs brings flexibilities to the demand side, which might alter the operations of electricity markets and require a redesign of electricity tariffs.

DERs brings various streams of benefits to different parties in the electricity sector. Studies have analyzed the benefits of DG[1][2], ES[3][4] and DR[5][6] from different perspectives and enumerated the streams of benefits each type of DERs can achieve. These benefits are defined based on the "avoided cost" method: how much costs can be avoided at the wholesale level due to the presence of DERs. The streams of benefits can generally be put into three categories: electricity supply, electricity transmission and distribution and other benefits. Each category contains several streams of benefits. The above studies have defined the streams of benefits belonging to each of the three categories. Apart from the studies that enumerate the streams of benefits, numerous studies focus on analyzing a specific benefit and carry out a detailed estimation of how much cost could be avoided with the presence of DERs and how to dispatch DERs in order to maximize these avoided costs. These studies provide benchmarks for the fair compensations of DERs for providing various services.

However, under the great majority of current market structures, methods based on the "avoided cost" are hard to implement because the end-use customers, in many cases the owners of DERs, do not interact directly with the beneficiaries. For example, DERs could reduce the peak demand on some transmission lines, helping the transmission company defer the upgrade of those lines and achieve savings from the deferred investment. But the transmission company has no direct contact with end-use customers. Without intermediate parties and proper mechanisms, the DERs owner cannot obtain the benefits directly from the transmission company. Similar issues affect many other streams of benefits. These issues pose obstacles for "avoided cost" methods to be implemented in practice.

These obstacles lead researchers to find alternative methods to reward DERs. Under the current electricity market structure, the Load Serving Entities (LSE) serve as intermediaries between customers and wholesale level parties: generation companies, transmission companies and distribution companies. The LSE collects payments from customers through electricity bills and pays generation companies, transmission companies and distribution companies for the services they provide. The presence of DERs alter their owners' demand profiles, leading to changes in the customers' electricity bills. The benefits of DERs can be gauged as the reduction in electricity bills, which is defined as tariff-based methods. Tariff-based methods provide a different mechanism to evaluate the benefits of DERs. These methods are relatively simple and easy to implement. However, as the subsequent chapters show, paying DERs through the reduction in bills may not be fair for either DERs or the LSE. Some of the DERs benefits are not represented by tariffs, so the tariff-based methods cannot not capture these benefits. Current tariffs may have corresponding components for other benefits, but the design of these components might not reward DERs fairly or even discourage DERs to produce or operate.

The goal of this research is to estimate the benefits of DERs and propose new valuation methods that could reward DERs with justified amounts for the multiple streams of benefits they provide. The literature review chapter will begin by enumerating the streams of benefits DERs bring. Then in-depth analyses on avoided cost-based methods and tariffs based methods for evaluating the benefits of DERs will be conducted. Next, a comparison between the two methods will be carried out to identify the advantages and disadvantages of each and suggest possible directions for improvement.

Two research directions are described: one on the design of tariff customized for DERs, the other on bridging DERs to wholesale level parties through aggregators. The first research study analyzes the impacts of DERs owned by commercial customers on the LSE. Assuming that DERs are rewarded based on the reduced bills, the study suggests that LSEs will lose money because its reduced payments are less than its lost revenue from customers with DERs. These results suggest that the tariffs should be redesigned to accommodate customer-owned DERs. Following the first study, the second study aims to design a tariff suitable for customers with DERs. The tariff transmits the system level situations and provide financial incentives for customers dispatch their DERs to reduce the resource procurement costs of the LSE.

The other research direction focus on scheduling energy storage for multiple streams of benefits. The third study focuses on LSE-owned energy storage and evaluates the optimal strategy for operating energy storage to maximize the benefits it can obtain. Since they are owned by the LSE, these energy storage facilities are not subject to tariffs. Avoided cost methods can be implemented to analyze how DERs can harness multiple streams of benefits simultaneously from different parties, including the benefits that tariffs fail to capture. The fourth study develops an aggregator model that schedules many customer-owned energy storages to achieve both customer and system level benefits.

The conclusion chapter summarizes the contribution of this research. The goal is to provide novel DER valuation mechanisms that can fairly reward DERs for their contribution. We also point out the possible future research directions.

Chapter 2. LITERATURE REVIEW

The literature review chapter consists four sections. The first section enumerates the streams of benefits different types of DERs provide. The second section explores previous work about quantifying DERs benefits based on system-level, avoided cost methods. The third section summarizes the existing literature about evaluating DERs benefits based on retail tariffs. Finally, the last section compares the benefits based on avoided cost and tariff-based methods.

2.1 DISTRIBUTED ENERGY RESOURCE BENEFITS

Distributed energy resources include distributed generation, energy storage and demand response. Numerous studies have been conducted to enumerate the benefits of the three types of DERs. These studies broadly categorize the streams of benefits DERs can provide to different system participants.

For distributed generation, the study conducted by the U.S. Department of Energy[1] lists the potential benefits of distributed generation (DG) as reducing peak power requirements, providing ancillary services, improving power quality, reducing land use and reducing vulnerability. The benefits are listed according to the different applications of distributed generation. This report also mentions rate-related issues that may impede the expansion of distributed generation. Since distributed generation in[1] is assumed to be dispatchable, some of the benefits require consistent and controllable production. However, non-dispatchable technologies, such as wind and photovoltaic, account for a large proportion of all the distributed generation installations. For non-dispatchable technologies, the streams of benefits that they can provide might be different from those of dispatchable DG. A study by the Rocky Mountain Institute[2] lists the benefits of photovoltaic solar generation (PV). Due to its intermittent and non-dispatchable nature, some of the benefits that require scheduling distributed generation in[1] cannot be achieved by PV.

Energy storage (ES) also provides various streams of benefits. The study conducted by Sandia National Lab[3] lists the benefits of energy storage according to their impact on different power system sectors: electric supply, ancillary service, grid system, end-user and renewable integration. The report also estimates the benefits and incidental benefits if the energy storage is dispatched for different applications. Another study by the Electric Power Research Institute[4] enumerates energy storage applications and evaluates their market potential. The study also provides a comprehensive study on energy storage technology options and their costs.

The benefits of demand response (DR) was investigated by the U.S. Department of Energy[5]. The report lists the benefits of demand responses for different market participants: the customers undertaking demand response actions, other non-DR consumers and other parties. The study also categorized the existing demand response programs. Woolf et al.[6] conduct an in-depth analysis of DR costs and benefits. In term of demand response program benefits, the study analyzed the avoided costs on different sectors: energy, capacity, transmission & distribution, ancillary services and environmental compliance costs.

Although the above studies enumerated the benefits for different types of DERs, most of the benefits have similar origins among all three types of DERs. To summarize the streams of benefits DERs provide, we categorize the benefits according to the sectors that they are present: electricity supply (energy, capacity and ancillary services), electricity transmission and distribution and other benefits. Table 2-1 summarizes the streams of benefits provided by different categories of DERs. Here we treat solar as a sub-type of DG, the benefits that are achievable by solar, which make up a subset of DG benefits, are specified in red color.

Table 2-1: Summary of benefits provided by distributed energy resources

Sectors		***Distributed Generation (Solar)***	***Energy Storage***	***Demand Response***
Electricity Supply	**Energy**	Reduced fuel costs	Energy arbitrage	Reduced generation
	Capacity	Capacity value	Capacity value	Capacity value
	Ancillary Services	Regulation service Spinning reserve Non-spinning reserve	Regulation service Spinning reserve Non-spinning reserve	Load balancing service Spinning reserve Non-spinning reserve
Electricity Transmission & Distribution		Overhead line/cable deferred investment Transformer deferred investment Reduced losses Relieved congestion	Overhead line/cable deferred investment Transformer deferred investment Relieved congestion	Overhead line/cable deferred investment Transformer deferred investment Reduced losses Relieved congestion
Other Benefits		Improved reliability Improved power quality. Environmental benefits	Improved reliability Improved power quality Environmental benefits	Improved reliability Environmental benefits

From Table 2-1 shows that most of the benefits are common among dispatchable distributed generation, energy storage and demand response. Though some benefits can be slightly different in a few instances: 1) distributed generation increases energy supply, demand response reshape/reduce energy demand while energy storage shifts the energy demand. 2) some demand response technologies cannot react fast enough to follow signals used for regulation service, but they can participate in other ancillary services with slower signals.

This section broadly lists and categorizes the streams of benefits provided by three types of DERs. The studies reviewed are high-level and briefly define the various streams of benefits from an avoided cost perspective. Numerous papers focus on a specific stream of benefits in more details. These studies offer different methods for estimating the same stream of benefit. In the next section, an in-depth literature review will be carried out to analyze the different methods for each stream of benefit.

2.2 REVIEW OF AVOIDED COSTS BASED DERS BENEFITS

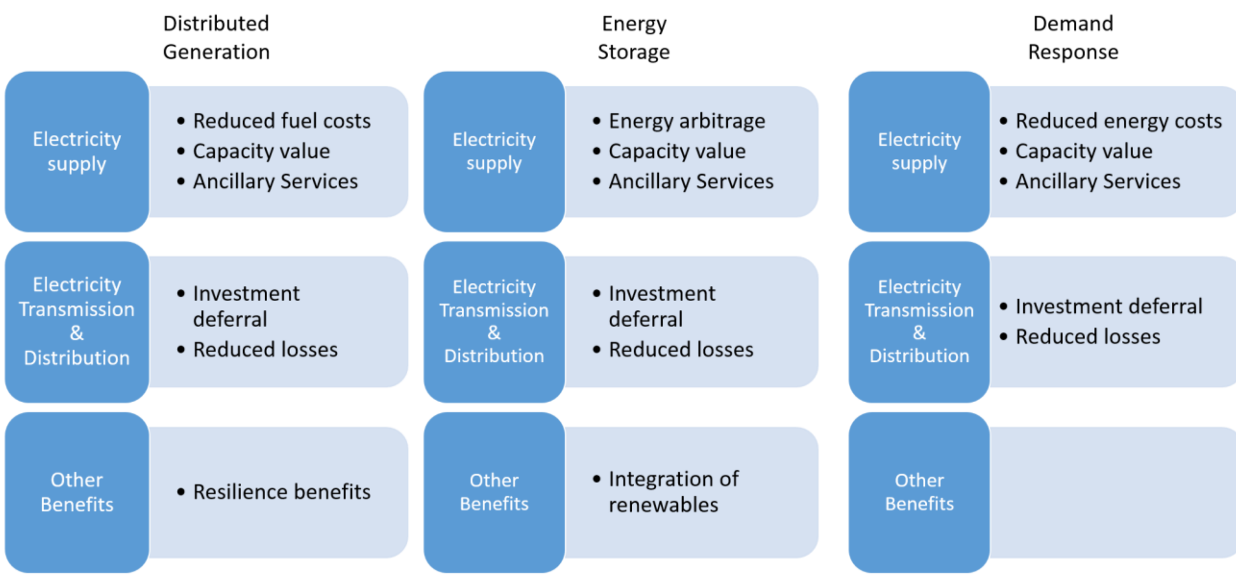

Figure 2-1: Benefits of DERs based on avoided cost

This section surveys papers dealing with the benefits of DERs based on avoided costs. The avoided costs reflect the value of DERs based on wholesale markets (energy, capacity and ancillary service markets) or reduced costs for loads serving entities, transmission companies, or distribution companies for grid infrastructure. Estimating the streams of benefits answers the question "how much should DERs be rewarded for providing certain types of services?" These studies contribute to finding a fair compensation to DERs for providing specific services. This section consists of three parts: electricity supply, electricity transmission and distribution and other benefits.

The “avoided cost” methods are distinct from other perspectives that evaluate customers’ savings from DERs based on reduced electricity bills, which will be discussed in the next section. The studies in this section provide benchmarks to the justified amount of compensations DERs should obtain.

Distributed Generation (DG) can be dispatchable (e.g. fossil fuel based distributed generation) or non-dispatchable (e.g. wind and solar). Some of the benefits of dispatchable DGs do not apply to non-dispatchable DGs. In the following paragraphs, dispatchable and non-dispatchable DGs are treated separately.

2.2.1 *Electricity supply benefits*

The electricity supply sector includes energy, generation capacity and ancillary services. The value of DERs in the above three categories will be analyzed. Figure 2-2 lists the methods used for estimating each stream of benefits on the energy supply sector.

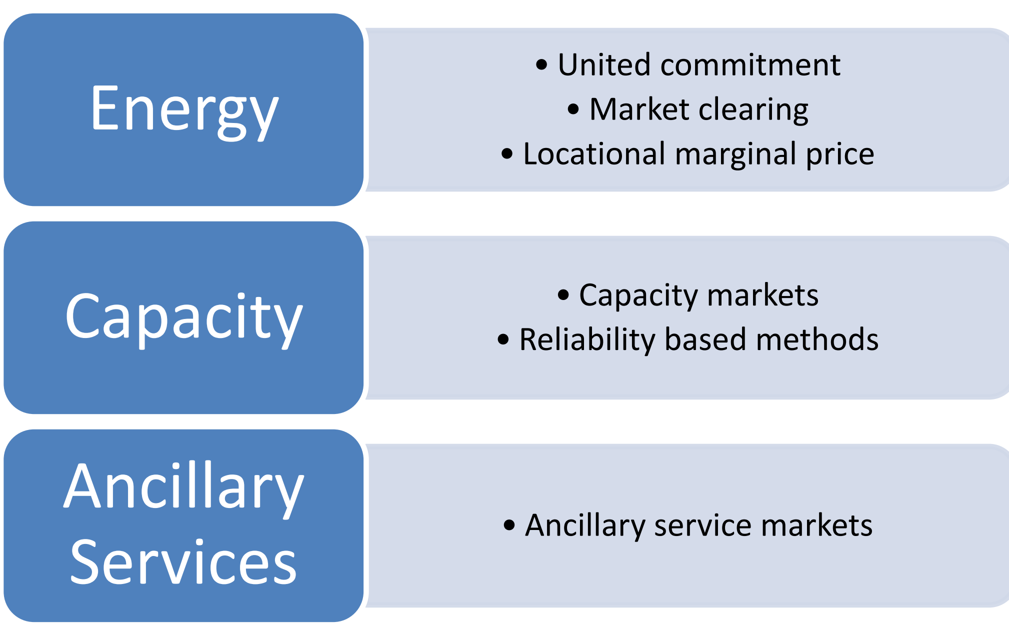

Figure 2-2: Benefits of DERs on the energy supply sector

Energy value of DERs

DGs affect the operation of wholesale energy markets. One way to estimate the values of DGs is to integrate them as generation resources in the wholesale markets. Palma-Behnke et al.[7] formulate a market structure that considers DGs as market participants and presents a day-ahead energy acquisition model for distribution companies. Based on reference[7], Palma-Behnke et al.[8] propose a market integration mechanism for DGs that includes energy and capacity payments. The DGs in these two references are assumed to be dispatchable.

For non-dispatchable DGs, the impact of solar on wholesale energy market clearing prices is studied in[9][10]. Bode et al.[9] evaluate the clearing prices reduction resulting from the integration of distributed photovoltaic generation on the German electricity market. A similar study by McConnell et al.[10] is conducted on the Australian National Electricity Market.

Energy storage can store energy when the price is low and discharge when the price is higher, acquiring the energy arbitrage benefits. Several studies have integrated energy storage into unit commitment models to evaluate its impact on energy prices. Pozo et al.[11] develop a generic energy storage model that can be easily integrated with complex optimization problems like unit commitment and analyzes the role of energy storage. Daneshi and Srivastava[12] study the security constrained unit commitment problem with wind generation and compressed air energy storage. It evaluates the impact of energy storage systems on locational pricing and economics.

Demand response resources are considered important elements for reliable and economic operation of the transmission system and the wholesale markets[13]. On the wholesale energy market level, the aggregated demand response may impact clearing prices and resource dispatch. Su and Kirschen[14] propose a new centralized complex-bid market-clearing mechanism that takes into consideration the load shifting behavior of consumers who submit price-sensitive bids to study the impact of demand response on electricity markets. Khodaei et al.[15] incorporate demand response into a security-constrained unit commitment for economic and security purposes. The study results show that DR could shave the peak load, reduce the system operating cost, reduce fuel consumptions and carbon footprints, and reduce the transmission congestion by reshaping the hourly load profile. Wang et al.[16] develop a stochastic unit commitment model to study the impact of uncertain demand response on unit commitment decisions. A robust unit commitment model considering worst-case demand response scenario is developed in[17] by Zhao et al.

According to the above papers the energy value of DERs can be estimated by integrating them into unit commitment formulations, integrating them into wholesale market models or through Locational Marginal Prices (LMP)[18]. Relying on unit commitment models can generate more accurate and suitable estimates for high penetration of DERs that alter the clearing prices considerably, but requires complex modeling and intensive computations. The LMP based method is more straightforward and easier to solve, but may be inaccurate if the penetration of DERs gets higher.

Capacity value of DERs

DERs have capacity value. Capacity represents a commitment of resources to deliver when needed, particularly in case of a grid emergency. Several ISOs establish capacity markets that define the markets structure, participants and market clearing mechanisms for generation capacity[19][20][21]. According to the capacity markets, the effective capacity of a source is reflected by its production during the periods coincident with the system's aggregated peak demand. One way to estimate the capacity benefits of DERs is through capacity markets. Apart from that, Dent et al.[22] discuss the definition of capacity value of DG arising from its ability to support additional demand without the need for new network capacity, by analogy with the definition of effective load carrying capability (ELCC) at the transmission level.

Although they cannot be dispatched, photovoltaic panels and distributed wind power plants can still have capacity value if their outputs coincide with the system peaks. Madaeni et al.[23] estimate the capacity of photovoltaic solar plants in the western U.S. through simpler approximation methods and more-complex reliability based methods.

The difference between ES and DG in providing capacity is that ES needs to be charged before discharging to supply power during the peak hours. Several papers focus on optimal scheduling of energy storage to provide peak shaving. The capacity shaved during peak hours reflects the capacity value of energy storage. Levron and Doron[24] describe an optimal peak shaving strategy that minimizes the power peak and derives an analytic design method for attaining optimal peak shaving schedules. Oudalov et al.[25] propose a sizing method that maximizes economic benefits by reducing the power demand payments. Rowe et al.[26] present a control method for energy storage to reduce peak demand in a distribution network.

Demand response also has capacity values. ISOs have designed emergency demand response programs that give incentives to customers to shave loads during peak hours when the system is under contingency. With the presence of capacity market, ISOs have replaced the emergency demand response programs by introducing demand response into capacity markets and let it compete with other capacity resources. Nolan et al.[27] present a preliminary method for estimating the capacity value of demand response utilizing demand response availability profiles and applying a response duration constraint. The capacity value of demand response can also be estimated from capacity markets.

The capacity value of DERs can be analyzed through market clearing prices of capacity markets, assuming the penetration of DERs is not high and their impacts on prices is negligible. The reliability based methods for estimating effective capacity are more complex and suitable if the penetration of DERs is higher. The peak shaving methods that estimate the contribution of DERs coincident with peak hours contribute to quantify the capacity value of DERs. ES and DR have availability constraints that may limit them from producing at their maximum output levels during peak hours. Therefore, a number of studies focus on scheduling and dispatching ES and DR to maximize their capacity values.

Ancillary service value of DERs

Another stream of benefit comes from providing ancillary services. Most ISOs have established ancillary service markets that include regulation, spinning reserve and non-spinning reserve. The above three services have different signals, require different response times and have different clearing prices. Depending on their characteristics, different DERs may choose to provide different services that are more suitable for them.

A study dating back to 2000[28] discusses the potential of DGs to provide some of these services. In particular, DGs can serve locally as the equivalent of spinning reserve and voltage support. Mashhour and Moghaddas-Tafreshi[29][30] address the bidding problem faced by a virtual power plant in a joint market for energy and spinning reserve. The virtual power plant consists of different DERs, including DGs. Non-dispatchable DGs cannot provide ancillary services without integration of other resources.

Energy storage systems can adjust their output very fast, which is ideal for providing ancillary services like regulation and spinning reserve. The benefits of energy and ancillary services are simultaneously considered in some studies. Sandia National Laboratory[31][32] develops deterministic linear programming models to schedule energy storage for energy arbitrage and regulation. Formulations to maximize revenue from energy, spinning reserve and regulation markets have also been developed for joint hydro and pumped-storage plants[33] and Vanadium redox battery energy storage[34]. Akhavan-Hejazi and Mohsenian-Rad[35] formulate a stochastic program that takes into account the fluctuating nature of market prices. He et al.[36] consider the effect of battery degradation cost on the provision of energy arbitrage and ancillary services.

Demand response can provide ancillary services such as spinning reserves and regulation. ISOs have set up reserves markets where demand response can bid. Schisler et al.[37] describes how a load serving entity works with commercial and industrial customers to provide reliable load reductions in these markets. In another study[38] Ma et al. describe and implement a method to construct detailed temporal and spatial representations of demand response resources and to incorporate these resources into power system models to analyze the economic value of demand response for ancillary services. Not only can large commercial and industrial customers participate in ancillary service markets, once aggregated, residential appliances can also provide ancillary services. Studies have been conducted to utilize HVAC loads to provide load balancing service[39], utilize water heater loads to provide regulation service[40]. The impacts of forecasting errors, minimum HVAC turn-off times, response delays, and consumer overrides on the performance of regulation service provided by HAVCs are evaluated in[41].

The above papers estimate DERs' benefits for providing ancillary services through the market clearing prices of ancillary service markets. Some of these services require participants to follow fast-changing signal while others require participants to adjust their output more slowly but sustain it for a certain amount of time. A specific type of DER, depending on its characteristics, may choose to participate in providing different ancillary services.

2.2.2 *Transmission and distribution*

DERs also provide several benefits in transmission and distribution, in particular investment deferral, loss reduction and congestion relief.

Investment deferral

Transmission and distributions network infrastructures are designed to meet the peak load. As the load grows, the aggregated peak load increases and could overload overhead lines, underground cables and transformers or cause safety issues. As a result, these costly components need to be upgraded or replaced. DERs could counter the impact of load growth by shaving peak loads, and defer the investments on network components.

In the transmission and distribution sectors, DGs are capable to defer the investments in overhead lines, underground cables and transformers; DGs can also reduce network losses by supplying energy locally; in addition, DGs may help relieve congestion in transmission and distribution networks. Gil and Joos[42] quantify the distributed network capacity deferral value of distributed generation according to the contribution of DG in shaving peak demand. The network capacity deferral benefit is combined with other benefits such as reduced losses and avoided wholesale market purchases to quantify the potential of benefits brought by distributed generation[43]. Piccolo and Siano[44] consider different regulations for distribution network operators ownership of DG and how they would influence the optimal connection of new generation within existing networks are examined in order to capture the effects of DGs on network investment deferral. Wang et al.[45] capture the potential security of supply benefits of DGs that incorporating the system security standards (N-1) into network planning formulations. The method is applied to a meshed distribution network.

Energy storage could reduce peak demand and therefore defer the need for investment in transmission and distribution infrastructure. The investment deferral benefits of energy storage are discussed in reference[46][47]. Chacra et al.[46] evaluate the impact of ES on peak shaving to reduce substation transformer peak load and defer the need to upgrade substation transformers. Oudalov et al.[47] compare different battery storage technologies for providing network investment deferral services.

Demand response could also defer the need for investments in transmission and distribution infrastructure. Martinez Cesena and Mancarella[48] develop a method to assess the economic value of deploying demand response for distribution network reinforcement planning.

The investment deferral benefit of DERs can be estimated by various methods. One category of approaches is to analyze how much DERs can produce during peak demand hours. The same method is also applied to estimate the capacity value of DERs. The production of dispatchable DGs can be estimated since they are always available. For energy storage and demand response, they are subject to availability issues during peak demand periods. For example, the energy storage might not have enough energy available when called to discharge to reduce the peak demand. Reliability based methods rely on more complex system models to estimate the investment deferral benefit of DERs.

Loss reduction

DERs can reduce network losses. DERs are located in the distribution network energy locally without going through the transmission network. When DERs supply energy to their owners, even the distribution network losses can be avoided. Quezada et al.[49] compute annual energy losses variations when different penetration and concentration levels of DERs are connected to a distribution network. In addition, the impacts on losses of different DER technologies are compared. Ochoa and Harrison[50] apply a multi-period AC optimal power flow to determine the optimal accommodation of renewable DERs in a way that minimizes the system energy losses. This reference also addresses the extra power losses benefits that can be harnessed through voltage control and power factor control of DERs.

Congestion relief

The congestion relief is a byproduct of DERs providing other services like energy, capacity and investment deferral. Network congestion happens when the lines are heavily loaded, which usually coincides with peak demand. By producing energy during peak demand hours, DERs reduce the demand and reduce the loading on congested lines. The benefit of congestion relief is reflected in reduced locational marginal prices.

2.2.3 *Other benefits*

Apart from energy supply and energy transmission & distribution sectors, DERs also have other streams of values. These benefits may require coordination of different resources. For example, energy storage could interact with photovoltaic solar power to achieve win-win situation for both parties. In addition, some of the benefits, for example, the back-up source benefit of DERs are not considered in the above two categories.

Interaction with renewable energy

The fast ramping capability of energy storage makes it ideal for smoothing the intermittent power output of renewable generation. The increasing penetration of renewable sources of energy may raise the requirement for balancing power and reserve capacity. Su and Gamal[51], Qin et al.[52] develop risk-limited energy storage dispatch models that smoothes the power output fluctuations of renewable energy resources and therefore reduce ancillary service requirements. Control strategies are developed in[53] to utilize energy storage to smooth out the power output of a wind farm. Artificial neural network strategies are developed in[54] to determine the size and schedule of energy storage that smooth the variability of wind farm output. Li et al.[55] propose a control method to reduce wind/PV hybrid output power fluctuations and regulating battery SOC. Liu et al.[56] coordinate energy storage with voltage regulators to solve the voltage rise problem caused by high photovoltaic penetration in distribution networks. Song et al.[57] develop a Markov-chain based photovoltaic-energy storage model that can assist planning and operations of energy storage and solar generation.

Back-up support

DGs can restore critical loads when natural disasters cut off the conventional electricity supply from the transmission network. By controlling switching devices, a distribution network can be sectionalized in several microgrids, each of which is supplied by DGs. Several studies have been conducted to analyze network restoration through microgrids powered by DERs. Lim et al.[58] presents detailed models for DGs and their inverters and a sequence of actions for microgrid black start. Li et al.[59] apply a graph theoretical spanning tree approach for finding optimal microgrid topology and providing a sequence of switching operations. Xu and Liu[60] propose a multi-agent coordination scheme for microgrid restoration. Castillo[61] presents a stochastic mixed-integer linear programming model; however, it requires the microgrids to be installed beforehand. Chen et al.[62] proposes a mixed-integer linear programming method that dynamically forms microgrids to achieve a resilient distribution system. It also provides distributed multi-agent coordination for global information discovery. Non-dispatchable DGs cannot secure their outputs to supply loads on their own.

2.3 REVIEW OF TARIFF-BASED DERS TARIFFS

The previous section conducted an in-depth study of different approaches for estimating each of the benefits DERs provide based on “avoided cost” methods. The “avoided cost” methods calculate the costs reductions for wholesale level parties when DERs provides certain services and estimates the value of DERs accordingly. These methods provide relatively fair compensations for DERs providing certain services. However, a large proportion of DERs are owned by end-use customers. In most cases, customers neither directly participate in the wholesale level markets nor have transactions with wholesale level parties. Instead they only interact with their load serving entity and pay their electricity bills according to tariffs. The load serving entities act as middlemen between customers and wholesale level parties. Therefore, another perspective to estimate DERs benefits is through their impact on electricity bills. This section presents an in-depth survey of methods used to estimate the benefits of DERs according to bill reduction. First, a brief introduction of residential and commercial tariffs and description of their components is carried out. Then tariffs based assessment of PV (non-dispatchable DERs) values are summarized. After the assessment of PV, we will analyze the tariff-based studies on dispatchable DERs (ES and DR).

2.3.1 *Summary of tariffs*

Customers acquire the benefits of their DERs through tariffs. Individual customers do not directly participate in wholesale markets, instead they interact with load serving entities (LSEs) and their bills reflect their demand profile. Installing DERs reshape their demand profile and therefore changes how much they pay to the load serving entities. So on the customer side, the values of DERs are reflected through reduced electricity bills.

There are hundreds of electricity LSEs in the U.S. Different LSEs offer various types of tariffs with different structures and designs. Most offer at least two categories of tariffs: residential tariffs and commercial tariffs. Residential tariffs are designed for residential customers whose sizes are relatively small. Commercial tariffs are designed for customers with greater sizes. A customer may have several tariff options with distinctive structures from the same load serving entity.

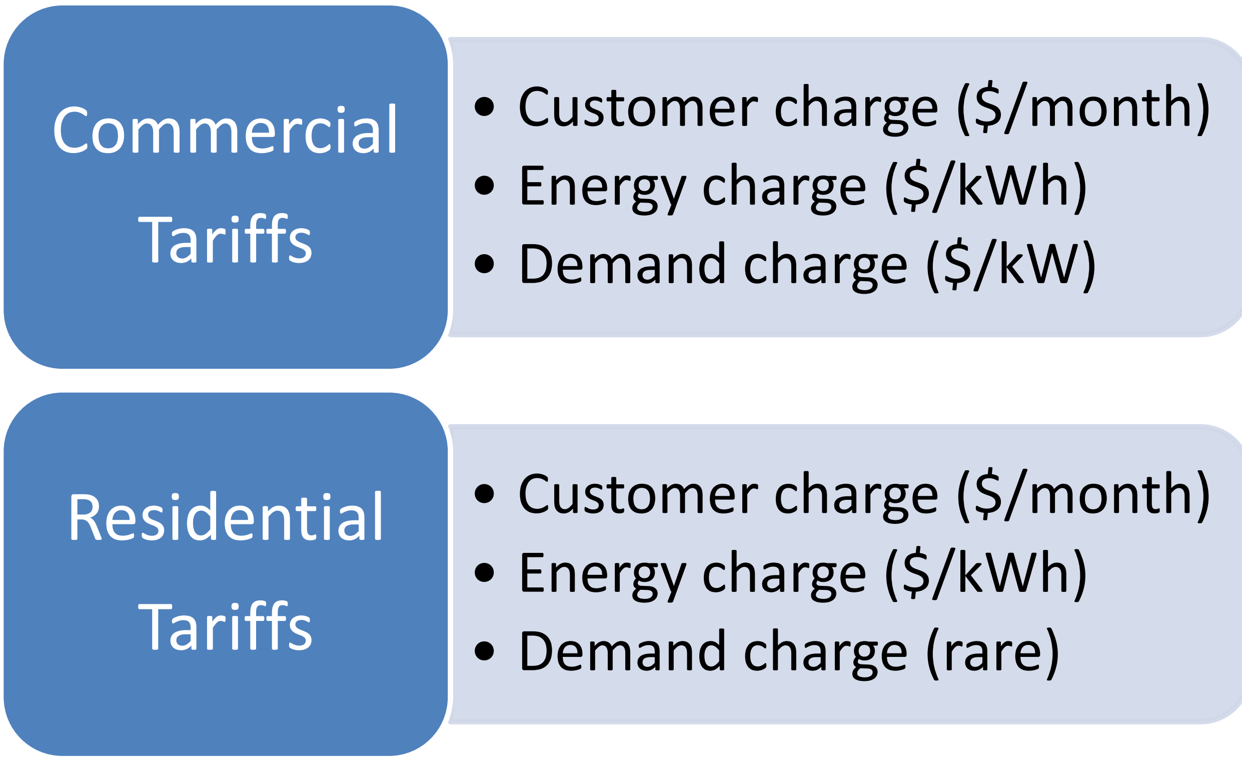

Figure 2-3: Benefits of DERs on the energy supply sector

Commercial tariffs

Commercial tariffs commonly consist of three components: a basic customer charge ($ per customer per billing period), an energy usage charge ($/kWh) and a demand charge ($/kW). The basic customer charge component is designed to cover the cost of metering, billing and other administrative work. The energy usage component accounts for at least the cost of fuel needed to generate this energy. It may also account for other costs, including the cost of procuring ancillary services[63][64] or the cost of delivering energy[65][66][67][68]. The rationale behind the demand charges is to recoup investments made in the generation, transmission, and distribution infrastructures. Some LSEs unbundle demand charges and quantify specific rates for transmission, distribution and generation capacity[69].

LSEs may offer their commercial customers the option of a fixed-rate or time-of-use tariff[70]. In most tariffs the energy component is either fixed, time-of-use or has critical peaks where the prices jump to several times the regular prices during windows of a few hours for a couple of days per year. In the U.S., tariffs with dynamic energy charge components which directly reflects the wholesale market clearing price are rare. Most commercial customers pay a demand charge based on their monthly peak usage of either the highest 15-min, 30-min or 1-hour interval.

Residential tariffs

Residential tariffs are usually simpler than commercial tariffs. Most residential tariffs have two components: a basic customer charge ($ per customer per billing period), and an energy usage charge ($/kWh). The energy charge can be fixed or increases in blocks as the monthly usage goes up[71]. There are also variable energy tariffs: time-of-use tariffs that divide the day into two or three price periods with different rates[72]; critical peak tariffs that charge customer on-peak rates several times the regular prices during several time windows for a couple of days per year, when the system aggregated demand approach the annual peak[73]; real-time pricing directly expose customers to the wholesale market clearing prices[74]. Charging customer real-time prices is the subject of current discussions. Roozbehani et al.[75] point out that since customers have more and more flexibility, they may react to real-time prices by modifying their demand profile and this might result in more volatile market prices. Although tariffs that charge residential ($/kW) charges do exist[74], they are not very common.

2.3.2 *Review of tariff-based DERs benefits of photovoltaic generation*

Currently there are two common solar tariff structures: feed-in-tariff and net metering. A feed-in tariff (FIT) is an energy-supply policy focused on supporting the development of new renewable power generation. The FIT contract provides a guarantee of payments in dollars per kilowatt hour ($/kWh) for the full output of the system for a guaranteed period of time (typically 15-20 years)[76]. There are two main methods for setting the overall return that renewable energy developers receive through FIT policies. The first is to base the FIT payments on the levelized cost of renewable energy generation; the second is to base the FIT payments on the value of that generation to the utility and/or society.

Germany's experience with feed-in-tariffs is often cited as a model to be replicated elsewhere. Germany has more than doubled its renewable electricity production since 2000 and has already significantly exceeded its minimum target of 12.5% set for 2010. However, the increasing penetration of renewable energy comes at a cost: roughly 7.5% of average electric prices go to subsidies for renewable generation and the feed-in-tariff of solar is about twice as much as the average electric prices[77]. Another study focusing on Ontario also shows that solar feed-in-tariffs are several times the average electricity prices[78]. A study on Australian feed-in-tariffs suggested that the feed-in-tariffs designed based on PV production costs are also much higher than customers' electricity prices[79]. Table 2-2 and 2-3 list feed-in-tariffs in Germany and Australia.

Table 2-2: Feed in Tariff in Ontario and Germany

Technology	Ontario FIT rates, 2011[a]				Germany FIT rates, 2011[b]				
	Size ranges	CDN ¢/kWh	Escalation[c] (%)	Uptake[d] (%)	Size ranges	€ ¢/kWh	CDN ¢/kWh[e]	Degression (%)	Uptake[f] (%)
Biomass				7.5	≤ 150 kW	11.55–22.44	15.8–30.7	1	18.7
					≤ 500 kW	9.09–19.98	12.4–27.3	1	
	≤ 10 MW	13.8–14.8	20		≤ 5 MW	8.17–17.08	11.2–13.9	1	
	> 10 MW	13–14	20		≤ 20 MW	7.71–10.68	10.5–14.6	1	
Biogas	≤ 100 kW	19.5–20.5	20	1.4	≤ 150 kW	11.55–20.46	15.8–28	1	12.9
	≤ 500 kW	16–17	20		≤ 500 kW	9.09–16.02	12.4–21.9	1	
	≤ 10 MW	14.7–15.7	20		≤ 5 MW	8.17–13.12	11.2–17.9	1	
	> 10 MW	10.4–11.4	20		≤ 20 MW	7.71–12.66	10.5–17.3	1	
Landfill gas	≤ 10 MW	11.1–12.1	20	1.1	≤ 500 kW	8.87–10.84	12.1–14.8	1	0.7
	> 10 MW	10.3–11.3	20		≤ 5 MW	6.07–8.04	8.3–11	1	
Solar PV rooftop	≤ 10 kW	80.2	–	3.0	≤ 30 kW	28.74	39.3	9[g]	11.7[h]
	≤ 250 kW	71.3	–		≤ 100 kW	27.33	37.3	9[g]	
	≤ 500 kW	63.5	–		≤ 1 MW	25.86	35.3	9[g]	
	> 500 kW	53.9	–		> 1 MW	21.56	29.5	9[g]	
Solar PV ground	≤ 10 MW	44.3–46.8	20	15.5	Any size	21.11	28.8	9[g]	
Wind onshore	Any size	13.5–16	20	72.6	Any size	4.97–9.81	6.8–13.4	1	36.6

Table 2-3: PV production cost and current feed-in-tariff in Australia

	State	Annual average radiation (kWh/m^2/day)	Annual average PV electricity production (kWh)	PV production cost in $/kWh	Current FIT
1	Victoria	4.44	1153	0.69	Up to 66 cents
2	Western Australia	5.32	1381	0.58	60 cents (July 2010) [11]
3	South Australia	5.15	1339	0.60	44 cents
4	Northern Territory	6.26	1628	0.49	TBA
5	Queensland	5.08	1321	0.60	44 cents
6	Australia Capital Territory	5.20	1352	0.59	50.05 cents
7	New South Wales	4.85	1257	0.64	60 cents
8	Tasmania	4.18	1087	0.74	20 cents

The above references indicate that averaged production cost of PV are still much higher than electricity prices. Feed-in-tariff credited PV owners according to the cost of PV, which encourages installation because the investments are guaranteed to be paid back. However, all customers, including the non-PV customers foot the bill of subsidizing PV, which is unfair. In addition, the feed-in-tariff is fixed and does not reflect the time varying streams of values that PV provides.

Another rate structure for distributed renewable generation is net metering. Net metering provides customers with PV bill credits for each unit of PV generation at the underlying retail rate, regardless of the temporal correlation between PV generation and customer load. Under net metering, the power produced by PV is paid the same price as the customer's demand, which is quite different from the much higher feed-in-tariffs. Mills et al.[80] analyze the impact of retail rate structures on the economics of commercial photovoltaic systems. The authors picked up several commercial tariffs, one with the $/kW charge to recover fixed costs and the other with $/kWh charge to recover the same costs. The results suggest that under $/kWh charge the benefits of PV are higher. Darghouth et al.[81] analyze photovoltaic systems installed by residential customers under three typical types of residential tariffs: fixed, time-of-use and real-time pricing. The results suggests that PV benefits are around 10% higher under a time-of-use tariff compared with benefits under a fixed-tariff and under a real-time tariff. Darghouth et al.[82] (a continuation of[81]) explored the impact of the following assumptions on the bill savings from residential PV: a wholesale electricity market design with a price cap (as opposed to an energy-only market); a retail rate with a fixed customer charge (as opposed to a fully volumetric rate); and increasing-block pricing (as opposed to a flat rate).

Critics of net metering point out that it allows PV owners to avoid paying fixed costs and shift those costs to non-net metering customers. Because of this unsustainable and potentially unfair cost shifting, several states have begun to shift away from net metering. Table 2-4 compares the characteristics of feed-in tariff and net metering.

Table 2-4: Comparison between feed-in tariff and net metering

	Feed-in tariff	**Net metering**
Definition	An energy-supply policy focused on supporting the development of new renewable power generation. Feed-in tariff provide a guarantee of payment in dollars per kilowatt hour ($/kWh) for the full output of the system for a guaranteed period of time.	Net metering provides customers with PV bill credits for each unit of PV generation at the underlying retail rate, regardless of the temporal match between PV generation and customer load.

Rates	Fixed energy charge	Depending on the tariff structure, could be fixed, time-of-use or real-time pricing.
Concerns	All customers, including non-PV customers subsidize the PV customers. Does not reflect the true value of PV.	Fixed costs of PV are shifted to other non-PV customers. Does not reflect the true value of PV.

2.3.3 *Review of tariff-based DERs benefits of dispatchable DERs*

Different from photovoltaic generation, energy storage and demand response are dispatchable and can be scheduled to minimize the electricity bills. Plenty of studies have targeted the scheduling of DERs owned by residential and commercial customers.

Household appliance scheduling has been drawing research interests over the past few years. Research works are diverse in terms of mathematical models and solution approaches. Pipattanasomporn et al.[83] tackle the load power control problem. The load serving entity determines the thresholds of energy consumptions that the aggregated customer demand should not exceed at different times. Then the load serving entity broadcast the signals to customers. Then customers make scheduling decisions to adapt to the utility signal based on the predefined appliance priority levels. Pedrasa et al.[84] optimally schedules DERs (including renewables) under time-of-use and critical peak pricing tariffs. The above two studies assumed that the appliances demands are deterministic and schedulable, without any uncertainty.

Many studies choose real-time pricing as the electricity tariffs. Real-time pricing reflects the time-varying energy production cost of the power system, which could possibly guide customers to better schedule their DERs[85]. However, since many customers may shift their demand to lower-price periods, real-time pricing may create market stability issues[86] i.e. market prices, instead of flattening, might become more volatile.

Developing home energy management systems under real-time pricing has become a hot research topic. Mohsenian-Rad and Leon-Garcia[87] develop an optimization framework is developed to schedule residential appliances to minimize customer electricity bills. The study also discussed prediction of real-time prices. Kim and Poor[88], Tischer and Verbic[89] employ dynamic programming to determine an optimal control policy to schedule different appliances to minimize the bills customers pay. Chen and Wu[90], Wallace et al.[91] develop algorithms to schedule various types of appliances under uncertain real-time prices by using rolling horizon online stochastic programming.

The above papers focus on energy management of residential customers subject to residential tariffs, which typically don't include demand charges. In fact, most residential tariffs allocate the capacity related costs (generation capacity, transmission & distribution investments) to the energy charges. Under this allocation, a kWh produced at any hour worth has the same capacity value, which is not very accurate.

Research on optimal scheduling of DERs owned by commercial customers are less common. Appliances in commercial buildings, for example HVAC systems, are much more complex compared with their residential counterparts. The models to simulate those commercial building appliances are still quite complex to apply in optimization problems. Instead, these models are incorporated in control-based algorithms to achieve some specific targets like peak shaving[91][92]. These studies suggest commercial customers can achieve demand charge savings by dispatching DERs to reduce peak demands.

2.4 COMPARISON BETWEEN AVOIDED COSTS BASED BENEFITS AND TARIFF-BASED BENEFITS

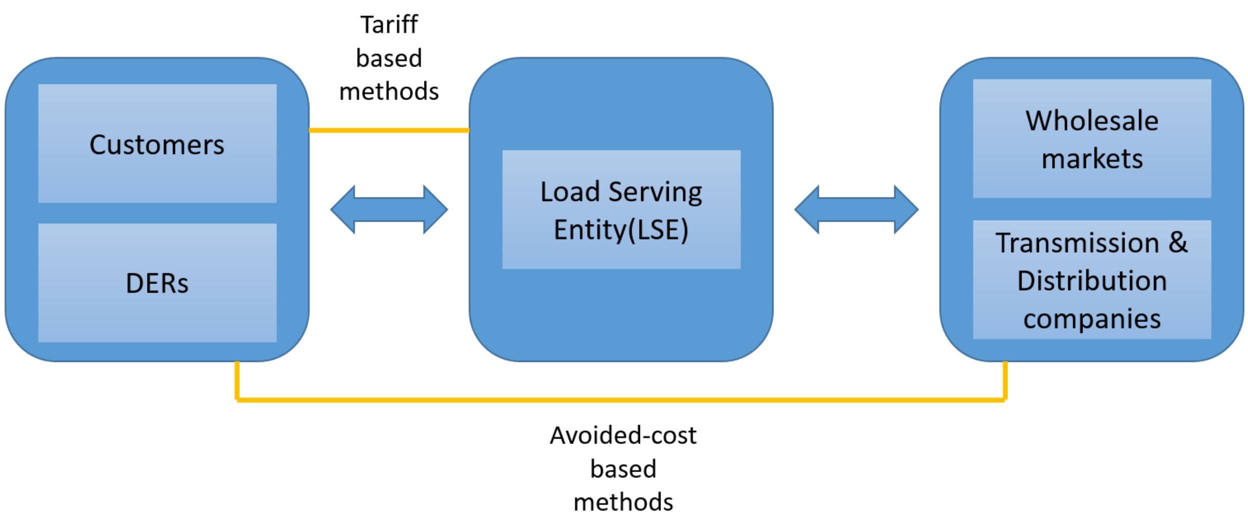

Figure 2-4: Illustration of avoided-cost-based methods and tariff-based methods

2.4.1 *DERs benefits evaluation: two perspectives*

In the last two sections, we have summarized the literature on the streams of benefits based on avoided costs and benefits based on electricity tariffs. Figure 2-4 illustrates the avoided costs based methods and the tariff based methods. In this section, we compare the two methods, state the deficiencies of each method and point out potential research directions.

2.4.2 *Deficiencies of avoided-cost based methods*

The avoided-cost methods can provide most accurate estimations on the benefits that DERs provides. These studies evaluate the impacts of DERs on the beneficiaries and estimates how much costs could be avoided due to the presence of DERs. However, among all these studies, few address the issue of allocate the avoided-costs to DERs.

Many studies estimate the aggregated impacts of many DERs on their beneficiaries. But most of the studies did not cover the methods/algorithms to distribute the benefits to DERs. For example, an aggregator can schedule and control a bunch of batteries to provide frequency regulation service and achieve considerable amount of revenues. Having collected the revenues from the market, the aggregator need to distribute the benefits back to individual batteries. The batteries have different power ratings, energy ratings, efficiencies, availabilities, degradation costs. The dispatches of different batteries could be very different. Considering these factors, developing fair methods to distribute the benefits back to DERs is a non-trivial task.

DERs can be owned by end-use customers, who has no direct financial interaction with many beneficiaries: generation companies and transmission companies. A single generation/transmission company could face potentially thousands or even millions of customers with DERs. To enable for generation companies and transmission companies distribute benefits to DERs, the modifications on communication infrastructure and operation costs are considerable. Establishing and maintaining interactions between the company and the DERs is a significant burden.

To fully utilize the avoided-cost methods, significant changes need to be made on the existing power system economics structure. This requires changes on tariff structure, market structure and a lot of investments for DERs to directly interact with their beneficiaries. Compared with the tariff based methods, avoided-cost based methods are more difficult to implement.

2.4.3 *DERs benefits not reflected in tariffs*

In addition to reshaping customers demand profiles, DERs can also provide other services that conventional customers cannot provide, e.g. ancillary services and back-up support. Since most tariffs are designed for conventional customers, they do not explicitly reflect the non-conventional benefits of DERs.

Ancillary Services

The first non-conventional benefits of DERs is the provision of ancillary service. Reference[28][29][30] analyze the potential of distributed generation in providing ancillary services. Reference[31][32][33][34][35][36] focus on the provision of ancillary services by energy storage. In particular, references[34][35][36] discusses optimal battery energy storage scheduling strategies to maximize revenue. References[37][38][39][40][41] evaluates demand response as a provided of ancillary services. Among other studies, references[39][40][41] provide scheduling strategies for the aggregation of appliances (HVAC and water heater) to provide ancillary services. The above references apply avoided-cost-based methods by letting the aggregation of DERs participate into ancillary service markets.

On the other hand, conventional end-use customers have no ability to provide ancillary services. LSEs divide the cost of ancillary services by their total energy usage and add the $/kWh charge to the energy charge[63][64]. So customers' payments for ancillary services are proportional to their energy usage. Therefore, it is not suitable for DERs to obtain ancillary service benefits simply through tariff itself. References[39][40][41] suggest individual DERs can be aggregated by aggregators. The aggregators schedule the DERs and bid their aggregated output into the ancillary service markets. Introducing aggregators has two advantages: first, the size of an individual DER may be too small to directly participate in the ancillary service markets. When DERs are aggregated, they meet ancillary service markets' minimal size requirements. Second, it's more difficult for an individual DER to follow the ancillary service signals than a bunch of DERs coordinated by an aggregator. Therefore, aggregation may facilitate DERs in obtaining ancillary service benefits. Figure 2-5. describes the market structure of DERs obtain ancillary service benefits through aggregator.

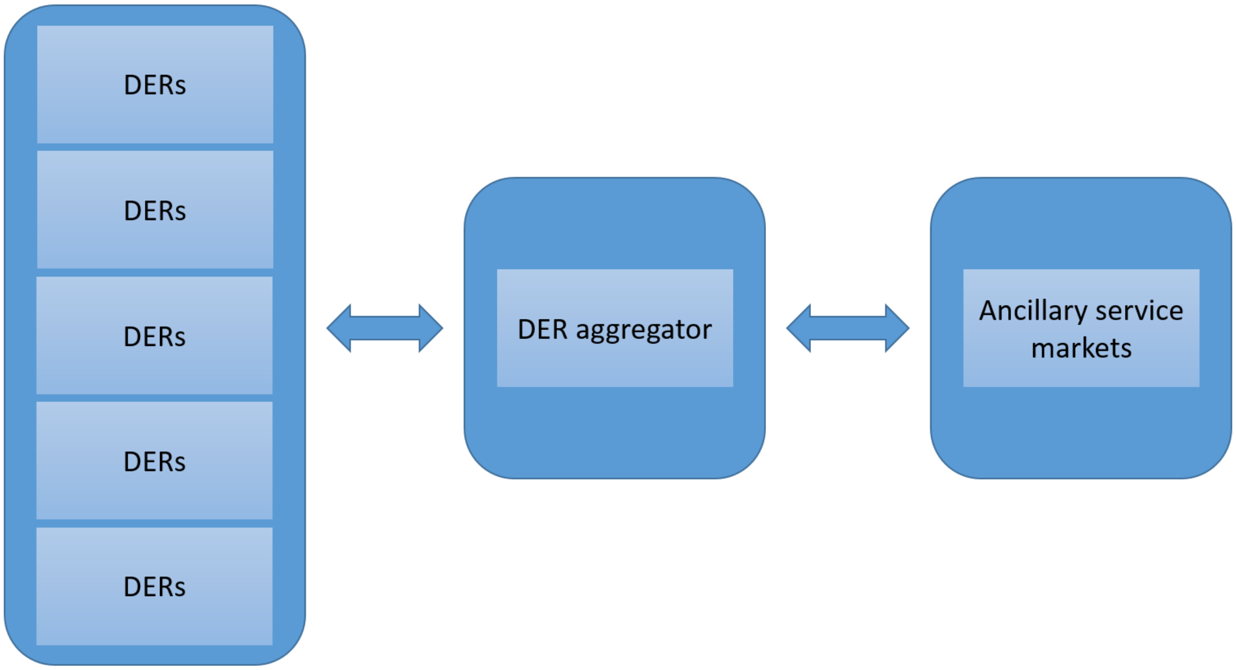

Figure 2-5: Structure of DER obtaining ancillary service benefits through aggregators

Back-up support

DERs can provide back-up support when outages happen that the conventional supply from transmission network is cut off. Reference[58][59][60][61][62] proposed DERs support for critical loads after outages by forming microgrids so some of the loads could be picked-up.

Although studies have been conducted to estimate the value of lost load, most load serving entities do not compensate customers when outages cut off their electricity supply. So the back-up support benefit is not reflected through electricity tariffs. Instead the critical loads picked-up during outages could in theory settle with DERs through bilateral transactions. A centralized dispatcher may be necessary in order to formulate microgrids and dispatch DERs if the load pick-up is determined through centralized optimization[61][62]. The pick-up plan could also be carried out through negotiations among agents[60].

Ancillary services and back-up support are two examples of benefits of DERs that are not reflected in tariffs. This suggests that the tariff-based methods do not capture some of the streams of benefits that DERs provide. For DERs to get these benefits, new market structures should be established with possibly additional market participants.

2.4.4 *DERs benefits misrepresented by tariffs:*

Although current tariffs do not reflect some of the DERs benefits, they do have components corresponding to other benefits. Commercial tariffs usually have two parts with an energy charge and a demand charge. The energy fuel cost of the LSE is recovered through the energy charge. In some tariffs the LSE cost of generation capacity, transmission and distribution are recovered through the demand charge. Other tariffs recover a certain proportion of the above costs through the energy charge and the rest through the demand charge. Most residential tariffs only have an energy charge. Therefore LSE’s energy fuel cost, generation capacity cost, transmission and distribution costs are all recovered through the energy charge.

For conventional customers, the existing tariffs are adequate in helping the LSE recover its costs. However, once customers install DERs the existing tariffs may not represent the benefits of DERs correctly. Situations where LSE over-compensate or under-compensate DERs are possible. This chapter presents a qualitative analysis of these situations. A quantitative analysis is presented in the next chapter.

Energy charge

In some tariffs, the energy charge is flat or involves incremental blocks. The flat tariff does not reflect accurately the benefits of DERs because it stays the same for the entire day, while the fuel cost varies throughout the day. For residential tariffs without demand charge, the energy charge is also responsible to recover other LSE costs. The cost of generation capacity, transmission and distribution is proportional to peak load, so the peak hours have more values than non-peak hours, yet the flat tariff does not capture the time-varying values of DERs.

Like the flat tariff, an incremental blocks tariff involves constant rates throughout the day. The rates get higher when customers' monthly usage gets higher, not because the cost of electricity gets higher. Subject to these two tariffs, DERs obtain benefits according to their monthly productions, which are likely to be much different from what they should be paid. Flat tariffs also offer no incentive for energy storage and demand response to be dispatched at specific hours of the day.

Other tariff designs, including time-of-use tariffs, critical peak pricing tariffs and real-time tariffs reveal the time-varying costs of electricity in greater and greater details. Reference[83] solved the DERs scheduling problem under a time-of-use tariff. Scheduling DERs under a real-time tariff is more challenging because the real-time price is not known in advance. References[87][88][89][90][91] solved the scheduling problem under real-time pricing from different perspectives.

In conclusion, among the different structures of energy charges, the flat tariff and incremental block tariffs offers little incentive for dispatchable DERs to operate. These two tariff structures misrepresent the energy value of DERs. The time-varying tariffs (time-of-use tariff, critical peak tariff and real-time tariff) provide better incentives for DERs to dispatch.

Demand charge

A customer's demand charge is usually equal to the $/kW rate multiplied by the customer's monthly peak demand measured over a specific interval (15min, 30min, or 1 hour). DERs reduce customers' demand payments by cutting the peak demand. Demand payments help the LSE recover its costs for generation capacity, as well as transmission and distribution services. These costs are calculated at the LSE's aggregated peak demand multiplied by the rates charged to the LSE at the wholesale level. So how much DERs benefit LSE depends on how much reduction DERs contribute to the LSE's aggregated peak demand. Some customers have peak demands not coincident with the LSE's peak demand, and thus have little impact on the LSE's peak demand. Therefore, they don't help LSE cut its capacity costs. The LSE observes reduced demand charge revenue from these customers but still pays the about the same capacity costs at the wholesale level. Alternatively, the outputs of DERs could coincide with LSE's peak demand while not coincide with the customers' peak demands. In that case, LSE observes relatively the same amount of demand charge revenues but pays less for capacity. Neither of these two cases is fair. Therefore, the ($/kW) demand charges may not be suitable for customers with DERs. The next chapter provides a detailed quantitative study of the economic impact of DERs on LSEs under the current demand charge design.

The $/kW demand charge may not be a good design for non-disptachable DERs like PV. Since PV cannot be dispatched, whether their production coincides with customer's peak demand is determined by meteorological factors such as solar irradiance, temperature that have significant randomness. The study[80] pointed out under $/kW demand charge, PV obtained much less revenue compared with a $/kWh charge.

In summary, the $/kW demand charge misrepresents the benefits of DERs if the customer peak demand does not coincide with the LSE's aggregated peak demand. The $/kW charge is not favorable to PV because it provides less benefits compared with the $/kWh charge.

2.4.5 *DERs obtaining multiple streams of benefits simultaneously:*

DERs could obtain multiple streams of benefits by providing multiple services simultaneously. For example, references[31][32][36] provide scheduling strategies for energy storage to provide energy arbitrage and ancillary services. Reference[43] estimates the benefit that distributed generation provides through energy arbitrage, loss reduction and investment deferral together.

2.5 ORGANIZATION OF THE FOLLOWING CHAPTERS

So far we have identified the streams of benefits DERs bring to various participants. We evaluated the references that quantify different streams of benefits. The methods to quantity DERs benefits can be divided into two categories: avoided-cost based methods and tariff based methods. We compared the two categories and pointed out the pros and cons of each category.

In the following chapters, we will present four studies evaluating the streams of benefits DERs bring. The first two studies adapt tariffs based methods while the following two studies adapt avoid-cost based methods.

The first study evaluates the financial impact of DERs owned by commercial customers on their LSE. In this study, we stick with the current commercial tariff. The savings brought by DERs to their customers are calculated based on the tariff. In addition, DERs also alter the aggregated demand profile of the LSE and reduce costs LSE pays to wholesale level participants for energy, generation capacity and transmission. Case studies suggest that customer savings outweigh the LSE's reduced costs, resulting in financial losses of the LSE.

To address the financial loss issue, the second study aims at redesigning the tariff for DERs. In the second study, we purpose two value of DERs tariffs that convey LSE's peak demand information to end-use customers in from of event-based charges. Simulations show that customers react to event-based charges by dispatching DERs and help the LSE shave its peaks. Compared with the current tariff, the DERs tariffs reward customers more savings and help the LSE reduce a lot more payments for generation capacity and transmission. Both customers and the LSE have financial incentives to switch to the DERs tariffs.

In the third study, we switch to avoided-cost based methods to evaluate DERs. We look at multiple streams of avoided-cost benefits. The study aims to maximize the streams of benefits a LSE-owned battery energy storage can achieve. In specific, we include the frequency regulation benefit, which can only be awarded through avoided-cost methods, as one stream of benefit. Case studies suggest that frequency regulation benefit account for a large share among the total benefits the storage achieves.

The last study aims to integrate tariff based methods: customer level energy arbitrage and peak shaving, with avoided-based methods: frequency regulation. We develop an aggregator model that coordinates many customer-owned batteries and dispatch batteries to achieve energy arbitrage, peak shaving and frequency regulation. To cope the computational burden from optimizing plenty of batteries, we develop a two-stage model that shift the computations to day-ahead stage model and effectively simplifies the real-time stage model that reduces the real-time stage solution time.

Chapter 3. FINANCIAL IMPACTS OF DERS OWNED BY COMMERCIAL CUSTOMERS ON THEIR LSE

3.1 BACKGROUND

This study analyzes the financial impacts of commercial customer-owned DERs on utilities. Specifically, we consider the impact of PV and energy storage systems (ESS). Impacts of DERs on the utility are twofold. First, when DERs supply part of the customers' demand, customers purchase less electricity and the utility loses revenue. Second, DERs reshape and/or reduce the aggregate demand profile, reducing the utility's costs for energy, capacity, and transmission charges. If a large number of commercial customers install DERs, the utility's reduced costs might not be adequate to compensate for the loss of revenue.

Since customer bill savings ultimately result in utility revenue losses, the structure and design of the customer's retail electricity rate plays a huge role in defining the financial impact of PV. Several studies have estimated the savings that customers achieve when they install PV panels. Darghouth et al. examine the bill savings that residential customers achieve under several retail rate structures. A further study projects customer savings under high renewable penetrations[81]. Reference[80] studies the impact of a two-part rate structures (i.e. separate energy and demand charges) on customers with PV systems in San Diego. They concluded that PV can help customers save approximately 30% in demand charges and 30% to 50% in energy charges. Another study focuses on a large PV system installed at a university under two-part rate structure[94]. The results showed that it will be very difficult for PV to demonstrate cost-effectiveness for large commercial customers, even if PV costs continue to drop. While these studies have focused solely on the role of rate design on bill savings, our research also considers the role of customer demand profiles and cost recovery on the utility side.

Bill savings due to energy storage is similarly dependent upon the rate structure. Lee and Chen[95] set up formulations to determine the optimal contract capacities and optimal energy storage system size for time-of-use rate customers, with several battery dispatch rules applied. The maximum economic benefits of battery energy storage systems for time-of-use rate customers can be estimated. Gantz et al.[96] investigate ESS that are simultaneously used for both outage support and economic dispatch under time-of-use tariff. Additional objectives, including improving utilization of grid assets and reduced emissions are incorporated in[97]. ESS can also be dispatched to minimize electricity bills by facilitating the integration of renewable distributed generation, including wind[98] and PV[99]. Each of these studies quantified customer savings. In contrast, our research investigates the financial impacts from the utility's perspective.

Utilities acquire electricity and related services through bilateral settlements and market transactions. Since DERs reduce or reshape the aggregate demand, utilities can, in most cases, purchase less energy from wholesale markets and avoid other related charges.

In determining DER benefits to the utility, this article considers avoided energy, generation capacity and transmission payments.

3.2 METHOD

In most tariffs, the energy component is either fixed or time-of-use (including critical peak pricing). In the U.S., tariffs that charge customers a dynamic price which directly reflects wholesale market clearing prices are rare. Most commercial customers pay demand charges based on their individual monthly peaks. The monthly bill of a commercial customer with this type of unbundled rate is described by Equation (3.1):

$$\text{Monthly bill}=\pi_{energy}^{onpeak}\sum\nolimits_{t\in Peak}E^{t}+\pi_{energy}^{offpeak}\sum\nolimits_{t\in Offpeak}E^{t}$$
$$+\pi_{capacity}D^{onpeak}$$
$$+\pi_{transmission}D^{onpeak} \tag{3.1}$$
$$+\pi_{distribution}D$$

where E^{t} is customer hourly energy usage, D^{onpeak} is the peak demand over the on-peak period of the month, and D^{onpeak} is the peak demand over the entire month. The four lines of Equation (1) correspond to the energy component, the capacity component, the transmission component and the distribution component of a customer's electricity bill, respectively.

To calculate bill savings, the electricity bill is unbundled into its energy, capacity and transmission parts. Suppose the customer's hourly energy usage, peak demand over the on-peak period and peak demand over the month are E_{DER}^{t}, D_{DER}^{onpeak} and D_{DER}, respectively. Savings due to the DERs in the energy, capacity and transmission components are:

$$\text{S\_Energy}=\pi_{energy}^{onpeak}\sum_{t\in T_{onpeak}}(E^{t}-E_{DER}^{t})+\pi_{energy}^{offpeak}\sum_{t\in T_{offpeak}}(E^{t}-E_{DER}^{t}) \tag{3.2}$$

$$\text{S\_Capacity}=\pi_{capacity}(\mathrm{D}^{onpeak}-\mathrm{D}_{DER}^{onpeak}) \tag{3.3}$$

$$\text{S\_Transmission}=\pi_{transmission}(\mathrm{D}^{onpeak}-\mathrm{D}_{DER}^{onpeak}) \tag{3.4}$$

3.3 CASE STUDY

We selected several commercial customer demand profiles as well as a time of use tariff with demand charge components unbundled. We then compared the utility's reduction in costs to its loss in revenue. Wholesale market clearing prices and transmission tariffs were selected to calculate utility savings. To measure the utility's cost recovery in different categories, the balance sheet is broken into accounts for energy, generation capacity and transmission.

The tariff chosen for this case study is Virginia Electric and Power Company's Schedule GS-2T. This tariff features a time of use energy usage charge that includes a fuel charge component and an energy delivery charge component. The demand charge component is unbundled into elements including generation capacity, transmission and distribution. Riders related to adjusted fuel cost as well as the expenses from wholesale market transactions are applied to adjust the rate. The on-peak period is defined as: June 1 through September 30, 10 a.m. to 10 p.m., Mondays through Fridays and October 1 through May 31, 7 a.m. to 10 p.m., Mondays through Fridays. All other hours are off-peak. Table 3-1 summarizes the components of selected tariff.

Table 3-1: Components of the selected electricity tariff

Components	**Rate**	**Symbol**
Basic Customer Charge	$26.17/month	$\pi_{customer}$
Generation kWh Charge	5.727¢/kWh, On-peak 3.096¢/kWh, Off-peak	π_{energy}^{onpeak} $\pi_{energy}^{offpeak}$
Distribution kWh Charge	0.025¢/kWh	$\pi_{delivery}$
Generation kW Charge	4.784$/kW, On-peak 3.375$/kW, On-peak	$\pi_{capacity}$ Jun. - Sep. $\pi_{capacity}$ Oct. – May
Transmission kW Charge	2.171$/kW, On-peak	$\pi_{transmission}$
Distribution kW Charge	3.387$/kW	$\pi_{distribution}$

The chosen utility company, Virginia Electric and Power Company lies within the PJM territory. Therefore, PJM's market clearing prices for wholesale energy markets and capacity markets as well as the transmission service rates are applied. The utility's hourly load profile is acquired from PJM. We assume that the selected utility has no generation or transmission assets, so that energy and capacity obligations are fulfilled solely by purchasing from the wholesale energy and capacity markets. We also assume that the DER penetration is not high enough to significantly impact market clearing prices.

Commercial customer demand profiles are extracted from the National Renewable Energy Laboratory. This dataset contains hourly demand profiles for 16 commercial building types that represent approximately 70% of the commercial buildings in the U.S. Models of commercial buildings were developed by the U.S. Department of Energy in conjunction with three national laboratories, integrated in the simulation software EnergyPlus. We select 4 locations within the jurisdiction of Virginia Electric and Power Company. The commercial customer demand profiles of the 4 locations are simulated using EnergyPlus.

Daily demand profiles of the 16 types of commercial customers in July are presented in Figure 3-1. The number at the end of each subplot's title is the number of customers in thousand. Lines in blue are weekday demand profiles while lines in green are weekends. This figure illustrates that each type of building has more or less a fixed demand profile pattern. Commercial establishments with similar functions but different sizes, (i.e. small offices, medium offices and large offices) share similar consumption patterns.

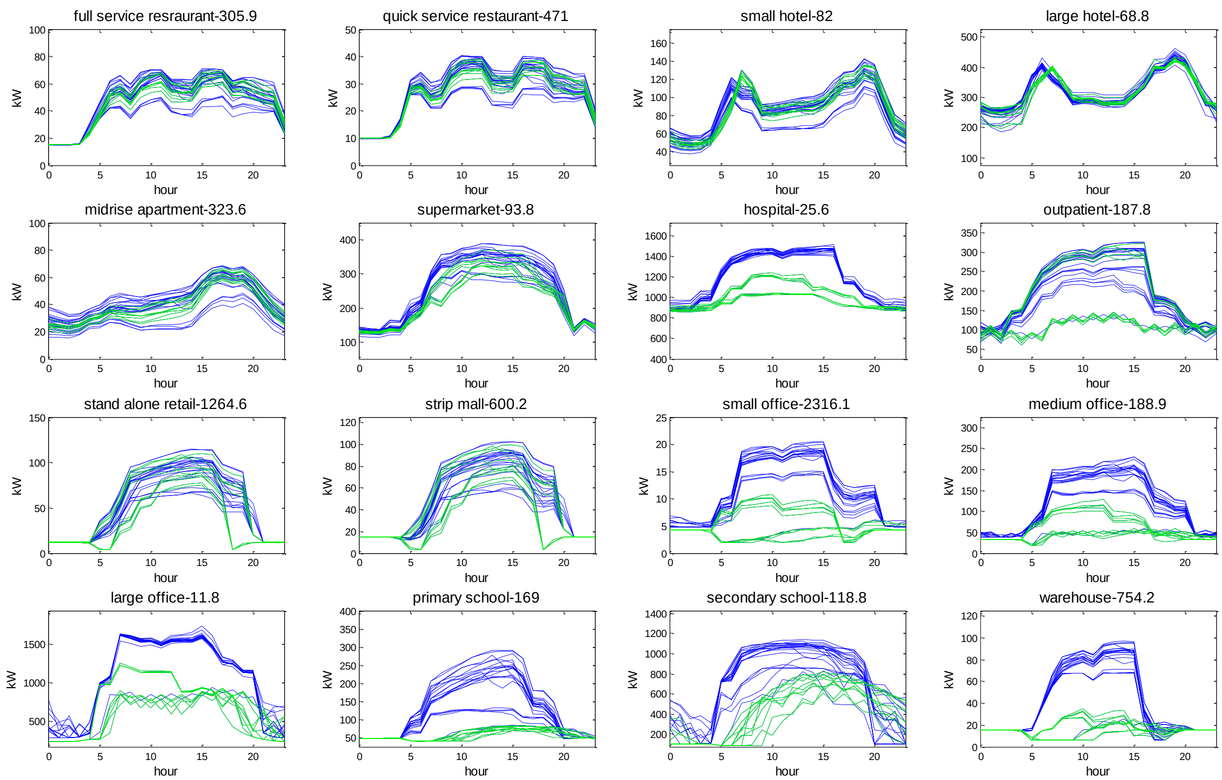

Figure 3-1: Customer monthly demand profiles by type, July

Three DER cases are considered. In the first case, a portion of the commercial customers install PV sized at 10% of their annual peak demand. Hourly solar irradiation data at the 12 locations where commercial customers are sited were obtained from SolarAnywhere. In the second case, the same portion of customers installs ESS with a power rating also equal to 10% of their annual peak demands. The energy rating is four times the ESS's power capacity. This means that at rated charging capacity, it takes 4 hours to fully charge the ESS. For both cases, the total installed DER capacity is set at 1% of the LSE's annual peak demand. The third case consists of two types of DR. The first represents emergency demand response, an event-based DR. The resource can only be dispatched several times per month and the duration of each dispatch is limited to 6 hours. The second represents economic demand response. This resource requires customers to make regular, everyday modifications to their consumption patterns. Comparing the two types of DR, the first type of DR has more demand reductions during events, but the total number of events is capped. The second type has a relatively lower magnitude of overall reduction but the impact of demand response is present every day. The demand response strategy includes dimming lights and adjusting temperature set-points for HVAC systems. Since most commercial establishment models in Energyplus use electricity for cooling but gas for heating, heating temperature set-points adjustment will not impact electricity consumption. In this study, the analysis of DR will be confined to summer months (from June 1 to September 30). For both types of DR, customers decide when to dispatch their demand resources to minimize their bills. DR capacity is defined as the average demand reduction when DR is dispatched. Again, for either type of DR, the total capacity is set at 1% of the LSE's annual peak demand. This penetration is assumed to be sufficient to have a considerable impact on the LSE's aggregated demand yet not large enough to alter the clearing prices in the wholesale market. The DERs are distributed among the 16 types of commercial customers in proportion to their population.

3.4 RESULTS

Before taking DERs into consideration, a reference case without DERs is used to examine the selected tariff. Utility revenue (bills paid by the customers) is broken into three categories: energy, capacity and transmission. We neglect other components, such as the basic customer charge and distribution charge, for simplicity. Utility expenses consist of energy market payments, capacity market payments and transmission charge payments, each corresponding to one category of revenue. Among the 16 types of commercial buildings, the ratios between their bills unbundled into three categories (rows in equation (3.1)), divided by their shares of the utility company's expenses in the corresponding categories, is presented in Figure 3-2 to illustrate the cost recovery ratio of the above three categories. This figure is to gauge the utility's cost recovery from its commercial customers.

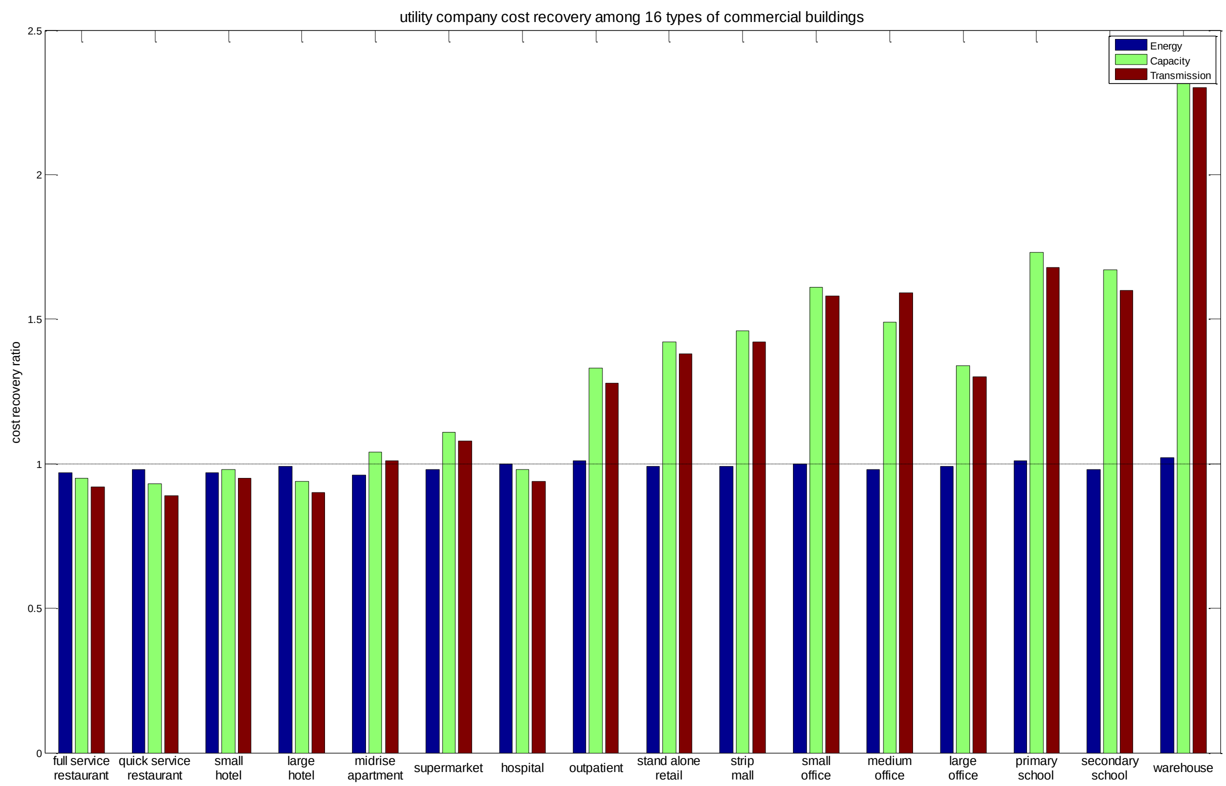

Figure 3-2: Utility company cost recovery ratios in three categories: energy, capacity and transmission

In the energy category, the cost recovery ratios for all 16 types of buildings are fairly close to 1, meaning the utility recovers its energy costs markets from the energy component of the customers' bills.

With respect to capacity and transmission categories, cost recovery ratios among different types of commercial customers vary substantially. Some types of commercial customers, including large offices, medium offices, outpatients, primary schools, secondary schools, small offices, standalone retails, and strip malls, have higher cost recovery ratios (1.5 to 1.7). Warehouses have exceptionally high recovery ratios. In general, all 16 profiles achieve a cost recovery ratio of at least 0.9. This means that the utility collects nearly all its share of capacity and transmission expenses back from these corresponding bill components.

One explanation for the variance in cost recovery ratios between the 16 types of customers lies in their distinctive consumption patterns. Customers pay capacity and transmission charges according to their own monthly peak demands. The utility, however, pays according to its daily peak aggregated demand. The aggregated demand of the utility selected for this study combines residential, commercial and industrial sectors. In this particular region daily peak demand hours are likely to happen late in the afternoon or evening during summer, early in the morning during winter, and either early in the morning or evening during spring and fall. Daily aggregate peak demands seldom happen during working hours (between 9am to 5pm). However, most commercial customers have higher demands during working hours. If one customer's hourly consumption does not coincide with the utility company's peak, then it contributes little to utility's expenses yet pays a lot for demand charges, resulting in a high cost recovery ratio for the utility company in both capacity and transmission categories. Therefore, customers with high daytime consumptions and low morning/evening consumptions: warehouses, schools, office buildings etc. provide higher cost recovery ratios than customers with evening peaks that coincide with the utility company's daily peak: hotels and restaurants.

Distributed Generation

The correlation between the PV generation profiles and the customer consumption patterns is a determining factor in reducing customers' demand charges. If customers have higher daytime demands when solar irradiance peaks, then solar generation will reduce the energy, capacity, transmission and distribution components of their bills. However, bill reductions for evening-peaking customers would mostly come from the energy component, since peak demands in the evening are less likely to be shaved by solar generation. In these cases, reduced payments for capacity, transmission and distribution charges are therefore less evident.

Figures 3-3 and 3-4 compare the LSE's overall annual savings in terms of capacity and transmission payments with the savings achieved by commercial customers. The annual savings are in $ per kW of installed PV.

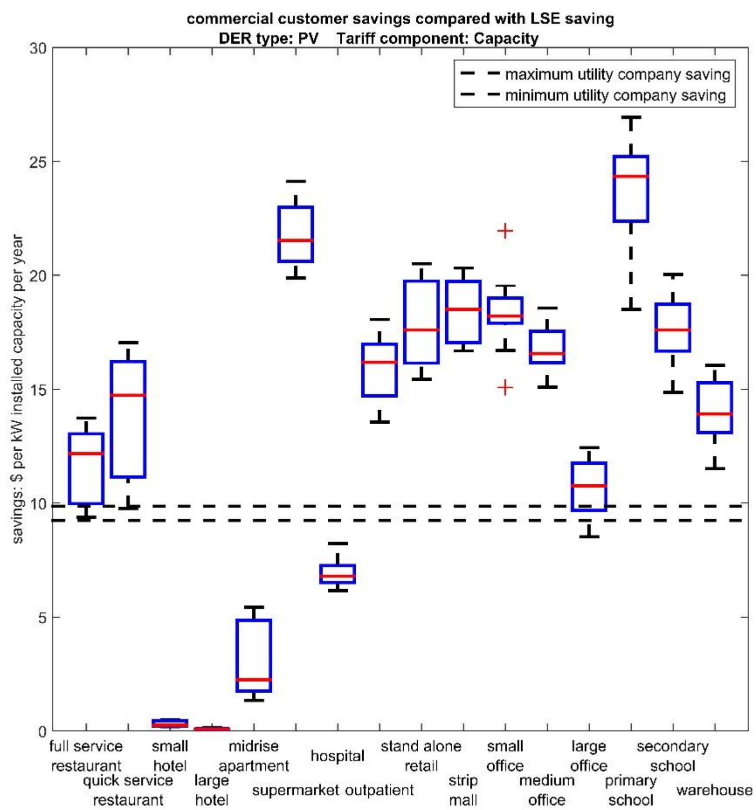

Figure 3-3: Comparison between the savings achieved by commercial customers and the LSE in terms of capacity charges due to customer-installed PV

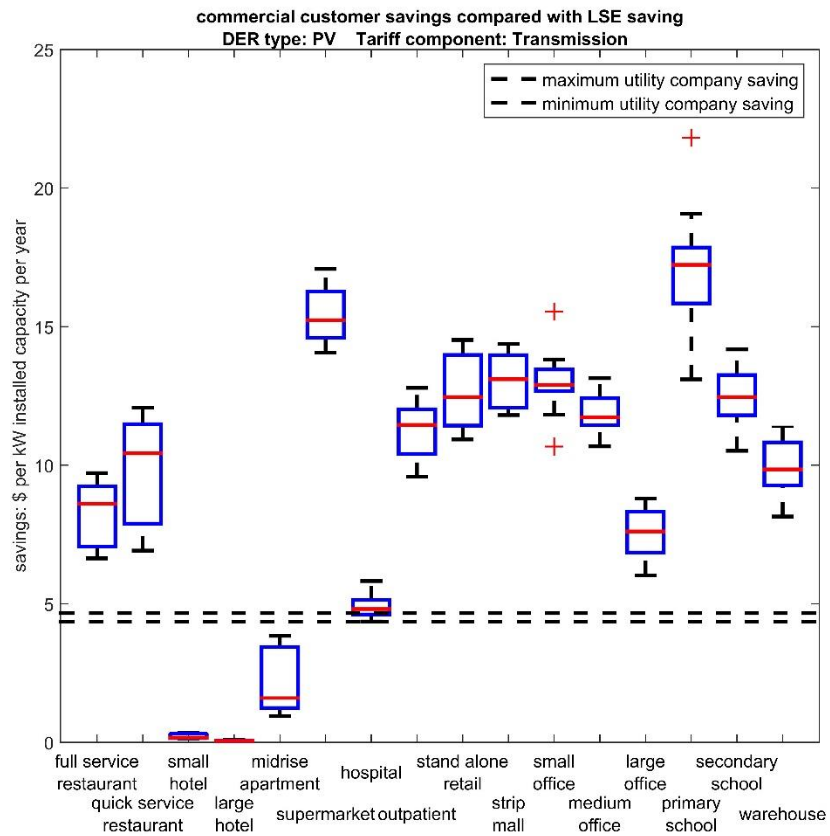

Figure 3-4: Comparison between the savings achieved by commercial customers and the LSE in terms of transmission charges due to customer-installed PV

The red line in the middle of each box indicates the median, the edges of the box indicate the 25th and 75th percentiles, and the whiskers extend to the extreme data points while the outliers are captured by plus marks. Two dashed lines represent the maximum and minimum LSE savings. This range in LSE savings reflects the possible variation in savings when PV panels are installed in different regions with various solar irradiation profiles across the company's service area. The upper bound occurs when all PV panels are installed in the sunniest location within the LSE's territory.

Figure 3-3 shows that, for 12 out of 16 customer types, the customer savings are higher than the range of LSE savings with respect to capacity charges. In particular, primary schools and supermarkets achieve the highest customer savings. PV performs poorly in helping hotels save on capacity charges. Overall, most customers save 10 to 25 dollars per year in capacity charges for each kW of PV they install, while the LSE only saves around 10 dollars. Figure 3-4 shows that similar conclusions can be drawn regarding transmission charges. Table 3-2 summarizes the financial impacts of PV on the LSE in terms of lost revenue and reduced expenses.

Table 3-2: Summary of the Financial Impacts of PV on the LSE

Components	**Lost Revenue (Million $)**	**Reduced Expense (Million $)**
Energy	15.40	15.94
Capacity	2.85	1.79
Transmission	2.02	0.85

The most significant portion of the LSE's lost revenue comes from the energy component. As distributed generators, PV produces power that offsets part of the customers' energy consumption. That is not the main problem for the LSE because it purchases less energy on the wholesale markets and the reduced expense outweighs the lost revenue by about 3%. However, reduced expenses account for only 63% and 42% of lost revenues in the capacity and transmission categories, respectively. The LSE would therefore lose a significant amount of money in these categories as a result of the installation of PV panels by its commercial customers.

Energy Storage

In this case, commercial customers install energy storage systems (ESS) and schedule their charge and discharge to minimize their electricity bills. Since customers are usually not able to forecast their demands perfectly, we introduce demand uncertainty in our simulation and assume that it is handled by robust optimization. For each customer that has installed an ESS, robust optimization schedules the storage against a worst-case scenario within an uncertain but bounded demand profile to maximize the customer savings. This approach produces more realistic results than assuming a perfect forecast.

Since ESS do not produce electricity, their main effect is to level the daily demand profile. Figure 3-5 shows that optimized ESS schedules save commercial consumers money primarily by reducing their demand charges. This makes sense because the on-peak energy price in the tariff under consideration is only slightly higher than the off-peak energy price, making energy arbitrage less profitable than shaving peak demand.

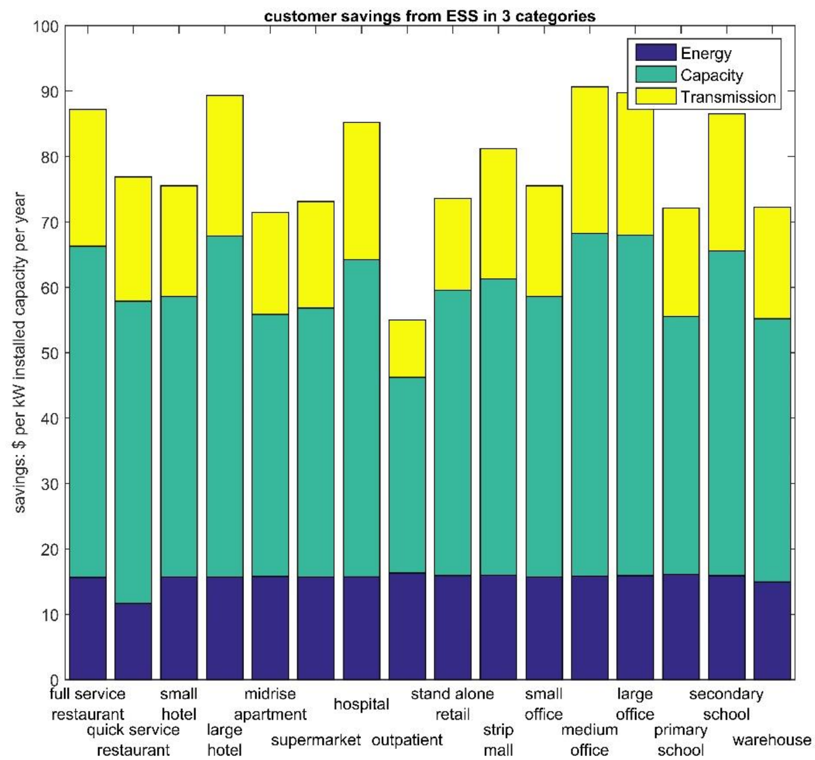

Figure 3-5: Customer’s energy, capacity and transmission savings due to ESS

Since the LSE’s aggregated demand profile is reshaped by the ESS installed by its customers, its expenses in terms of energy, capacity and transmission are affected. Figures 3-6 and 3-7 compare the LSE’s and the commercial customers’ annual savings in these three categories. These figures show that many types of commercial customers save 3 to 4 times as much as the LSE. The boxes capture the uncertainty in demand profiles due to the forecast inaccuracy.

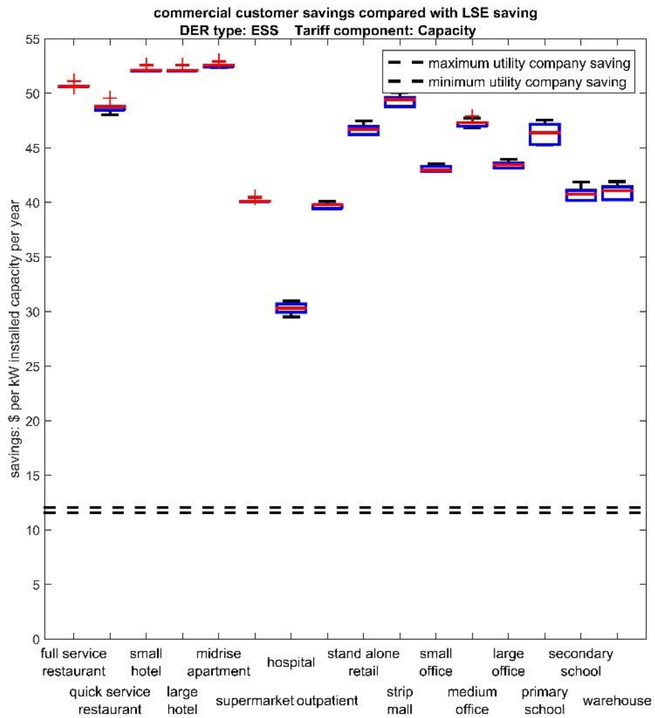

Figure 3-6: Comparison of customer capacity savings and LSE capacity savings due to customer-installed ESS

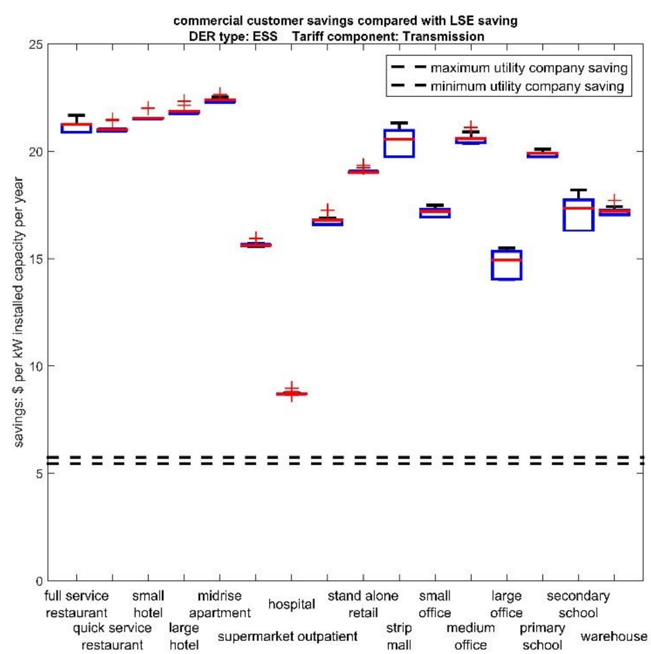

Figure 3-7: Comparison of customer transmission savings and LSE transmission savings due to customer-installed ESS

Peak shaving is more effective for customers with spiky consumption patterns. Customers with morning and evening peaks, such as restaurants, hotels and apartments save more with ESS. Hospitals with ESS installed save less than any other customer type, primarily because hospitals' weekday daily demand profiles over the entire month are similar and their demand during the daytime is relatively flat.

Table 3-3 summarizes the financial impacts of ESS on the LSE in terms of lost revenue and reduced payments. Compared with PV of equal capacity, ESS achieves higher generation capacity and transmission bill savings. The LSE's reduced energy, capacity and transmission expenses amount to only 55%, 26% and 31% of the lost revenues in these categories.

Table 3-3: Summary of the Financial Impacts of ESS on the LSE

Components	Lost Revenue (Million $)	Reduced Expense (Million $)
Energy	2.96	1.63
Capacity	8.45	2.20
Transmission	3.38	1.05

Demand Response

We consider two types of demand response in the case study: an event-based type and a long term demand shape modification type. Due to safety reasons, hospital and outpatient facilities are excluded from our DR analysis. The DR strategy involves dimming lights and increasing HVAC system cooling set-points. The first type of DR dims the lighting to two thirds of its baseline level and increases temperature the set-point two Celsius degrees higher. The demands drop sharply when this type of DR is dispatched. Though occasional sharp reductions in demand might be acceptable, deploying the same strategy every day will be uncomfortable, so the second type only dims lighting to ninety percent of its baseline level and increases temperature set-point one degree higher. The first type DR has exactly 4 events per month, in total 16 events per summer. Each event lasts 6 hours and the customers decide when to dispatch their DR resources according to their own interests. The second type of DR is dispatched every day throughout the entire summer. There is no limitation on the duration of the demand shape modification. Customers modify their demand shapes to attenuate periods of high demands during the day. The analysis is limited to the summer because most commercial buildings in the case study use gas for their heating systems. Adjusting the heating set-points would therefore not significantly affect their electricity consumption. Since lighting only accounts for a small fraction of a building's electricity demand, dimming lights would hardly make a difference. Table 3-4 summarizes the characteristics of the above two DR strategies.

Table 3-4: Summary of the DR characteristics

Components	**Event Based**	**Long-term Demand Modification**
Control-Lighting	Reduced to two thirds	Reduced to 90 percent
Control-HVAC	Increase 2 ℃	Increase 1 ℃
Per Event Duration	6 hours	Not applicable
Event Limit Per Month	4 times	Everyday

Lighting and HVAC set-point schedules of baseline and DR cases are fed into Energyplus to generate electricity consumption profiles with hourly granularity for the entire summer. The difference between the two consumption profiles yields demand reduction due to DR. The average demand reduction when DR is dispatched is defined as the average DR capacity. When DR dispatch is over and the set-points are adjusted back to normal values, the overall consumption in the DR cases is higher than that for the baseline cases because of the demand rebound phenomenon. If designed improperly, the rebound could coincide with customer daily peak and result in higher demand charges. The demand rebound is not taken into account for determining DR capacity.

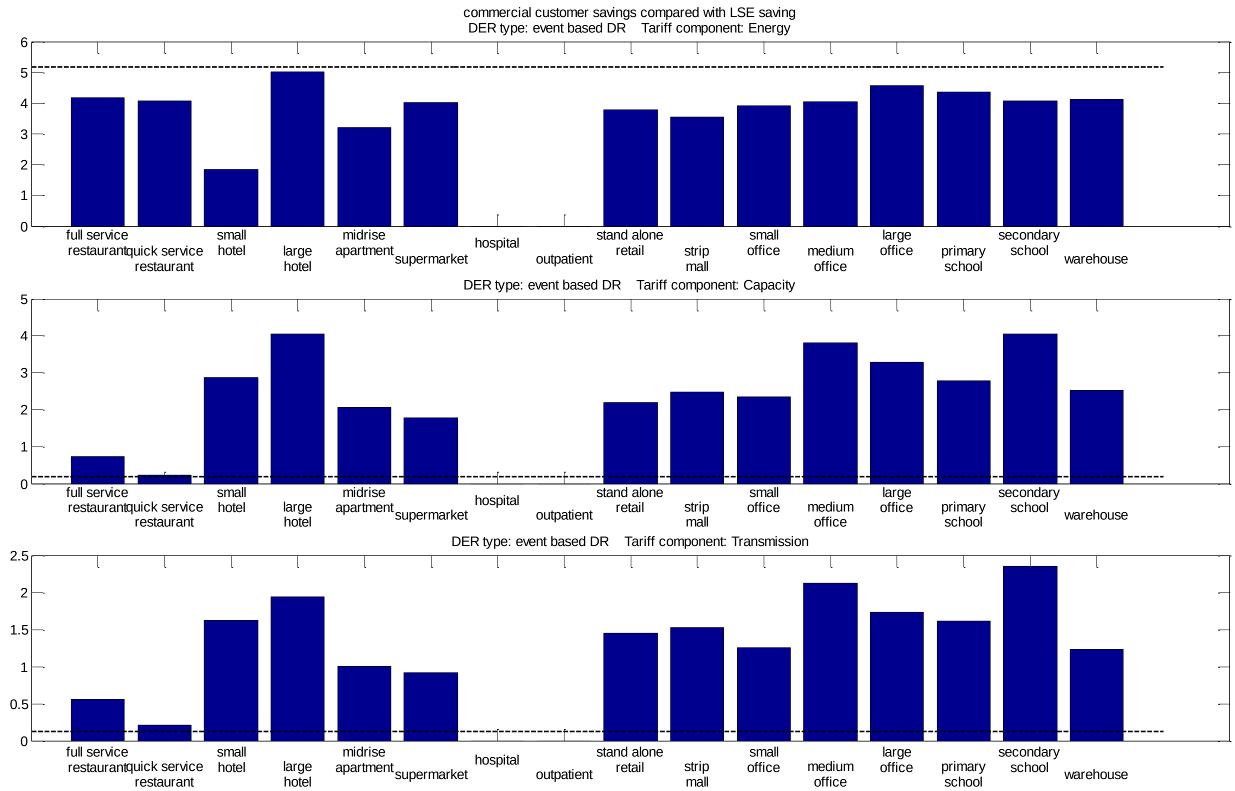

Figure 3-8: Comparison of customer savings and LSE savings on energy, capacity and transmission due to event-based DR

Firstly, we conduct an analysis of the impact of event-based DR on LSEs. We assume the objective of customers is to minimize their electricity bills. Customers dispatch DR during four days of highest demands, enabling demand reductions during event that reduce monthly peaks and minimize demand payments. Demand reductions also lower energy consumption during events that reduce the energy charge. Again the individual demand reduction of DR customers are summed to analyze their impact on the LSE. Figure 3-8 shows the customers' savings in terms of energy, capacity and transmission charges per kW DR capacity. The dashed line is the LSE's savings.

Figure 3-8 shows that the LSE saves more in terms of energy charges than it loses in energy related revenue. But for the capacity and transmission components, the LSE savings are far less than its reduced revenue. The extra savings in the energy category are due to the fact that the locational marginal prices are higher than the energy retail rate during the summer months because the selected LSE is summer peaking. Customers dispatch DR to reduce their demand charges, but their demand reductions do not usually coincide with the LSE's daily peak demand. In addition, for some types of customers, their demand rebounds when the LSE's aggregated demand is at its daily peak, thus increasing instead of reducing the LSE's capacity and transmission payments. The total number of hours of DR dispatch is limited to 96 (6 hours per event times 16 events), so unlike PV and ESS that are dispatched throughout the year, event-based DR results in lower annual customer savings. Another factor that limits savings is the event limitation per month. For a commercial customer, DR could significantly reduce demands on the four peak days, but the fifth peak might be very close to the monthly peak, leading to poor demand savings. The time-of-use structure is not preferred for event-based DR.

A critical peak pricing tariff that occasionally has energy charges that can be several times larger than the normal charge would be preferable for event-based DR. DR could then be dispatched during high price events to help customers avoid paying extreme energy charges. The savings that customer achieve from event-based DR thus depend heavily on the tariff design. In addition, with critical peak pricing the LSE decides the timing of high energy charges, which provides it the opportunity to incentivize DR in its favor. Since the bill savings are limited by the number of DR events, long-term demand modification would make possible increased bill savings. This leads us to the second type of DR, i.e. demand shape modification.

Compared with event-based DR, demand shape modification is smaller in terms of DR capacity but does not have limits on the number of events. Since this type of DR is "dispatched" every day, it should provide more opportunities for savings by the customers. Demand shape modification also differs from event-based DR in that event-based DR has a fixed continuous 6 hour DR dispatch duration, while demand shape modification does not impose any limit on continuity or event duration. For example, full service restaurants have noon and evening peaks, so their DR could be designed to dispatch from 10:00 to 14:00 and from 17:00 to 21:00 every day to shave their daily peaks. Figure 3-9 shows the savings that different categories of commercial customers might achieve in terms of energy, capacity and transmission per kW DR capacity.

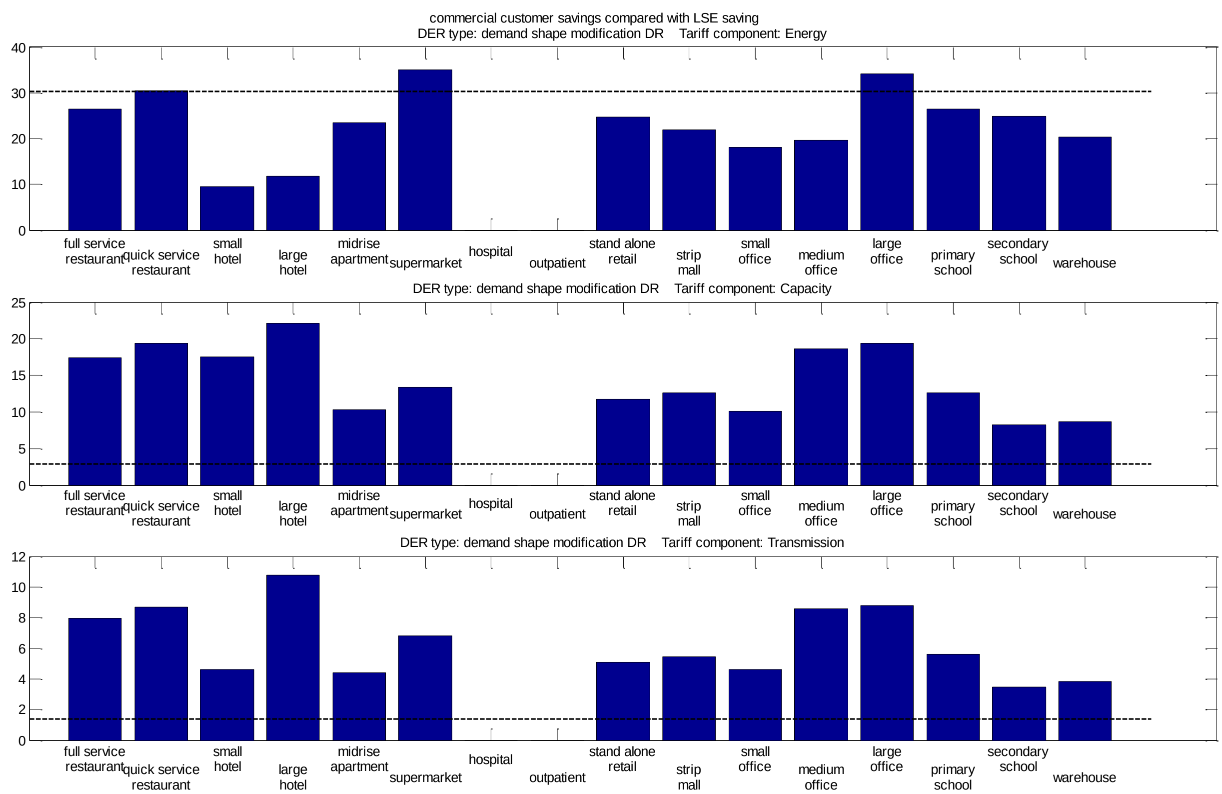

Figure 3-9: Comparison of customer savings and LSE savings on energy, capacity and transmission due to demand shape modification DR

This figure shows that, compared with event-based DR, customers save more money in energy, capacity and transmission categories. Here the HVACs and lights as demand response resources are dispatched more often compared with the event-based DR, which explains the larger savings in the energy category. The reason behind higher capacity and transmission savings is the modification of the demand shape. Figure 3-6 illustrates that buildings have consumption patterns. These patterns are modified by DR to make the consumption pattern flatter. Although DR is dispatched only for 4 months, customer savings in capacity and transmission charges are comparable to that of PV. Similar to that of event-based DR, the LSE saves more in the energy category than it loses revenue from customers. In the capacity and transmission categories, DR contributes little to reduce the LSE's demand payments. Table 3-5 summarizes the financial impacts of the two types of DR on the LSE.

Table 3-5: Summary of the Financial Impacts of DR on the LSE

Components	**Lost Revenue (Million $) Type 1/Type 2**	**Reduced Expense (Million $) Type 1/Type 2**
Energy	0.73/4.40	0.97/5.68
Capacity	0.53/2.18	0.03/0.54
Transmission	0.30/0.95	0.02/0.26

3.5 DISCUSSION

In the previous section, we quantified the financial impacts of three types of DERs on LSEs: photovoltaic systems (PV), energy storage systems (ESS) and demand response (DR). Each of these has distinct characteristics. PV is a non-controllable type of DER that customers cannot dispatch. ESS and DR are both controllable resources that customers can operate to maximize savings. PV is always an energy producer and will never increase its owner's metered demand. However, ESS and DR increase their owner's demand due to losses or demand rebound effect. PV and ESS can operate throughout the year, while DR in this study is assumed to be available only during the summer. The event-based type DR is limited to 4 events per month, further constraining its availability. PV helps customers shave demand, ESS contributes by shifting demands, and DR lies between these two, involving both demand shaving and demand shifting.

Since PV is not controllable, we assume that it is installed similarly among all 16 establishments, that their production capacities are the same, and that they are determined by the local weather, solar irradiance and other meteorological data. Similar production patterns yield similar energy charge savings per kW capacity but distinct demand charge savings. The correlation between customer demand profiles and PV production patterns plays an important role in determining demand charge savings. ESS and DR, however, are controllable and their owners can tailor the dispatch schedules to their demand patterns. ESS can easily double or triple demand charge savings compared to PV. Event-based DR achieves less savings because of its event limit. In addition, demand profiles are repetitive. So in order to shave peak demand, DR needs to be dispatched several days over a month. Demand shape modification results in higher savings than event-based DR and its effect is comparable to PV. It is worth noting that demand shape modification is only available for 4 months while PV is available throughout the year. This case study shows that controllable DERs achieve higher demand charge savings. In terms of energy savings, PV leads the other two. This is because unlike the ESS and DR, PV is an energy producer and its production is high during on-peak hours as currently defined by the tariff.

In the energy category, the LSE is almost financially neutral when customers install PV: reduced expenses make up for the lost revenue. Speaking of demand response, both types of DR help the LSE save more than its lost revenues. However, ESS leads to financial losses that reduced expenses cannot recover. The positive financial impact in the energy category is due to the discrepancy between locational marginal prices that the LSE pays and the energy rate it collects. Locational marginal prices changes on an hourly basis, but the time-of-use energy rate has only an on-peak and an off-peak value, and remains fixed for the entire season. The time-of-use energy tariff cannot reflect the volatility of locational marginal prices. If DERs produce when the locational marginal price is higher than the energy rate, then the LSE would save money. Otherwise, it would lose money.

In both the capacity and transmission categories, all three types of DERs save more for customers than for the LSE. The LSE's capacity and transmission payments are determined by its daily peak aggregated demand, so the production of DERs at that peak hour will impact the LSE's payments. However, the tariff used in this study, like many other commercial tariffs, insulates customers from the LSE's aggregated demand. Customers pay their demand charges based on their own monthly peak, which may or may not coincide with the LSE's aggregated peak. Thus the DERs are operated in customers' favors, regardless of the LSE's needs. Like the energy rate, the demand rate could be designed in a time-of-use structure. The higher on-peak period with a higher demand charge, should cover the aggregated peak. The off-peak period with a lower demand charge should not cover a period when the aggregated peak is likely to happen. Such a time-of-use demand charge would, to a certain extent, pass information about the LSE's peak to the customers.

Since different commercial establishments have distinct consumption profiles, they may choose to install different types of DERs. For establishments with a working hour peak (e.g. supermarket, stand-alone retail, strip mall and offices), installing PV is a good choice. PV production is relatively high during regular business hours, helping customers save energy and demand charges. Other establishments with morning or evening peaks (such as restaurants and hotels), should install ESS or deploy DR as this might bring benefits that outweigh that of PV, especially in terms of demand charges. We assume that all establishments install the same type of DERs with capacities proportional to their peak demands. Customers may choose to install different types of DERs or install more than one type of DER at their facilities, which will potentially pose a larger financial challenges for LSEs. Designing tariffs that allow LSEs to recover a justified amount of revenue under certain penetration of DERs is a meaningful research direction.

3.6 CONCLUSION

We have analyzed the financial impacts that the deployment of DERs by commercial customers would have on their LSE if the current tariff structure does not change. In terms of energy revenues, the LSE is neutral to PV, collecting roughly the same amount of revenue needed for energy purchases with or without PV installed. On the one hand, the LSE under-collects energy revenue when storage is installed. On the other hand, the LSE over-collects energy revenue with either event-based DR or demand shape modification. With respect to demand charges (capacity and transmission), all three types of DERs save more money to the commercial customers than the LSE would save in reduced wholesale market costs. Overall, ESS and DR have a more severe impact on the LSE than PV because the dispatchable DERs enable customers to operate these resources to minimize their bills. Under the current tariff, this bill minimization strategy may not be as favorable for the LSE as it is for its customers. The growing penetration of DERs may prompt LSEs to redesign the energy and demand charge components of their tariffs.

Customers under a time-of-use tariff are incentivized to dispatch their ESS only when the retail price is high, and this does not always correlate well with higher prices in the wholesale market. Replacing a two-level, time-of-use tariff with a real-time locational marginal price would make wholesale locational marginal prices visible to customers. This would encourage them to dispatch their controllable DERs during periods of high wholesale prices. It would thus align their interests with those of the LSE.

The deployment of DERs by commercial customers would reduce the LSE’s revenues by a greater amount than its expenses for generation capacity and transmission charges. In order for the LSE to accommodate DERs without losing money, the tariffs applied to commercial customers should be redesigned. Demand charges should be based not only on the customers’ monthly peaks, but also on the customer’s demand at hours coincident with the peaks in the LSE’s aggregated demand. A time-of-use demand charge would be desirable once customers choose to install DER.

Chapter 4. VALUE OF DER TARIFF

4.1 BACKGROUND

In the previous chapter, we concluded that, under the current tariff, the deployment of DERs by commercial customers would reduce the LSE's revenues by a greater amount than its expenses for generation capacity and transmission charges would decrease. For the LSE to accommodate DERs without losing money, the tariffs applied to commercial customers should therefore be redesigned. In this chapter, we design two DER tariffs for commercial and industrial customers that consider the timing of the LSE's peak loads and provide incentives for DERs to dispatch in a way that helps the LSE shave its peak loads. By reducing its peak loads, the LSE pays less for generation and transmission services, which offsets the loss of revenue caused by the DERs. It is very important to keep the consistency of the reference database file in the writing process, especially when you work on multiple computers.

We begin this study by reviewing some of the current tariffs, for both residential and commercial customers. In addition, we go over studies that quantify the economic benefits of DERs under different tariffs.

4.2 LITERATURE REVIEW

Residential customers can choose from many different tariffs. Most LSEs offer residential customers fixed tariffs, incrementing block tariffs[71] and time-of-use electricity tariffs[72]. Some utilities offer residential customers a Peak Day Pricing option[73]. Peak Day Pricing is an optional rate that offers customers a discount on regular summer electricity rates in exchange for higher prices during 9 to 15 Peak Pricing Event Days per year, typically occurring on the hottest days of the summer. The duration of each event is fixed at 4 hours, from 2:00pm to 6:00pm. The rate is a

$/kWh charge during every hour of the events. One LSE offers dynamic pricing to its residential customers[74], which means that it charges its customers based on the real-time LMP.

Some tariffs are specially designed for DERs. As we have discussed in previous chapters, there are two primary categories of solar tariffs: feed-in-tariff and net metering. The feed-in tariff rewards PV based on their costs, which pays PV a rate much higher than average tariffs. Our literature review and the research described in the previous chapter question the fairness of net metering. Since the two primary categories of solar tariffs have major drawbacks, alternative rate structures have been proposed. For example, the authors of[112] propose a value of solar tariff that compensates PV based on its contributions to the energy and demand components. Customers' demands and PV productions are subject to two different tariffs: the value of solar tariff applies to the PV production while the customers' load is still charged per the conventional tariffs. The value of solar tariff designed in[112] has the following components: the energy charge component, the capacity charge component, the transmission charge component and the distribution charge component. All these components take the form of $/kWh, the tariff is a fixed tariff with components covering energy, capacity, transmission and distribution costs:

$$\pi_V^t = \pi_{ene}^t + \pi_{cap}^t + \pi_{trans}^t + \pi_{dist}^t \tag{4.1}$$

A study conducted by Lawrence Berkeley National Laboratory and the National Renewable Energy Laboratory[113] explores demand charge savings from residential PV. This study analyzes the demand charge savings of residential PV under many different demand charge designs including non-coincident monthly peak, seasonally varying demand charges, with ratchets and with averaging intervals of varying lengths. The study shows that the savings on the PV demand charge vary a lot under different demand charge designs.

Our research aims at designing tariffs for commercial and industrial customers. Typically, tariffs applied to commercial and industrial customers are binomial that they involve both a $/kWh energy charge and a $/kW demand charge which aims to cover the cost of generation capacity, transmission capacity and distribution capacity[114]. However, some tariffs allocate part of the generation capacity, as well as the transmission and distribution charges to the $/kWh component. Some LSEs offer Peak Day Pricing options to commercial customers[115].

Some studies develop DERs scheduling strategies and analyze customer level savings under commercial tariffs. For example,[116] develops a stochastic optimization model that schedules battery energy storage to help commercial customers minimize their demand charges. The study described in[117] develops an optimization model that dispatches a PV-battery storage system to help customers reduce their demand charges. Case studies suggest that the PV-battery system helps customers achieve significant reductions in non-coincident peak load.

This chapter is organized as follows: In the next section, we will discuss the design of the energy, generation capacity and transmission components of the proposed DER tariffs. The tariffs reflect the peak loads of the LSE to end-use customers and encourage them dispatch their DERs accordingly. Once the structures and rates of the proposed tariffs are determined, we evaluate its impact on customers with three types of DERs and on the LSE. We conclude this chapter by highlighting the major findings and providing some directions for future research.

4.3 Design of Value of DER Tariff

To evaluate the fairness and effectiveness of the proposed DER tariffs, we consider several criteria: 1) The electricity bills based on DER tariffs for customers that do not install DERs should be roughly the same compared with their bills calculated based on the current tariffs. This criterion ensures that customers will not face much different electricity costs if they switch to a DER tariff.

2) If all the customers switch to the proposed tariffs, the LSE's total revenue should not be less than its current revenue. This criterion provides the LSE economic validation to design and implement the DER tariffs. 3) When customers dispatch their DERs under the proposed DER tariffs, their impacts on the LSE should be financially better than what happens under the current tariff. We observed from the previous study that under the current tariff, the deployment of DERs by commercial customers would reduce the LSE's revenues by a greater amount than its reduced expenses for generation capacity and transmission charges. The new tariff should encourage DERs to dispatch during the LSE's peaks and help the LSE reduce its peak demand, thereby reducing what it is charged for generation and transmission capacity.

4.3.1 *Electricity bills based on the current tariff*

Before going through the components of DER tariffs, we review the components of the current tariffs. We select the typical binomial tariff[114] that is used in the previous study as the current tariff. The equations below detail the energy, capacity, transmission and distribution charges:

$$B_{energy}^{ref} = \sum_{m=1}^{12} \pi_{energy}^{onpeak,m} \sum\nolimits_{t \in Peak,m} P^t + \pi_{energy}^{offpeak,m} \sum\nolimits_{t \in Offpeak,m} P^t \tag{4.2}$$

$$B_{cap}^{ref} = \sum_{m=1}^{12} \pi_{cap}^{m} D^{onpeak,m} \tag{4.3}$$

$$B_{trans}^{ref} = \sum_{m=1}^{12} \pi_{trans}^{m} D^{onpeak,m} \tag{4.4}$$

$$B_{dist}^{ref} = \sum_{m=1}^{12} \pi_{dist}^{m} D^{m} \tag{4.5}$$

Equations (4.2-4.5) defines the annual charges on energy, capacity, transmission and distribution of a commercial or industrial customer, where m stands for month. The energy rate is a two-tier time-of-use charge. The capacity and transmission charges are calculated as the applicable rates multiplied by the monthly peak demand during the on-peak period. The on-peak periods are defined by the LSE as: June 1 through September 30, 10 a.m. to 10 p.m., Mondays through Fridays and October 1 through May 31, 7 a.m. to 10 p.m., Mondays through Fridays. The distribution charge is calculated as the rate multiplied by the monthly peak demand. The annual charge is the sum of the 12 monthly charges for the above four components. In the following sections, we compare the annual charges under DER tariffs against the current tariff to evaluate the impacts of different tariffs on DERs customers and on the LSE.

Our goal is to design the structure and rates for the energy, generation capacity and transmission components. Due to the lack of data about the distribution system costs, we leave the design of the distribution component for future research.

4.3.2 *Design of the energy component*

We apply dynamic energy rate in our proposed DER tariffs. The rate for energy should thus reflect the wholesale energy market clearing prices to customers and DERs. The question is whether this rate should be based on the Day-ahead LMP or the real-time LMP. The day-ahead LMP is less volatile (less price spikes) than the real-time LMP. In addition, the system operator publishes day-ahead LMP signals in the afternoon before the day, providing customers enough time to schedule their DERs.

Furthermore, since the real-time LMP is the sport market clearing price, its value remains unknown until the hour ends. End-use customers may therefore find it difficult to cope with a more-volatile, less-predictable price. For these reasons, we use the day-ahead LMP for the energy component of the DER tariffs that we design.

Next, we formulate a simple optimization problem to determine the rates of the DER tariff energy charge component.

$$\min : \sum_i \phi_{i,energy} \tag{4.6}$$

Subject to:

$$\phi_{i,energy} = \left| \frac{B_{i,energy}^{ref} - B_{i,energy}^{DERs}}{B_{i,energy}^{ref}} \right|_2^2 \tag{4.7}$$

$$\pi_{ene}^{t} = \pi_{DA-LMP}^{t} + \pi_{offset} \tag{4.8}$$

$$B_{i,energy}^{DERs} = \sum_{t=1}^{8760} \pi_{ene}^{t} P_i^t \tag{4.9}$$

$$\sum_i n_i B_{i,energy}^{DERs} \ge \sum_i n_i B_{i,energy}^{ref} \tag{4.10}$$

The objective function (4.6) minimizes the sum of the square of the payment deviations of many types of customers. The subscript *i* represent customer type *i*. The payment deviations are defined in (4.7) as the difference between the energy charges under the DER tariff and these charges under the current tariff, divided by the energy charges under the current tariff. The payment deviations are unit less. If the payment under the DER tariff is equal to that under the current tariff, the deviation $\phi_{i,energy}$ is equal to 0. The energy component of the DER tariff is defined as the day-ahead LMP plus an offset π_{offset} (4.8). This offset is adjusted to ensures that the LSE collects sufficient energy charge payments from the customers. Equation (4.9) defines the annual energy payment $B_{i,energy}^{DERs}$ under the DER tariffs. Equation (4.10) ensures that the LSE would not be worse off, in terms of total energy payments, if all its commercial & industrial customers switch to the DER tariff. n_i is the number of customers of type *i*.

Equations (4.6-4.10) thus define the energy component of the DER tariff. The rate is time-varying and exposes end-use customers to the wholesale energy prices.

4.3.3 *Design of the generation capacity and transmission components*

The capacity and transmission components should represent the capacity and transmission values of DERs respectively. The avoided cost method to estimate the benefits of DERs in terms of generation capacity and transmission suggest that the contribution of DERs should be reflected through their outputs coincident with the system level peak demands. In fact, demand response programs have been designed to capture the peak hours that happen occasionally. Several ISOs have emergency demand response programs[13] that compensate DERs at rates several times higher than the average retail rates for several dozens of hours each year when the system level aggregated loads approach their peaks. If the DER tariff is designed solely based on methods based on the avoided cost, π_{cap}^{t} and π_{trans}^{t} will be greater than zero for only a few dozens hours per year.

However, distributing the capacity and transmission values over only a few dozens hours per year makes the tariff very volatile and may discourage DERs from producing consistently. If the components are designed solely based on avoided cost methods, they resemble the current design of \$/kW charge because only peak hours are valuable whereas for the vast majority of hours over the year the tariff provides no benefits to DERs at all. In fact, some LSEs have realized this issue and provide the Peak Day Pricing tariffs to end-use customers[115]. The demand charges based on monthly peaks are discounted. On the other hand, customers face a high \$/kWh charge during events.

As with the Peak Day Pricing tariff structure mentioned above, we also divide the demand charge into two parts:

$$\pi_{cap} = \begin{Bmatrix} \pi_{cap}^{event} \\ \pi_{cap}^{kW} \end{Bmatrix} \tag{4.11}$$

$$\pi_{trans} = \begin{Bmatrix} \pi_{trans}^{event} \\ \pi_{trans}^{kW} \end{Bmatrix} \tag{4.12}$$

The first part is applicable to peak events. We assume that there are about 20 events throughout the year and that each event lasts about 3-6 hours. The LSE notifies its customers about the time and duration of these events on the day-ahead. The π_{cap}^{event} and π_{trans}^{event} charges only apply to those events. The second part π_{cap}^{kW} and π_{trans}^{kW} is similar to the demand charge components. Since the LSE aims to only recover a portion of capacity and transmission costs through π_{cap}^{kW} and π_{trans}^{kW}, the rest of the costs is recovered through the event-based charges π_{cap}^{event} and π_{trans}^{event}. The rate of π_{cap}^{kW} is different from that of the current tariff.

We provide two designs of the event-based component: the \$/kWh design and \$/kW design. The first design is similar to Peak Day Pricing, and the event-based rate are $\pi_{cap}^{event,kWh}$ and $\pi_{trans}^{event,kWh}$. The rate applies to every hour of the events $t \in T_{event}$. Therefore, a customer's annual capacity and transmission charges are:

$$B_{cap}^{DERs} = \sum_{m=1}^{12} \pi_{cap}^{kW,m} D^{onpeak,m} + \pi_{cap}^{event,kWh} \sum_{t \in T_{event}} D^t \tag{4.13}$$

$$B_{trans}^{DERs} = \sum_{m=1}^{12} \pi_{trans}^{kW,m} D^{onpeak,m} + \pi_{trans}^{event,kWh} \sum_{t \in T_{event}} D^t \tag{4.14}$$

The second design is the \$/kW design, where the event-based rates are $\pi_{cap}^{event,kW}$ and $\pi_{trans}^{event,kW}$. These rates apply to the peak demand during each event. The capacity and transmission charges of the \$/kW design tariff are:

$$B_{cap}^{DERs} = \sum_{m=1}^{12} \pi_{cap}^{kW,m} D^{onpeak,m} + \pi_{cap}^{event,kW} \sum_{j \in event} D_{peak}^j \tag{4.15}$$

$$B_{trans}^{DERs} = \sum_{m=1}^{12} \pi_{trans}^{kW,m} D^{onpeak,m} + \pi_{trans}^{event} \sum_{j \in event} D_{peak}^{j} \tag{4.16}$$

To better understand the proposed tariff structure, let us consider the activities of the LSE. Every day, the LSE forecasts its aggregated demand profile for the next day. If the forecasted demand profile is very high, the LSE issues an event notice to its customers, informing them about the starting and ending hours of the event. During the event, the LSE charges its customers the event-based charges. In return, the rates for monthly peaks: π_{cap}^{kW} and π_{trans}^{kW} are discounted.

As with the energy component, we introduce optimization models to calculate the values of the capacity and transmission components of the proposed \$/kW and \$/kWh tariffs. We discuss only the method used to calculate the rates for the capacity components because the model for the transmission component is quite similar.

$$\min : \sum_{i} \phi_{i,cap} \tag{4.17}$$

$$\phi_{i,cap} = \left| \frac{B_{i,cap}^{ref} - B_{i,cap}^{DERs}}{B_{i,cap}^{ref}} \right|_2^2 \tag{4.18}$$

$$\pi_{cap}^{kW} = \pi_{cap}(1 - r_{event}) \tag{4.19}$$

$$\sum_{i} n_i B_{i,energy}^{DERs} \geq \sum_{i} n_i B_{i,energy}^{ref} \tag{4.20}$$

The objective function is similar to that of the energy component model, i.e. to minimize the sum of the squares of the deviations. Equation (4.19) defines the ratio of between the event-based charge and the capacity payment. $r_{event} = 0.3$ means that 30% of the capacity payment is expected to recover from the event-based charge (second term in equation 4.13 or 4.15) and the remaining 70% is recovered from the monthly charge (first term in equation 4.13 or 4.15). The last equation ensures that the LSE will not be worse off if all its commercial and industrial customers switch to the DER tariffs. We can use either the \$/kWh design (equations 4.13-4.14), or the \$/kW design (equations 4.15-4.16), to solve for event-based charge rates.

4.4 CASE STUDY: DETERMINING THE VALUES OF THE DER TARIFF COMPONENTS

In the previous section, we defined the structure of DER tariffs and formulated models to calculate the rates. In this section, we present case studies illustrating the implementation of these DER tariffs.

4.4.1 *Data*

As in the previous study, we select the same commercial customer demand profiles and the same time of use tariff. Commercial customer demand profiles are based on data from the National Renewable Energy Laboratory[118].

The utility's hourly load profile is acquired from PJM[119]. We assume that the selected utility has no generation or transmission assets, which means that its energy and capacity obligations are fulfilled by purchases from the wholesale energy and capacity markets and purchases of transmission services. We extract the day-ahead LMP and LSE demand profile of the entire year 2016 from PJM[120] and remove February 29th to make the year 8760 hours, and thus compatible with our customer demand profiles. We also assume that the DER penetration is not high enough to significantly impact the market clearing prices.

4.4.2 *Energy Component*

Using the model (4.6-4.10), we calculate the optimal value of π_{offset} and determine the energy component of the proposed DER tariff to be $\pi_{offset} = 0.0145\$/\text{kWh}$. The mean of the time-varying energy component of DER tariff is about 0.0425$/kWh. Figure 4-1 illustrates the energy component over the entire year.

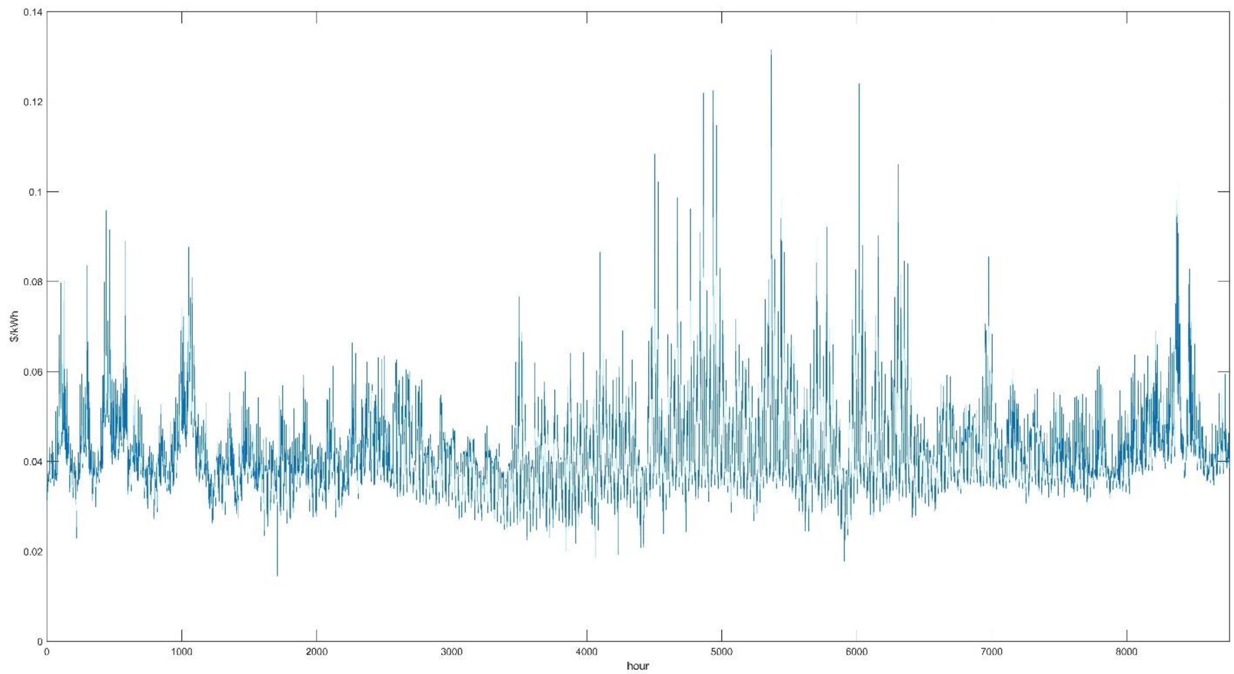

Figure 4-1: Energy component rate of the DER tariff

From figure 4-1 it is easily seen that the rate of the energy component has seasonal and daily patterns. During the winter and summer, the rates during peak hours are higher, and appear as the “spikes” in the figure. This happens because the demand during those hours are higher and the more expensive generators are dispatched to meet the demand.

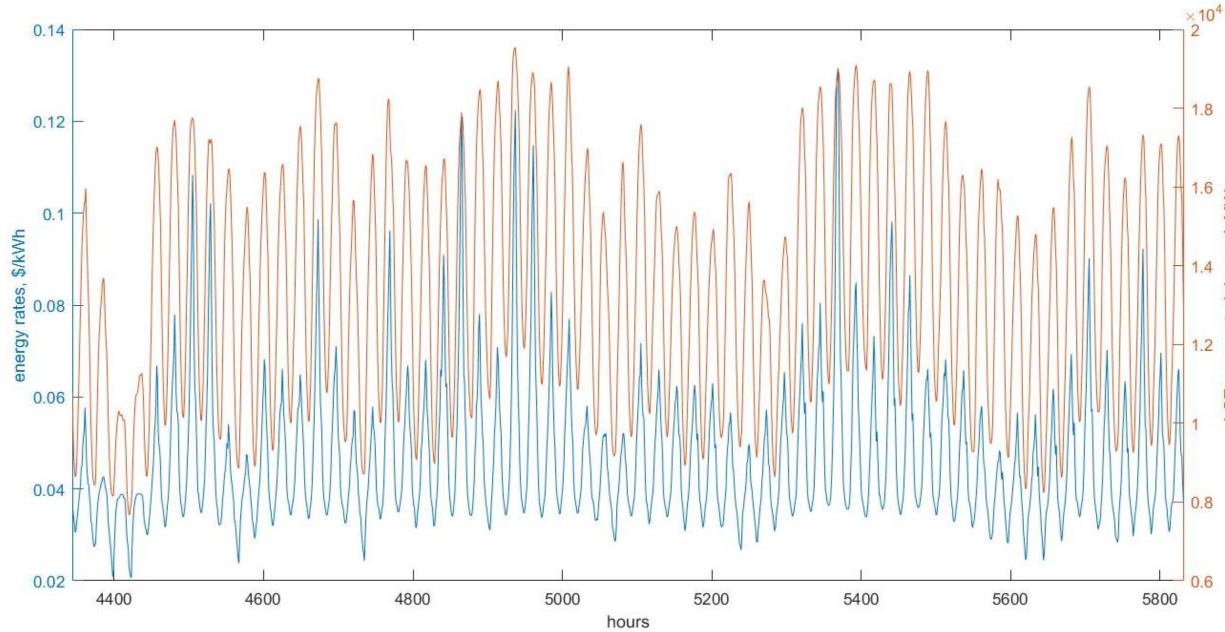

Figure 4-2: Energy component and LSE aggregated load

Figure 4-2 selects two months, July and August to illustrate the relationship between the energy component rate and the LSE's aggregated load profile. Every day the price goes up and down, providing DERs the opportunity for energy arbitrage. The energy rate is higher during the peak hours of the day. The time-varying energy rate thus serves as a good indicator of the LSE's aggregated demand. Charging customers this time-varying rate could encourage DERs to assist the LSE achieve peak-shaving and valley-filling goals.

4.4.3 *Capacity & Transmission Component*

In order to design the event-based tariff, the LSE must specify the total number of hours of events (for the $/kWh design) or the number of events (for the $/kW design). For this case study, we chose 20 events, with a total of 105 hours. The events and hours are selected based on peaks of the LSE's demand profile. Three events happen in winter and in the morning. The rest happen in July and August, during late afternoon and evening. Table 4-1 shows the timing: date, start hour and end hour of the events over the year.

Table 4-1: Distribution of the events over the year

Hour /date	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1/18																								
2/13																								
7/13																								
7/17																								
7/22																								
7/23																								
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8/15																								
8/16																								
8/25																								
12/5																								

Based on the model (4.17-4.20), we can calculate the rates for the capacity and transmission components. We vary the ratio r_{event} and get a series of rates based on different values of r_{event} ratios. Tables 4-2 and 4-3 summarize the rates for the \$/kWh design and \$/kW design respectively.

Table 4-2: Rates of event-based part of capacity and transmission component, \$/kWh design

r_{event}	$\pi_{cap}^{event,kWh}$ (\$)	$\pi_{cap}^{event,kWh}$ (\$)
0.05	0.024	0.013
0.1	0.048	0.027
0.15	0.072	0.040
0.2	0.095	0.053
0.25	0.119	0.066
0.3	0.143	0.080
0.35	0.167	0.093
0.4	0.191	0.106
0.45	0.215	0.119
0.5	0.239	0.133

Table 4-3: Rates of event-based part of capacity and transmission component, \$/kW design

r_{event}	$\pi_{cap}^{event,kW}$ (\$)	$\pi_{cap}^{event,kW}$ (\$)
0.05	0.144	0.080
0.1	0.287	0.160
0.15	0.431	0.239
0.2	0.574	0.319
0.25	0.718	0.399
0.3	0.861	0.479
0.35	1.005	0.559
0.4	1.148	0.638
0.45	1.292	0.718
0.5	1.435	0.798

4.4.4 *The impact of the DER tariffs on non-DER customers*

We evaluate the effects of DER tariffs with the rates calculated in the previous section on the annual bills of various types of customers. We assume that even for the same type of customers (e.g. restaurants) located in the same area, there demand profiles are different. Therefore, we add some random perturbations to the customer demand profile to create many demand profiles simulating the variance customer demand profiles.

We define its annual bill ratio as the amount paid based on the DER tariffs divided by the amount paid based on the current tariff. Figure 4-3 shows the annual bill ratios of 16 types of customers. Each type has two columns representing the two locations. The dashed lines show the range [0.97, 1.03]. For each type of customer, the first box indicates the range of bill ratio with the $/kWh tariff, the second box indicates the range of bill ratio with the $/kW tariff.

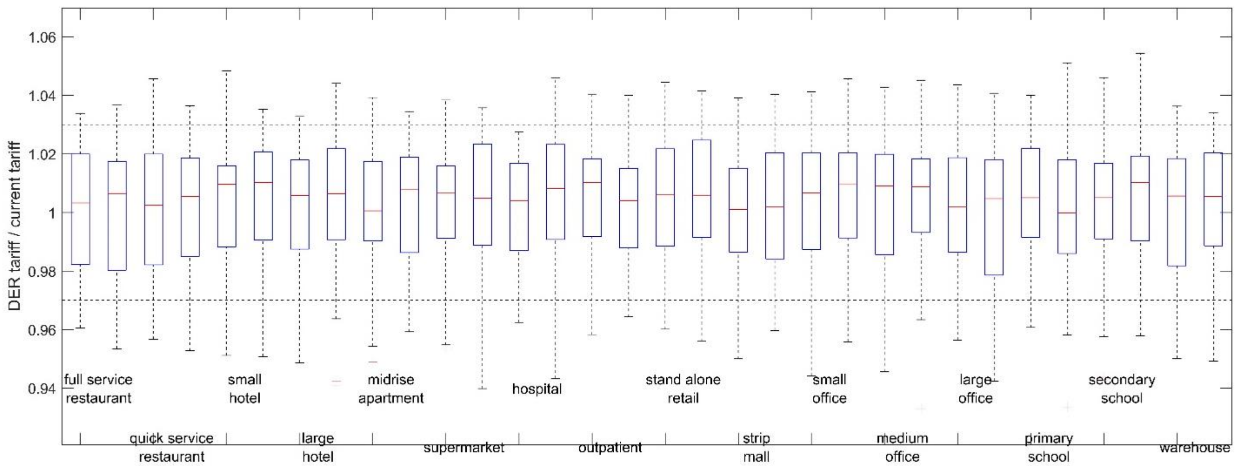

Figure 4-3: Annual bill ratios of 16 types of customers

For each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles. The whiskers extend to the most extreme data points not considered outliers. From this figure we can observe that most of the bill ratios lies within the range [0.97, 1.03]. This means for customers without DERs, their annual bills calculated by the proposed DER tariffs are roughly the same compared with their bills calculated using the current tariff.

These results validate the rate design of the proposed DER tariffs. Non-DERs customers will pay roughly the same amount under DER tariffs compared to what they pay with under the current tariff. In the following sections, we evaluate the impacts of the proposed tariffs on customers with various types of DERs and on the LSE.

4.5 CASE STUDY: IMPACT OF THE PROPOSED DER TARIFFS ON DERS CUSTOMERS AND THE LSE

In this section, we assume that customers install DERs to help them minimize their electricity bills. We showed previously that, if customers are charged based on the current tariff and dispatch their DERs accordingly, the LSE is not able to recover the capacity and transmission costs because the decreased revenues from customers outweigh the reduced expenses. To tackle this issue, the proposed DER tariff is designed to reflect the LSE's peak periods through event-based charges and provide incentives for customers to dispatch DERs in a way that helps the LSE shave the peaks. We will evaluate the impacts of three types of DERs: PV, energy storage and demand response.

For each customer, we calculate the annual bills with and without DERs. The differences between the two amounts give us the annual saving achieved by the DERs. We divide the savings by the installed capacity of the DERs to normalize the annual saving into "saving per kW capacity". The equations below show how these savings are calculated:

$$S_{ene} = (B_{ene}^{w/o\ DER} - B_{ene}^{w/\ DER}) / P_{rating}^{DER} \tag{4.21}$$

$$S_{cap} = (B_{cap}^{w/o\ DER} - B_{cap}^{w/\ DER}) / P_{rating}^{DER} \tag{4.22}$$

$$S_{trans} = (B_{trans}^{w/o\ DER} - B_{trans}^{w/\ DER}) / P_{rating}^{DER} \tag{4.23}$$

Given a customer with DERs, we can calculate its annual bills based on the current tariff with and without DERs which helps us get the "saving per kW capacity" based on the current tariff. Similarly, we also calculate the "saving per kW capacity" based on the kWh design and kW design of the DER tariffs. In the following case study, the term "saving per kW capacity" will be frequency mentioned as we gauge the savings of energy, capacity and transmission under different tariffs may help us evaluate the effects of DER tariffs on customers.

On the other hand, we aggregate the customers' demand profiles, with and without DERs to analyze the system level impacts of DERs on the LSE. DERs alter LSE's aggregated loads and result in the LSE paying less on the wholesale markets for the procurement of energy, capacity and transmission.

4.5.1 *The impact of DER tariffs on PV*

PV is generally considered to be a non-controllable resource because customers cannot schedule and dispatch PV. Therefore, applying different tariffs will not change the production of PV. In this case study, we assume that the customers install PV with a rated capacity equal to 20% of their peak demand. PV production profiles from various locations within the LSE territory are extracted from the National Renewable Energy Laboratory's PVWatts Solar Calculator[121]. We use these profiles to represent PV productions.

From equations (4.21-4.23), we calculate the saving per kW of PV under the three tariffs. Figure 4-4 and 4-5 show the per kW capacity and transmission savings under three tariffs: current, kWh design and kW design.

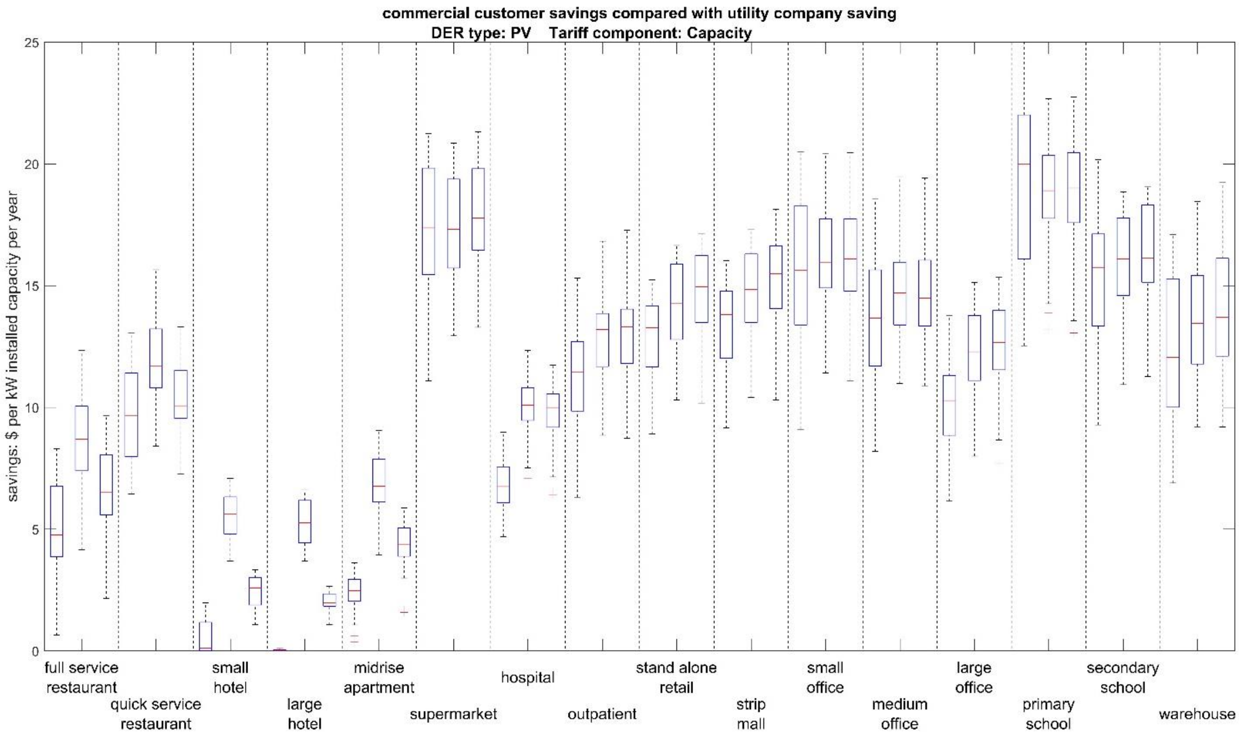

Figure 4-4: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: PV tariff component: capacity

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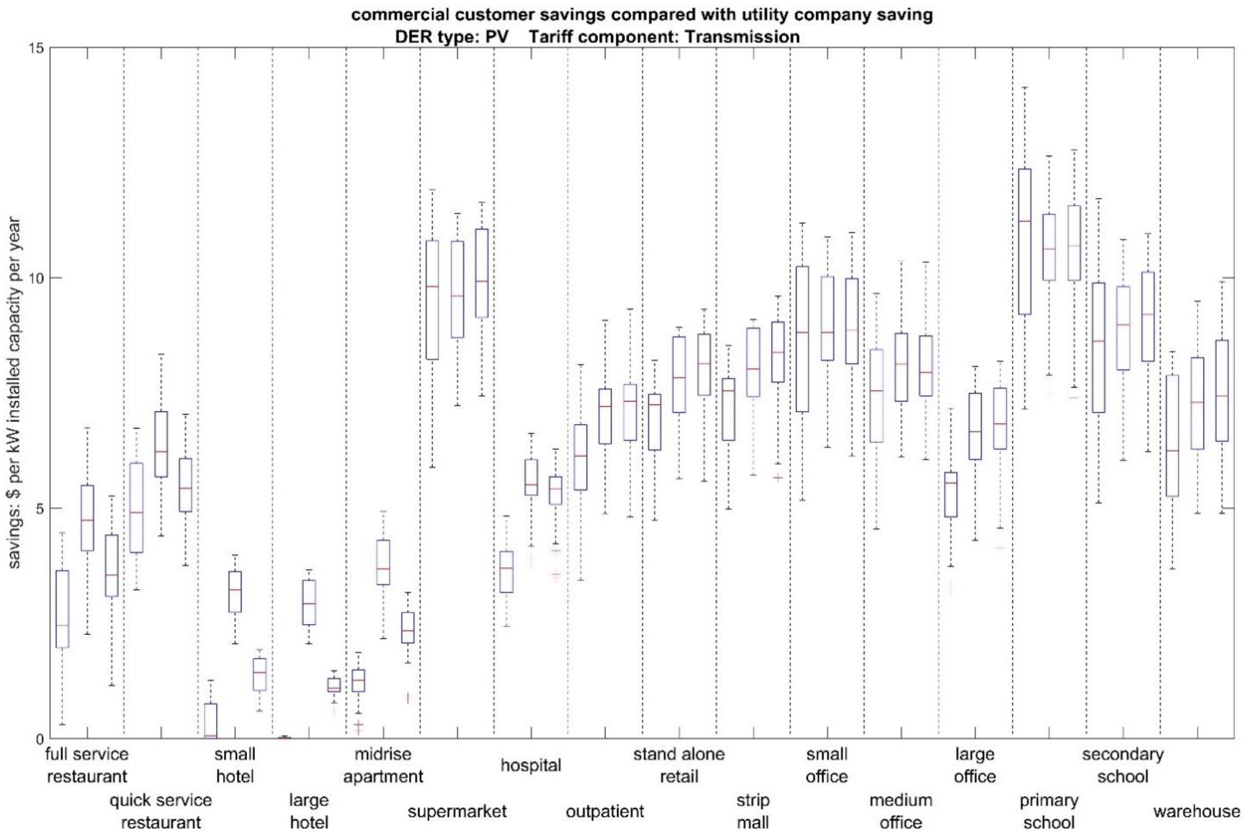

Figure 4-5: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: PV tariff component: transmission

From the above figures we observe that for most types of customers the savings under the three tariffs are within the same range. For a few types of customers (restaurants, hotels and midrise apartments), the kWh tariff reward PV with more savings than the other two tariffs. However, even under the kWh tariff, the savings of these customers are still less that the level of savings that other types of customers can achieve.

The reason lies in the demand profiles of these customers. Since customers cannot dispatch their PV, two PVs installed by two customers at the same location and with the same configuration should have the same production profiles. PV production is directly related to the sunlight. The power production peaks around noon and gradually drops to zero towards sunset. Restaurants, hotels and apartments typically have evening peaks, when PV production is less. Thus, PV contributes little to a reduction in these customers' peak demands.

The per kW savings are smaller when calculated using the current tariff. On the other hand, the kWh design applies the same rate during every hour of the events. Many events encompass afternoons when the PV production is still considerable. Therefore, the kWh design rewards PV with more savings. The kW design calculates the event charge based on the peak of each event. For the above three types of customers, their peaks during events are more likely to happen during evenings than afternoons, when PV produces some energy. The kW design thus rewards PV less than the kWh design. Other customers generally have peaks during working hours, which align their production profiles with that of the PV. Therefore, the savings for those customers are generally higher.

Since PV is non-controllable, we can assume that PV production is not affect by tariffs. The LSE's aggregated load profile will therefore be the same regardless of the tariff structure. Depending on the penetrations of DERs, the LSE's "reduced cost per kW" is within the range of [$10.43, $11.12] for generation capacity and [$4.85, $5.41] for transmission. The "reduced cost per kW capacity" is still lower than the "savings per kW capacity" of most customers.

Table 4-4 shows the total customer savings under three tariffs (LSE's lost revenues) and the LSE's reduced costs. In these figures, we have assumed that commercial customers account for 30% of the LSE's load and that half of the commercial customers install PV.

Table 4-4: Summary of financial impacts of PV on the LSE (lost revenues/reduced costs)

Unit: Million $	Energy	Capacity	Transmission
Current	43.53/28.23	7.06/9.15	3.83/6.55
kWh	41.31/28.23	7.99/9.15	4.38/6.55
kW	41.31/28.23	7.90/9.15	4.33/6.55

This table shows that the amount of lost revenue/reduced costs in the energy component outweighs that of capacity and transmission components. Under all three tariffs, the LSE will lose money on the energy component. On the other hand, the LSE profits on the capacity and transmission components since its reduced costs are higher than the corresponding lost revenues.

4.5.2 *The impact of DER tariffs on energy storage*

Unlike PV, energy storage is dispatchable. Customers who own energy storage can schedule its charge/discharge schedule to minimize their electricity bill. The customer demand profile and tariff structure are important factors that affect the dispatch of energy storage.

The current tariff has no uncertainty: customers know well in advance its structure and rates. On the other hand, the proposed tariff involves some uncertainty. A customer doesn’t know the exact values of energy charge and timing of peak events until the day-ahead when the energy rate and the duration of any event for the next day become available to customers so they can schedule their energy storages. If we assume that customers can forecast their demand perfectly, they can solve a deterministic optimization problem on the day-ahead to schedule their energy storage dispatch.

However, demand forecasts are not perfect. In fact, forecasting the demand profiles of commercial customers could be a challenging task. Studies have been conducted to forecast the demand profiles of distribution network demand profiles, which is easier to forecast since distribution network aggregates demand profiles of many customers. But even for aggregated profiles, forecasts are not perfect. In this study, we adapt several methods discussed in the study[122] to conduct day-ahead forecasts for commercial customer demand profiles.

To cope with the uncertainties of customer demand profiles, we rely on the demands forecasts generated by methods mentioned in[122] as our forecast scenarios. Then we use a stochastic optimization to help energy storage make dispatch decisions. The stochastic optimization is executed once per day at day-ahead and determines the energy storage dispatch schedule for the following day:

$$\min:\sum_{t=1}^{24}\pi_{ene}^{t}(P_{chg}^{t}-P_{dsg}^{t})+\sum_{s=1}^{S}\theta^{s}[(\pi_{cap}^{kW}+\pi_{trans}^{kW})\xi^{onpeak,s}+\pi_{dist}\xi^{s}+B_{event}^{s}] \tag{4.24}$$

The objective function is to minimize the total cost. In the objective function, the first term is the cost from energy charge, where π_{ene} is the energy rate at hour t; P_{chg} and P_{dsg} are the battery charging and discharging powers; S is the number of scenarios; θ_{s} is the probability of scenario s. π_{cap}^{kW} and π_{trans}^{kW} are monthly peak rates of capacity and transmission. ξ_{onpeak}^{s} is the on-peak demand violation of scenario s; π_{dist} is the distribution rate; ξ^{s} is the monthly peak violation of scenario s. Since there is only about 20 events per year, the event-based charges B_{event}^{s} are absent during most days. In case there is an event on the following day, the customer include the event-based charges B_{event}^{s} into the objective function and dispatch energy storage accordingly.

$$0\le P_{chg}^{t}\le P^{\max}\alpha^{t} \tag{4.25}$$

$$0\le P_{dsg}^{t}\le P^{\max}(1-\alpha^{t}) \tag{4.26}$$

The above two constraints prevent simultaneously charging and discharging. $P^{\max}$ is the power rating of energy storage. α^{t} is a binary variable that indicates whether the battery is charging or discharging.

$$L^{t,s}-P_{chg}^{t}+P_{dsg}^{t}\le D_{prev}^{onpeak}+\xi^{onpeak,s}\quad t\in T^{onpeak} \tag{4.27}$$

$$L^{t,s}-P_{chg}^{t}+P_{dsg}^{t}\le D_{prev}+\xi^{s} \tag{4.28}$$

$$\xi^{onpeak,s},\xi^{s}\ge 0 \tag{4.29}$$

Constraints (4.27) and (4.28) define the peak demands and peak violations. $L^{t,s}$ is the forecasted load of scenario s at hour t; D_{prev}^{onpeak} and D_{prev} define the on-peak peak demand and overall peak demand so far. The peak demand over the entire month should not be less than the peak demand observed from the beginning of month till so far. ξ_{onpeak}^{s} and ξ^{s} are peak demand violations. Their values are positive in case the peak demands of the following day are higher than the corresponding peak demands so far. If the peak demands of the following day are not higher the corresponding peak demands so far, ξ_{onpeak}^{s} and ξ^{s} are 0.

$$E^{\min} \le E^{t} \le E^{\max} \tag{4.30}$$

$$E^{t+1} = E^{t} + \eta P_{chg}^{t} - P_{dsg}^{t} / \eta \tag{4.31}$$

$$E^{24} = E^{0} \tag{4.32}$$

Constraint (4.30) forces the energy stored in battery to be between its lower and upper bounds $E^{\min}$ and $E^{\max}$. Constraint (4.31) relates battery charging and discharging with battery energy. Constraint (4.32) ensures that the state of charge at the end of day is the same as that at the beginning of day.

The last term in the objective function B_{event}^{s} only applies when there is an event for the following day. B_{event}^{s} may take different forms, depending on the tariff design.

$$B_{event}^{s} = (\pi_{cap}^{kWh} + \pi_{trans}^{kWh}) \sum_{t \in T_{event}} (L^{t,s} + P_{chg}^{t} - P_{dsg}^{t}) \tag{4.33}$$

Based on the kWh design, the event charge is the sum over capacity and transmission rates, multiplied by the sum over net demands during the event period.

$$B_{event}^{s} = (\pi_{cap}^{kW} + \pi_{trans}^{kW}) D_{event}^{s} \tag{4.34}$$

$$L^{t,s} - P_{chg}^{t} + P_{dsg}^{t} \le D_{event}^{s} \quad t \in T_{event} \tag{4.35}$$

Based on the kW design, the event charge is the sum over capacity and transmission rates, multiplied by the peak demand during the event period.

As with PV, we also assume that the power rating of an energy storage device is 20% of its owner's annual peak. The energy to power ratio of energy storage is set at 4, which means $E^{rating} = 4P^{\max}$. The upper and lower bounds of energy are $0.95E^{rating}$ and $0.1E^{rating}$. Charging and discharging efficiencies are both assumed to be 0.95.

Together the stochastic model determines the optimal storage dispatch under various load profile scenarios. On the following day, the storage is dispatched according to the schedule made at day-ahead.

We conducted a series of simulations on realistic cases under non-perfect forecasts. We rely on the stochastic optimization to generate the energy storage dispatch schedule for the following day. On the following day, we apply the storage dispatch to the actual demand to get the net demand. Based on the net demand, we calculate the annual bills and therefore the annual savings from energy storage. Figure 4-6 shows the annual savings per kW storage capacity for different types of customers.

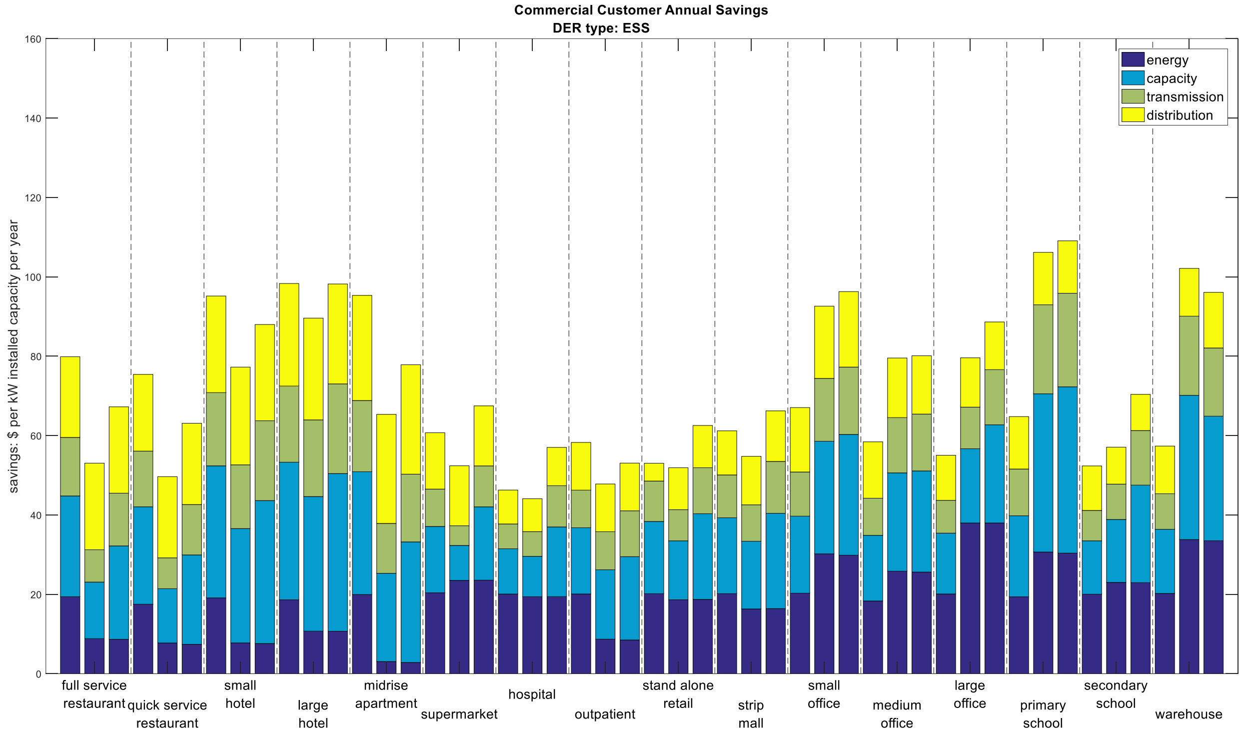

Figure 4-6: Annual per kW savings of energy storage under normal forecast

Under the current tariff, customers with sharper peak, such as restaurants, hotels and midrise apartments, achieve higher levels of savings than other customers with flatter peaks. The DER tariffs help some customers boost their storage savings from all energy, capacity and transmission components. To get a closer look at the energy storage savings, we break down the annual savings to energy, capacity, transmission and distribution components. Figure 4-7 and 4-8 illustrate the per kW savings on capacity and transmission under three tariffs: current, kWh design and kW design.

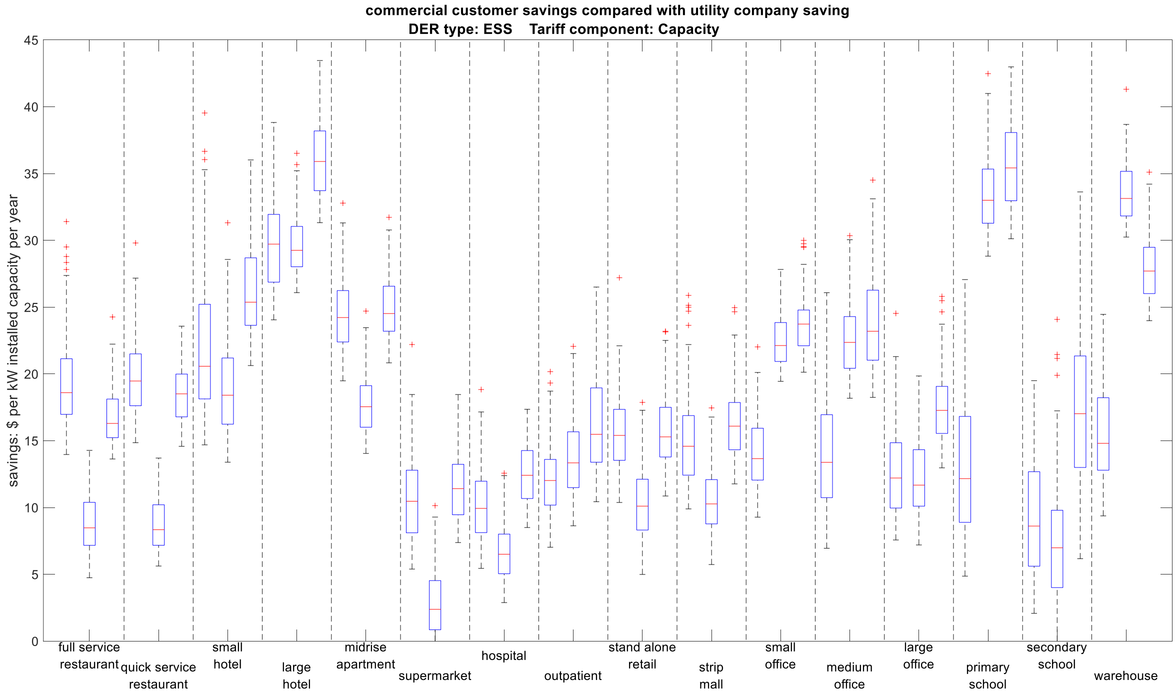

Figure 4-7: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: ES tariff component: capacity

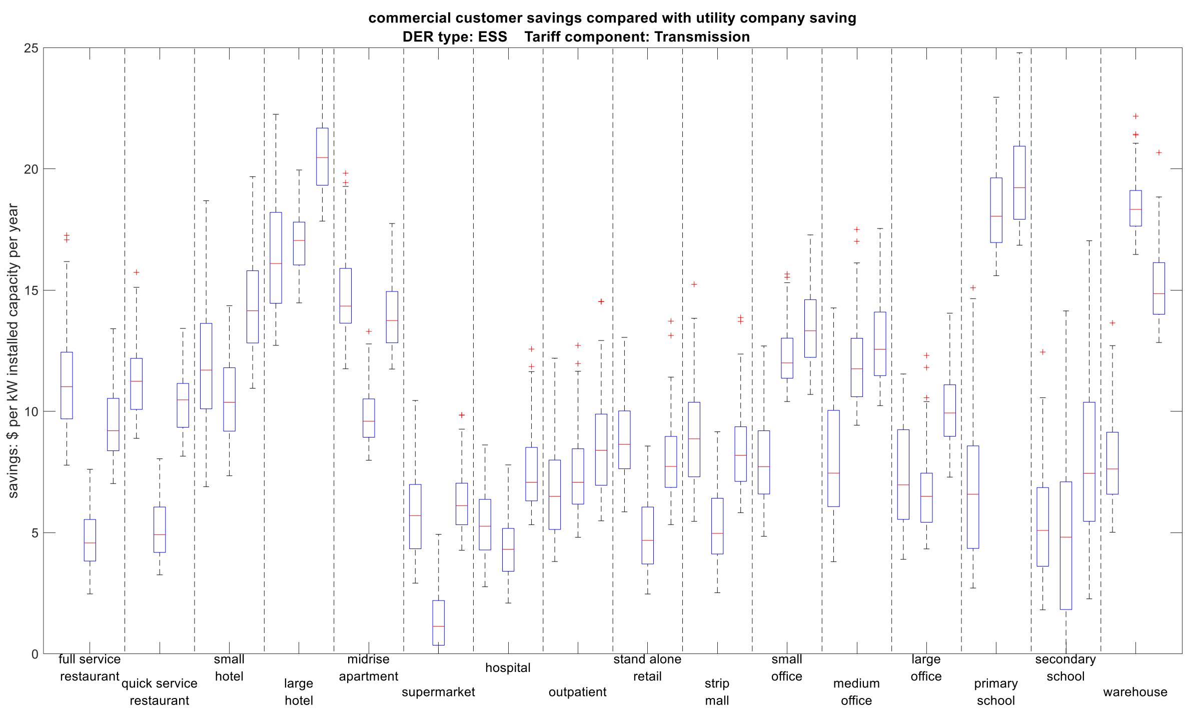

Figure 4-8: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: ES tariff component: transmission

From the above two figures, we observe that for most customers, the savings under the current tariff or the kW design tariff outweigh the savings under the kWh tariff. The kWh tariff applies a $/kWh rate during each hour of the events, requiring the storage to dispatch throughout the entire event. However, the events could reach up to 6 hours but the storage can only discharge at full capacity for no more than 4 hours. Therefore, energy storage may not be able to take full advantage of the kWh design. On the other hand, the current design and kW design are based on peaks, either the monthly peak or the peak during events. Energy storages in this study are better at shaving peaks, especially sharp peaks rather than at discharging for many hours.

Next, let’s evaluate the impact of energy storage on the LSE. The kWh and kW tariffs are designed to encourage customers to react during the LSE’s peaks. Here we will evaluate the peak reduction effects of energy storage on LSE’s aggregated demand profiles. As in the PV case, we assume that the commercial customers account for 30% of the total demand. Among the commercial customers, half of them are assumed to install energy storage. These customers dispatch their energy storage differently under the three tariffs. There will therefore be three aggregated demand profiles corresponding to the three tariffs. For each of the demand profile, we sort the 8760 hourly demands in descending order and pick the top 100 hours that represent the highest demand over the year. Figure 4-9 shows the peak demands of four cases: no DER, current tariff, kWh tariff and kW tariff.

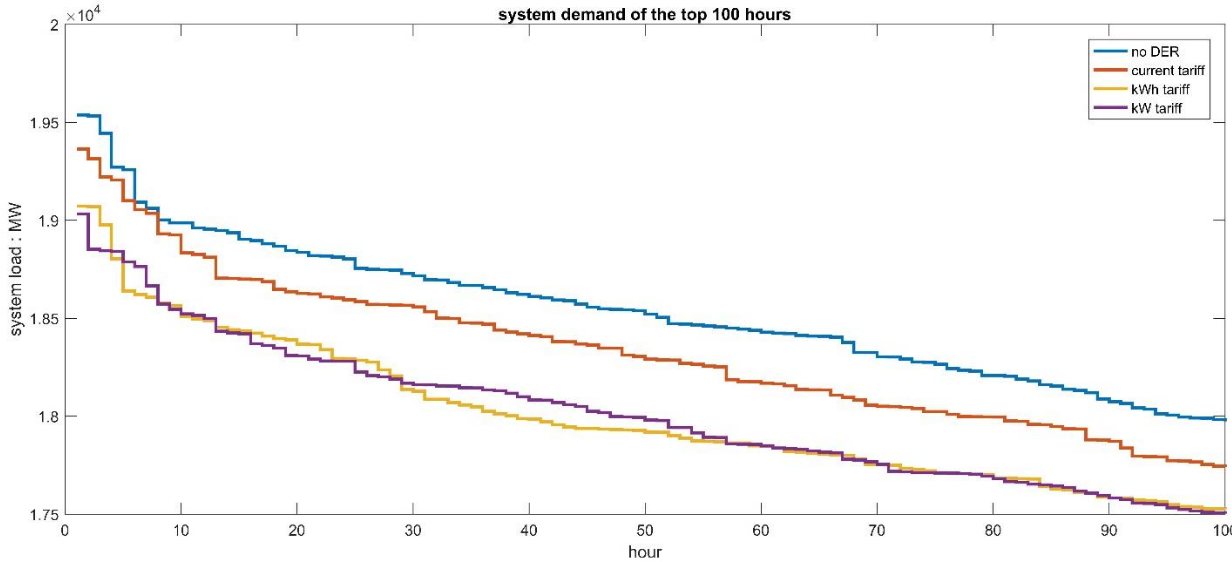

Figure 4-9: Top 100 hours of the LSE's aggregated demand, sorted in descending order

Table 4-5 summarizes the financials impacts of energy storage on the LSE, under the current tariff and the two proposed tariffs.

Table 4-5: Summary of financial impacts of ES on the LSE (lost revenues/reduced costs)

Unit: Million $	Energy	Capacity	Transmission
Current	8.21/3.16	11.60/5.94	6.50/4.26
kWh	8.58/8.23	12.88/18.11	7.12/12.97
kW	8.53/8/19	15.96/15.42	8.84/11.04

Compared with PV, energy storage in total does not cause as big a loss of revenue or a reduction in costs. Unlike PV, energy storage does not produce energy. Savings in the energy component therefore arise from energy arbitrage rather than selling energy. On the other hand, energy storage achieves higher customer savings on capacity and transmission components (lost revenues) since they can be dispatched for demand charge management purposes.

Speaking of the energy component, the LSE is financially balanced under the kWh and kW tariffs. These two tariffs transmit wholesale level energy prices to customers. However, under the current tariff the LSE's lost revenue in the energy component is much larger than its cost reduction. This happens because the energy component of the current tariff is decoupled from the day-ahead LMP that the LSE pays to the wholesale energy market.

Under the current tariff, the LSE will also suffer losses in the capacity and transmission components. As mentioned in the previous study, the demand charge structure of the current tariff does not provide any information about the LSE's demand profiles and peak hours. In contrast, the event-based tariffs, both the kWh and kW design, convey peak hour information to the customers through event-based charges. The customers thus can help the LSE reduce its peaks because they are economically encouraged to discharge their energy storage during event hours. In the kWh design, the LSE benefits on both the capacity and transmission components. In the kW design, the LSE is almost neutral on the capacity component and saves on the transmission component. In addition, under the proposed two tariffs the total customer savings in capacity and transmission components are higher, compared with the total customer savings under the current tariff. Therefore, both customers and the LSE have an economic incentive to switch from the current tariff to the proposed DER tariff.

4.5.3 *The impact of DER tariffs on demand response*

Like energy storage, demand response is dispatchable. Customers can modulate the settings of their appliances to alter their demand profiles and reduce their electricity bills. Therefore, different tariff designs may result in different reactions from the customers.

In the case study, we consider two types of demand response: an event-based type and a long-term demand shape modification type. The event-based DR is dispatched about 20 times per year. Under the current tariff, the event-based DR is dispatched twice per month. The two events correspond to the two days with highest demands over the month. Each event is 4 hours long.

Under the DER tariffs, the events are defined according to the system level peaks. The duration of these events ranges from 3 to 6 hours. Overall, a customer with event-based DR is expected to dispatch its load around 20 times annually, for a total of around 100 hours per year.

The demand shape modification type modifies the settings of appliances more constantly. We apply the demand response strategies to customers every weekday. Under the current tariff, customers modify their demand shapes to reduce their own daily peaks. DR is dispatched during a few hours when the customers' demand approaches their daily peak. Under the DER tariffs, customer dispatch their DR in the same manner on non-event days. However, on event days, the schedules of DR are overridden by and DR are dispatched based on events.

Due to safety reasons, hospital and outpatient facilities are excluded from the demand response analysis. We consider the remaining 14 types of customers to provide demand response. The DR strategy involves dimming lights and altering the HVAC temperature set-points. The event-based DR dims the lighting to two thirds of its baseline level and increases the temperature set-point two Celsius degrees higher (in summer) or lower (in winter). The demand drop sharply when this type of DR is dispatched. Though occasionally sharply reducing demand might be acceptable, deploying the same strategy every day makes customers uncomfortable, so the second type DR only dims lighting to 90 percent of its baseline level and changes the temperature set-point by only one degree Celsius. These demand response strategies have been tested by Lawrence Berkeley National Laboratory[123]. We alter the settings in EnergyPlus input files, then execute EnergyPlus to get the building demand profiles with demand response.

Figure 4-10 and 4-11 illustrate the per kW savings under three tariffs: current, kWh design and kW design. Figure 4-10 shows the savings of event-based DR. Figure 4-11 shows the savings of demand shape modification type DR.

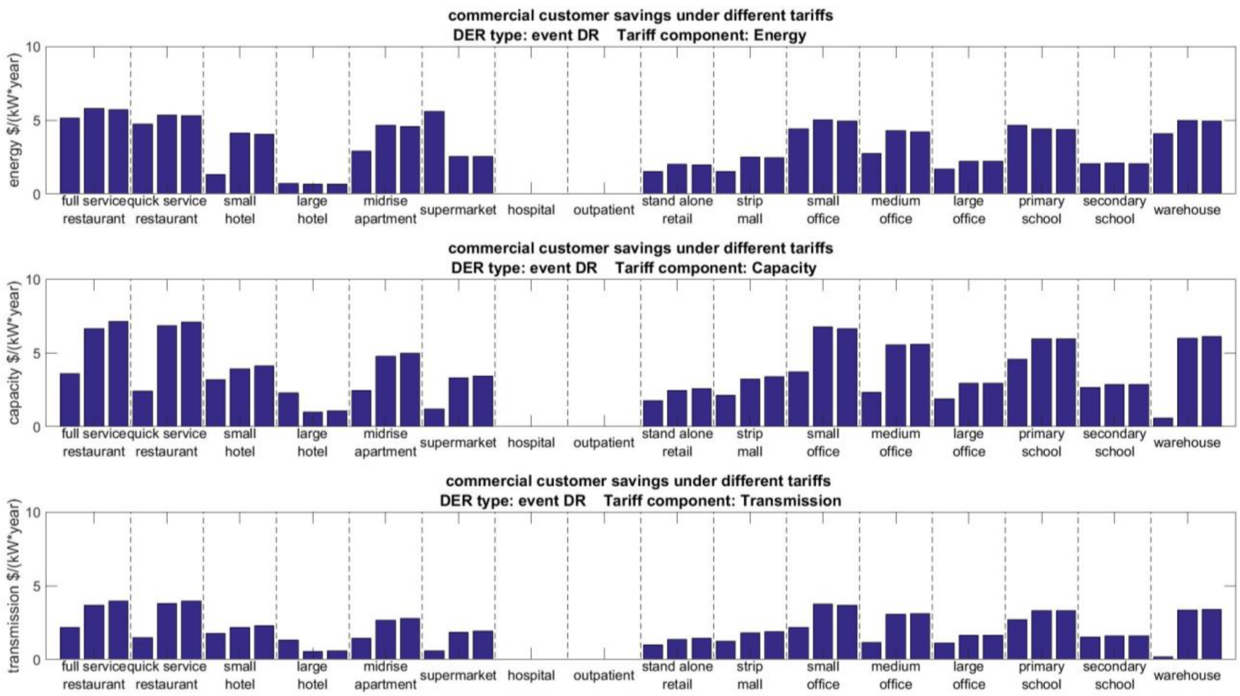

Figure 4-10: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: event DR

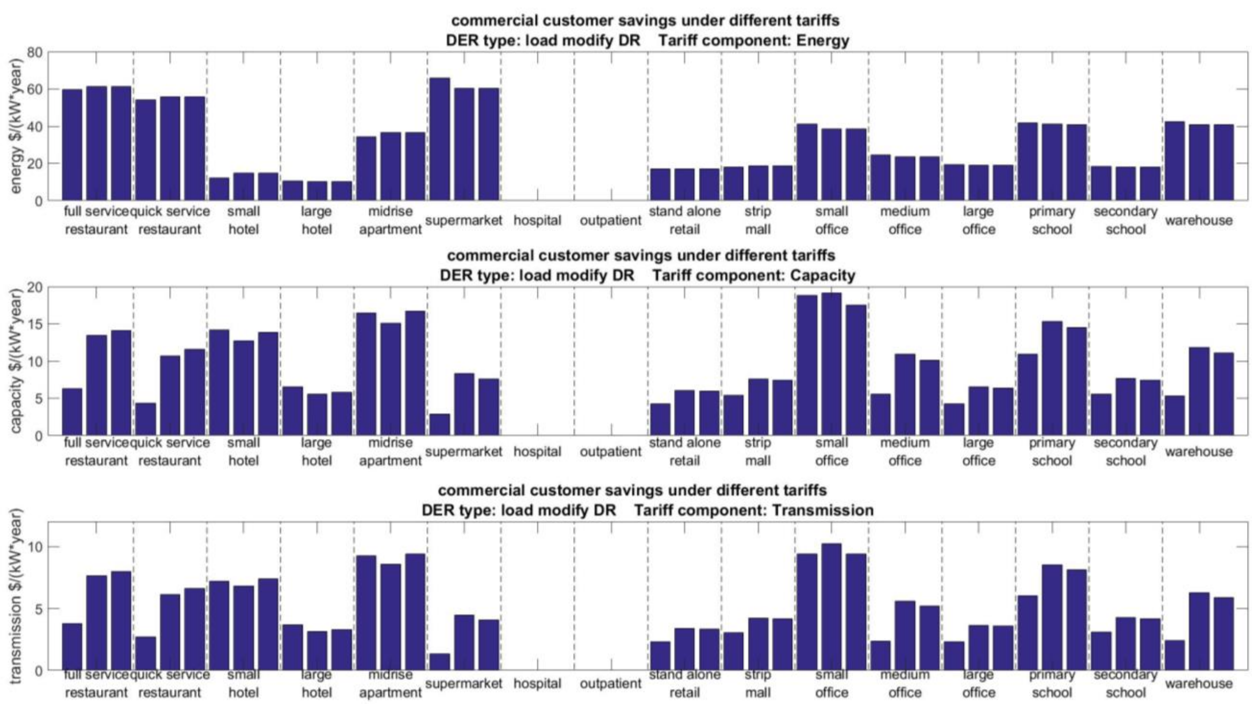

Figure 4-11: per kW savings of commercial customers under three tariffs (current: left, kWh design: middle, kW design: right), DER: demand shape modification DR

From figure 4-10, we observe that under the DER tariffs demand response achieve more savings in capacity and transmission categories. According to the DER tariffs, customers dispatch their demand response resources only during events. The event-based charges of the DER tariffs are considerable, so customers can achieve significantly larger savings. In contrast, under the current tariff the demand charges are based on the monthly peak demands. With demand response dispatched twice per month customers manage to shave the peaks demand of the highest and second highest demand days. Therefore, the savings come from the difference between the monthly peak and the peak demand of the third highest day. Based on the commercial customer profiles that we have; the differences are not significant for some customers. In the energy category, the difference between savings under current tariff and under DER tariffs are less considerable.

Compared with the event-based DR, load shape modification dispatches the DR resources much more often. Therefore, the annual savings of load shape modification DR are much higher than the savings of event-based DR, especially the savings in energy payments. For most customers, their savings in energy payments under the three tariffs are about the same. Under the DER tariff, savings on capacity and transmission come from two sources: customer peak shaving and system peak shaving. Therefore, customers achieve higher levels of savings in capacity and transmission payments under DER tariffs.

To summarize the impacts of demand response on the LSE, Table 4-6 and 4-7 list the lost revenues and reduced costs of the LSE under event-based and load shape modification DR respectively.

Table 4-6: Summary of financial impacts of event-based DR on the LSE

Lost Revenues/Reduced Costs (Million $)			
	Energy	Capacity	Transmission
Current	2.59/1.84	2.58/0.30	1.47/0.21
kWh	3.12/1.70	3.99/6.12	2.22/3.97
kW	3.09/1.70	4.09/6.12	2.28/3.97

Table 4-7: Summary of financial impacts of load shape modification DR on the LSE

Lost Revenues/Reduced Costs (Million $)			
	Energy	Capacity	Transmission
Current	26.67/18.68	7.06/2.93	4.81/1.81
kWh	26.47/18.14	9.85/11.78	7.43/8.44
kW	26.43/18.14	9.58/11.78	7.30/8.44

From Table 4-6 we observe that the LSE's lost revenues outweigh its reduced costs in energy component. The reason is that the energy components of the current tariff and of the two proposed DER tariffs are higher compared with the day-ahead LMP. The DER tariffs distinguish themselves from the current tariff in capacity and transmission components. Under the current tariff, customers can achieve certain levels of demand charge savings. But customers' peaks usually do not coincide with LSE's peaks, so their dispatch of demand response contribute little to shave LSE's peaks. In contrast, under the DER tariff, customer dispatch demand response resources during events, which effectively helps the LSE reduce its payments for capacity and transmission services. Under the DER tariffs, customers enjoy more demand charge savings and the LSE reduces its costs for capacity and transmission.

Load shape modification DR are dispatched more frequently. Therefore, customer savings and the LSE's reduced costs are higher. Since average energy rates are higher than average day-ahead LMP, we still observe the situation that the LSE's lost revenues outweigh its reduced costs in the energy component. Considering the demand charge component, the customers achieve higher savings under the DER tariffs. The LSE's lost revenues are greater than its reduced costs under the current tariff. In contrast, the LSE's lost revenues are less than its reduced costs under the DER tariffs. In conclusion, both customers and the LSE should favor the DER tariffs.

4.6 DISCUSSION

In the previous sections, we have designed two types of DER tariffs. These two DER tariffs apply a dynamic energy component and a combination of monthly peak and event-based charges for demand components. The DER tariffs transmit the system level demand profile and pricing information to end-use customers. By doing so, the LSE provides financial incentives for customers to dispatch their DERs and shave system level peak demands.

We formulated optimization models to determine the rates of the DER tariffs. These rates are chosen to ensure that the annual bills of most customers under the DER tariffs are in the range of 97% to 103% of their annual bills under the current tariffs. In the case study, customers can install either PV, storage or demand response as their DERs. We break down the savings of DERs into their energy, capacity and transmission components. To compare savings from different customers with different DERs, we adopt the "annual savings ($) per kW DERs capacity" as our metric.

In the case study, we analyze customer savings from three types of DERs: PV, energy storage and demand response. Considering the savings from PV, most customers have roughly the same annual savings per KW under these three tariffs. A few types of customers with evening peaks have the highest savings under the kWh design. For energy storage, we developed a storage scheduling model that takes the demand forecast uncertainty into account. The savings under the kW design outweigh the other two tariffs for most customers. Under the kWh design tariff, savings for evening-peak customers tend to be less than savings under the other two tariffs. However, savings for afternoon-peak customers under the kW and kWh tariffs are about the same, and both are higher than the savings under the current tariff. We evaluate two types of demand response in the case study: event-based DR and load shape modification DR. The event-based DR dispatches about 20 times per year while the load shape modification DR dispatches every weekday. For most customers, no matter which type of DR is chosen, their savings under the two DER tariffs outweigh the corresponding savings under the current tariff. Overall, the kW and kWh tariffs generally give DERs more savings, compared with the current tariff.

From the perspective of the LSE, the impact of DERs is twofold: on the one hand, customers use DERs to help then save on their electricity bills, which translates into the LSE's lost revenues; on the other hand, the LSE's demand profile changes because of DERs, which helps the LSE reduce its costs of purchasing from the wholesale markets for energy, capacity and transmission. In the case study we aggregate the individual customers and analyze their system level impacts. Considering the impacts of PV, the LSE's lost revenues outweigh its reduced costs in energy, under all three tariffs. In capacity and transmission components, the LSE's lost revenues are less than its reduced costs. PV is not dispatchable, so designing DER tariffs cannot encourage customers to change their PV outputs. Speaking of energy storage, under the current tariff the LSE suffers losses in all three categories: energy, capacity and transmission. In contrast, under the two DER tariffs the LSE is neutral on energy and enjoys profits in capacity and transmission. Similar results can be found when we switch from storage to demand response: the LSE suffers losses in all three categories under the current tariff, but achieves savings in capacity and transmission categories under the two DER tariffs.

Overall, compared with the current tariff, both customers and the LSE can achieve higher savings/less losses under the two DER tariffs. The DER tariffs are thus better for both customers and the LSE.

In the two DER tariffs we developed, one tariff charges customers a $/kWh charge during each hour of every events, the other tariff charges customers a $/kW charge for the peak hourly demand of every event. To determine the rates of event-based charges, the LSE needs to determine the total annual event hours (kWh tariff) or the total number of events (kW tariff) a year ahead. Determining the number of events/event durations is an interesting research question. Too few events might not help the LSE effectively shave its peak demand. In addition, the price during events might become so volatile that it distorts customers' normal operation. On the other hand, too many events might require the customers to react very often. For customer with energy storage, more dispatch means more battery degradation costs. For demand response, too many events will affect customers' comfort levels. Keeping the cost recovery ratio fixed, increasing the number of events (total hours) also means reducing the $/kWh and $/kW rates. The decrease in event-based rates discourages customers from dispatching their DERs.

In the case study, we analyze the financial impacts of DERs on a single LSE. This methods of tariff determination and analysis of financial impacts on customers and the LSEs can also be applied to other test cases.

4.7 CONCLUSION

This research focuses on designing novel DER tariffs for commercial and industrial customers. Currently most tariffs for C&I customers are binomial with a time-of-use $/kWh energy charge and a $/kW demand charge based on customer's monthly peak demand. The study described in the previous chapters showed that DERs help customers save more on capacity and transmission charges, than their contributions to the LSE in reducing its payments for capacity and transmission. To address this issue, we design two DER tariffs with dynamic energy charges and a mixture of event-based and monthly peak demand charges. The proposed tariffs transmits the system level demand conditions to end-use customers.

Case studies on customer savings and LSE impacts are conducted. We analyze three cases in which customers install PV, storage and demand response separately. Comparing the current tariffs with two DER tariffs, we find that customers achieve higher levels of savings in capacity and transmission components under DER tariffs. In addition, the LSE reduces more costs than its lost revenues under the DER tariffs, providing the LSE financial incentives to switch to DER tariffs from the current tariff.

Future research could focus on customizing the DER tariffs for different DERs. For example, since PV are non-dispatchable, designing a tariff specific for PV might better reflect the impacts of PV on the LSE and system level participants. Another interesting research direction is the distribution charge component. Due to lack of available data, this research does not investigate the design of the distribution charge component. However, notifying end-use customers about the distribution system conditions through tariffs could also boost DERs savings and at the same time reduce or defer distribution system investment and upgrade costs.

Chapter 5. OPTIMAL SCHEDULING OF ENERGY STORAGE UNDER FORECAST UNCERTAINTIES

5.1 BACKGROUND

The last two studies focus on the analysis of tariff based methods. In this chapter, we will switch our research on avoided-cost based methods. In this study, we stand from the perspective of load serving entity which owns DERs and directly interacts with wholesale level parties. The allocation of benefits becomes trivial since the DERs can be directly rewarded from wholesale markets/services. This study aims to maximize the total benefits harnessed from multiple streams of benefits.

Energy storage is attracting considerable interest as an enabling technology for integrating variable renewable generation into the grid, addressing grid reliability challenges, and increasing the utilization of the existing infrastructure. The declining cost of battery energy storage systems makes them an increasingly attractive option for these purposes. Some analysts and vendors project that the costs of battery systems will drop to approximately $350/kWh by 2020[100].

Swierczynski et al.[101] choose the suitable energy storage technology to integrate with wind power and provide frequency regulation service. In this work, the revenue from frequency regulation only accounts for part of the total revenue. Part of the storage capacity is allocated for energy arbitrage, peak shaving and deviation minimization purposes.

Peak shaving provides another stream of benefit. Many papers have covered scheduling of energy storage to shave customers' peak demands. Alam et al.[102] provide a method to utilize electric vehicle battery to shave peak demands of household level customers. Wang et al.[103] provide novel photovoltaic and load forecasting algorithms and dispatch energy storage to minimize customer energy and demand charges based on the forecasts. Distribution network load forecasts are more accurate than household customer load forecasts. With less uncertainty, energy storage peak shaving performance for distribution network's aggregated loads could be better than for individual customers. In addition, since customers pay their demand charge based on monthly peak load, scheduling energy storage to shave the peak load over the entire month is difficult. On the other hand, LSEs settle their peak demand charge daily, which shortens peak shaving horizon to just one day.

The bulk of an LSE's energy purchases are in the day-ahead energy market. LSEs forecast hourly customer loads and submit the forecasts as load bids in the day-ahead market. The difference between the actual loads and the quantity acquired on the day ahead is settled in the real-time energy market. Since the real-time energy market is highly volatile, a risk averse LSE would prefer that its actual loads be as close to the day-ahead bids as possible. However, renewable portfolio standards (RPS) have been widely adopted[104]. The increasing penetration of intermittent renewable energy may pose challenges with respect to the adequacy of ancillary services. Considerable penetration of renewable resources may require additional ancillary service resources whose costs are eventually passed to the LSE. To reduce reserve capacity requirements, references[51] and[52] develop risk-limited energy storage dispatch models that facilitate power balancing. In summary, the LSE has good economic reasons to reduce the deviations between its actual load and its day-ahead bids. Perez et al.[105] schedule energy storage to coordinate with photovoltaic that manage the power deviations with regard to the commitments made in the daily and intraday electricity markets, with the objective of reducing economic penalties. We also consider other benefits in order to maximize the total storage revenue. The multiple streams of benefits result in different dispatch strategies and more revenues.

We assume that the LSE owns a three-phase distributed energy storage system connected to a node in one of its distribution networks. Roberts and Sandberg[106] provides some characteristics of distributed energy storage including common energy and capacity ratings. We further assume that the network has a substantial photovoltaic (PV) penetration and propose an optimal energy storage scheduling method that takes into account simultaneously energy arbitrage, regulation service, peak shaving and forecast deviation minimization benefits. By combining these benefits, the energy storage produces higher total revenues. The strategy developed in this study provides a short-term optimal schedule that spans 24 hours and repeats on a daily basis.

The main contribution of this chapter is optimally segment energy storage capacity day-ahead for regulation and other benefits to maximize the total revenue. Case studies suggests the regulation services account for about half of the revenue. Peak shaving and deviation minimization account for the other half of benefits. Energy-arbitrage benefit is negligible compared with the other three streams of benefits.

5.2 FORMULATION

PV generation in the distribution network reduces the amount of energy that LSEs have to purchase in the day-ahead market. However, day-ahead solar forecasts can easily have mean absolute percentage errors of 15%-20% or even higher, especially during cloudy or rainy days. Since shorter forecast horizons have a significantly better accuracy, we design a two-stage scheduling formulation for optimal storage schedule. This formulation consists of a day-ahead optimization and a series of real-time optimizations. The day-ahead optimization determines the hourly bids schedule for the day-ahead energy market and creates preliminary storage dispatch schedules, which are updated by the hourly (or real-time) optimizations based on more accurate forecasts, as illustrated on Figure 5-1.

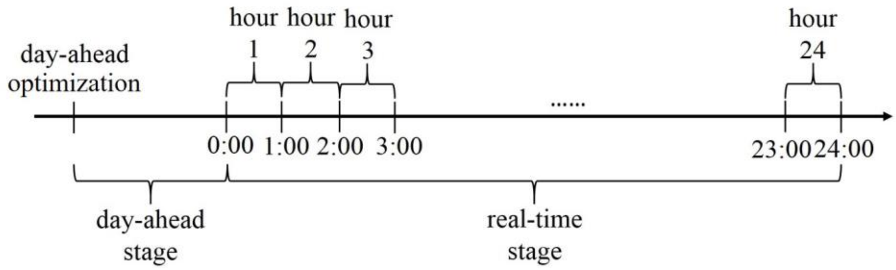

Figure 5-1: Timeline of the proposed two-stage optimization

Next, we present a day-ahead stage problem formulation without frequency regulation and another that takes the provision of frequency regulation services into account. We then present the formulation of the problem to be solved at the real-time stage.

5.2.1 *Day-ahead model without frequency regulation*

The LSE submits its hourly aggregated load bids D_f^t to the day-ahead energy market. For each hour *t*, the aggregated load combines all nodal loads with the outputs of photovoltaic generation and the inputs or outputs of energy storage. Ideally storage should contribute to minimizing the deviation between LSE's actual load and its day-ahead bid. Since forecasts of prices, loads and PV generation are not perfectly accurate, we capture the forecast uncertainties by introducing S_1 scenarios of prices, loads and solar generation to represent the set of possible realizations.

For the first formulation, the objective function of the day-ahead stage problem is:

$$\min: \sum_{s=1}^{S_1} \rho^s \begin{bmatrix} \sum_{t=1}^{24} \pi_{DA}^{s,t} D^{s,t} + \pi_d D_{\max}^s \\ + \pi_{dev} \sum_{t=1}^{24} \left| D^{s,t} - D_f^t \right| \end{bmatrix} \tag{5.1}$$

The first term in objective function is the energy charge, the second term is the demand charge and the third term is the penalty cost for deviations. The objective function is the weighted average over S_1 scenarios. ρ^s is the probability of scenario *s*. $\pi_{DA}^{s,t}$ is the day-ahead energy price of scenario

s at hour t. π_d is the unit price of the demand charge, which combines the charges for generation capacity and transmission services. π_{dev} is the price of deviation, which is based on the difference between the load $D^{s,t}$ and its day-ahead bids D_f^t . $D^{s,t}$ is the net aggregated load of scenario s at hour t. D_f^t is the LSE's day-ahead energy bid at hour t. $D_{\max}^s$ is the daily peak load of scenario s.

$$D_{\max}^s = \max(D^{s,1}, D^{s,2} ..., D^{s,24}) \ s \in S_1 \tag{5.2}$$

Constraints (5.3) and (5.4) are the power flow balance equations for nodes without energy storage and the nodes where energy storage is located, respectively.

$$\sum_{i:i->j} \Lambda_{ij}^{s,t} + I_j^{s,t} = \sum_{j:j->k} \Lambda_{jk}^{s,t} \ j \notin ESS, s \in S_1, t \in T \tag{5.3}$$

$$\sum_{i:i->j} \Lambda_{ij}^{s,t} + I_j^{s,t} - P_{chg}^{s,t} + P_{dsg}^{s,t} = \sum_{j:j->k} \Lambda_{jk}^{s,t} \ j \in ESS, s \in S_1, t \in T \tag{5.4}$$

$\Lambda_{ij}^{s,t}$ is the three-phase complex power flowing from node i to j, if i and j are connected. $I_j^{s,t}$ is the nodal injection at node j. This injection includes the demand and the PV generation at that node.

$$v_j^{s,t} = v_i^{s,t} - S_{ij}^{s,t} z_{ij}^H - z_{ij} (S_{ij}^{s,t})^H \ \ s \in S_1, t \in T \tag{5.5}$$

$$v^{\min} \le diag(v_j^{s,t}) \le v^{\max} \ \ s \in S_1, t \in T \tag{5.6}$$

Equation (5.5) calculates the voltage drop across line i to j. Equation (5.6) sets upper and lower bounds on the nodal voltages. $v_j^{s,t}$ is a 3x1 complex vector of three phase voltages for scenario s at node j and hour t. $v_j^{s,t} = V_j^{s,t} (V_j^{s,t})^H$ is a 3x3 matrix. $S_{ij}^{s,t}$ is a 3x3 line power matrix approximation of the three-by-one single phase power $\Lambda_{ij}^{s,t}$, $S_{ij}^{s,t} = \Gamma diag(\Lambda_{ij}^{s,t})$ where Γ is a matrix of approximation parameters.

$$SOC^{s,t} = SOC^{s,t-1} + \eta^{chg} P_{chg}^{s,t} - P_{dsg}^{s,t} \ / \eta^{dsg} \ \ s \in S_1, t \in T \tag{5.7}$$

$$SOC^{\min} \le SOC^{s,t} \le SOC^{\max} \ \ s \in S_1, t \in T \tag{5.8}$$

$$0 \le u^{s,t} P_{chg}^{s,t} \le P^{\max} \ \ s \in S_1, t \in T \tag{5.9}$$

$$0 \le (1 - u^{s,t}) P_{dsg}^{s,t} \le P^{\max} \ \ s \in S_1, t \in T \tag{5.10}$$

$$SOC^{s,T} = SOC^{s,0} \ \ s \in S_1 \tag{5.11}$$

Equations (5.7) – (5.11) enforce the constraints on the energy storage. Equation (5.7) describes the evolution of the State of Charge (SoC) from hour *t-1* to *t*. η^{chg} and η^{dsg} are the charging and discharging efficiencies. $P_{chg}^{s,t}$ and $P_{dsg}^{s,t}$ are the charging and discharging powers. $u^{s,t}$ is a binary decision variable that prevents simultaneously charging and discharging. Equation (5.8) constrains the SoC during each interval and for each scenario to remain within the storage's lower and upper bounds. Equations (5.9) and (5.10) define the minimum and maximum charging/discharging powers. Equation (5.11) forces the SoC after the last interval to be equal to the SoC at the beginning of day.

$$D^{s,t} = \sum_{\Phi} real(\Lambda_{sub}^{s,t}) \ \ s \in S_1, t \in T \tag{5.12}$$

Equation (5.12) defines the net aggregated loads as the summation of three phase real power at the substation node. The net aggregated load combines the nodal loads, the photovoltaic generation and the energy storage outputs across the network, downstream from the substation.

The day-ahead stage optimization determines the hourly aggregated power bids D_f^t . At the real-time stage, energy storage is dispatched to minimize the deviation between the realized net aggregated demand and its corresponding day-ahead bid D_f^t . Although the demand charge and deviation charge are settled at the real-time stage, they are still included in the day-ahead model, because ignoring them distorts the hourly energy bids, which in turn affects the real-time optimizations.

5.2.2 *Day-ahead model without frequency regulation*

The above formulation considers energy arbitrage, peak shaving and deviation minimization benefits. In this section we integrate frequency regulation benefit into the day-ahead model. To comply with the regulation market structure, the LSE needs to decide its hourly bidding capacity (in kW or MW) on the day ahead. The next day, the capacity settled in the regulation market follows the dispatch signal sent by the ISO. The remaining battery capacity is dispatched for other benefits.

To take the regulation benefit into account at the day-head stage, the LSE must determine the hourly energy storage capacities that it bids into the regulation market for the next day. Thus, the day-ahead stage objective function is modified as follows:

$$\min \sum_{s=1}^{S_1} \rho^s \begin{bmatrix} \sum_{t=1}^{24} \pi_{DA}^{s,t} D^{s,t} + \pi_d D_{\max}^s \\ +\pi_{dev} \sum_{t=1}^{24} \left| D^{s,t} - D_f^t \right| - \sum_{t=1}^{T} \pi_{reg}^{s,t} C_{reg}^t \end{bmatrix} \tag{5.13}$$

The first three terms are similar to those in Equation (5.1): day-ahead energy market payments, demand payments and deviation payments. The last term represents the revenue from providing regulation service. $\pi_{reg,s}^t$ is the hourly price of regulation for scenario *s* at hour *t*. C_{reg}^t is the hourly storage capacity bid into the regulation market.

Equations (5.7), (5.9) and (5.10) must be modified because part of the storage capacity is reserved for the provision of regulation service. The rest equations are the same as in the previous model.

$$SOC^{s,t} = SOC^{s,t-1} + \eta^{chg} P_{chg}^{s,t} - P_{dsg}^{s,t} / \eta^{dsg} + R^{s,t} \mathrm{C}_{reg}^{t} \;\; s \in S_1, t \in T \tag{5.14}$$

$$0 \le u^{s,t} P_{chg}^{s,t} \le P^{\max} - C_{reg}^{t} \;\; s \in S_1, t \in T \tag{5.15}$$

$$0 \le (1-u^{s,t}) P_{dsg}^{s,t} \le P^{\max} - C_{reg}^{t} \;\; s \in S_1, t \in T \tag{5.16}$$

Equation (5.14) adds an additional term that represents the impact of providing regulation on the SoC. The parameter $R^{s,t}$ is the time integral over the 1-hour regulation signal divided by 1 hour. $R^{s,t}$ multiplied by regulation capacity C_{reg}^{t} reflects the impact of the regulation signal on the battery stage of charge. Since a portion of the energy storage capacity is reserved for regulation service, the available capacity for other services is reduced. Equations (5.15) and (5.16) limit the charging and discharging power to the total capacity minus the capacity reserved for regulation.

5.2.3 *Real-time stage*

At the real-time stage, the proposed approach applies model predictive control, for a series of receding horizon optimizations. An optimization is executed at each hour with updated forecasts ranging from current hour T_c to the 24th hour. Although every optimization provides energy storage trajectories from T_c to the end of the day, only the energy storage dispatch for the current hour is implemented. Storage dispatches for future hours are determined by subsequent optimizations. The objective of each real-time optimization is:

$$\min \sum_{s=1}^{S_2} \theta^s \begin{bmatrix} \pi_{RT}^{s,T_c} (D^{T_c} - D_f^{T_c}) + \pi_{dev} \left| D^{s,T_c} - D_f^{T_c} \right| \\ \sum_{t=T_c+1}^{24} \pi_{RT}^{s,t} (P_g^{s,t} - D_f^{t}) + \pi_{dev} \sum_{t=T_c+1}^{24} \left| D^{s,t} - D_f^{t} \right| \\ \pi_d \max\left(D_{\max}^{s,T_c}, D_{\max,\,future}^{s} \right) \end{bmatrix} \tag{5.17}$$

T_c represents the end of an hourly interval, e.g. $T_c = 5$ represents the interval from 4:00 am till 5:00 am. For every T_c, the first two terms in (5.17) are real-time energy charge and deviation charge for the current hour. For the current hour T_c, we determine the battery dispatch $P_{chg}^{T_c}$ and $P_{dsg}^{T_c}$. π_{RT}^{s,T_c} is the real-time energy price of scenario s at hour T_c.

The third, fourth and fifth terms represent the energy, demand and deviation charges from hour $T_c + 1$ to the last hour. To address forecast uncertainties, S_2 scenarios with probabilities θ_s are chosen for each real-time stage optimization to represent possible realizations of load and solar generation from hour T_c to the last hour. The expected demand charge in the objective function is calculated based on either the maximum realized load so far, $D_{\max}^{T_c}$ or the expected peak demands $D_{\max, future}^{T_c}$ of scenario *s*.

$$D_{\max}^{s,T_c} = \max(D^1, D^2 ... D^{s,T_c}) \tag{5.18}$$

$$D_{\max, future}^{s} = \max(D^{s,T_c+1}, .D^{s,T_c+2} .., D^{s,T}) \tag{5.19}$$

Real-time stage constraints are similar to the day-ahead stage constraints, but with some differences: 1) each optimization starts from the current hour T_c and extends until the 24th hour T, instead of the entire 24-hour period; 2) the S_2 scenarios are updated hourly and are thus different from previous real-time forecasts and day-ahead forecasts.

Each real-time optimization settles the hourly transaction in the real-time energy market for the current hour. The deviation charge for that hour is also calculated. After the last hour, the hourly real-time energy charges and the deviation charges are summed over all 24 hours and the demand charge is determined based on the actual peak demand.

5.3 CASE STUDY

After introducing the data used for this case study (i.e. network configurations, PV and ES ratings, energy and frequency regulation prices and PV forecasts), we illustrate the effectiveness of the proposed two-stage approach. We then compare the benefits that can be achieved with and without frequency regulation services.

5.3.1 *Data*

This case study is based on the IEEE 37 node distribution test feeder. Figure 5-2 shows the topology of this test feeder, the locations of the PV generation and of the energy storage system. An energy storage system of 50kW per phase (150kW total) is located at node 702, which is close to the substation. Energy/power ratios of 1h, 2h, 3h, 4h and 5h are compared. PV accounts for about 30 percent of the peak load. Table 5-1 lists the size of the PV installations at 13 nodes across the network.

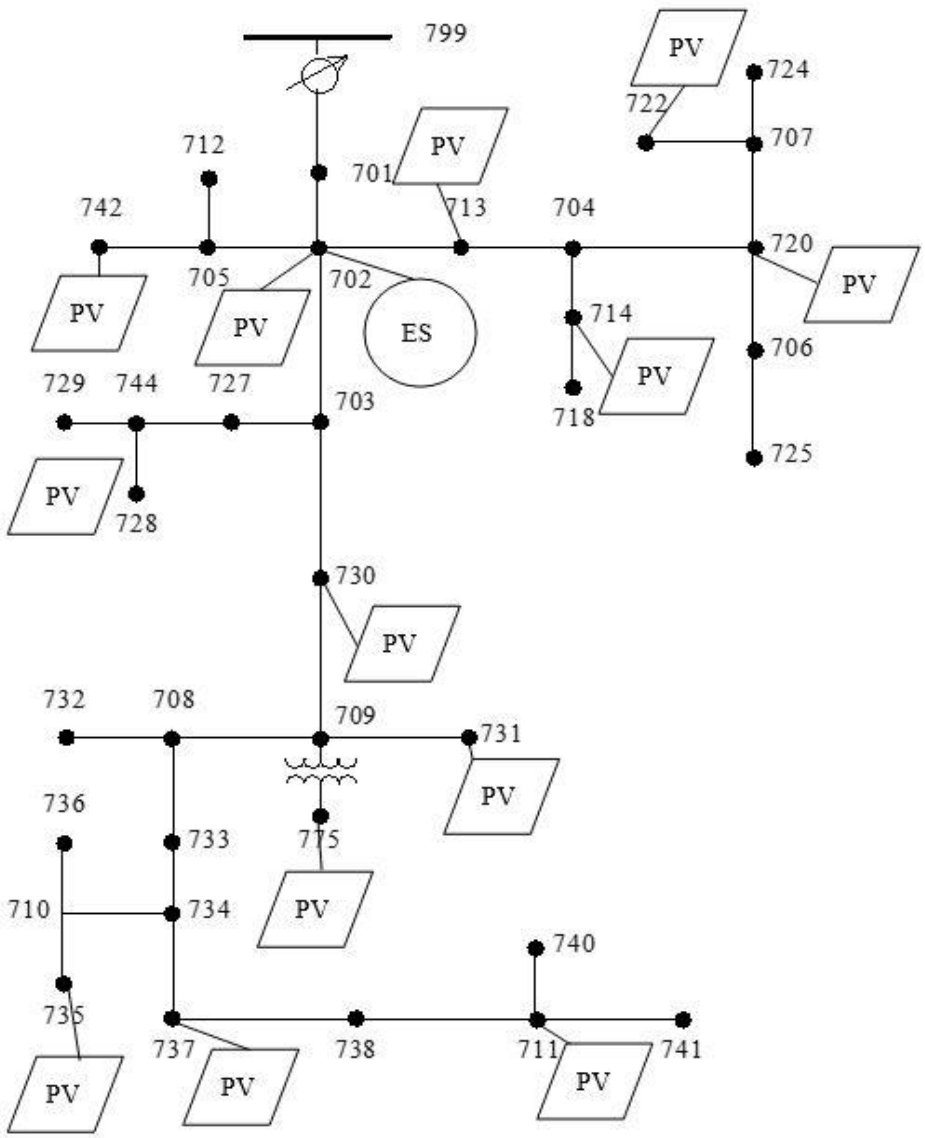

Figure 5-2: Topology of the distribution network and location of energy storage

Table 5-1: Some parameters for the two-stage model

DER Type	Node	Ratings (kW)		
		Phase A	Phase B	Phase C

PV	702	30	30	30
PV	711	0	0	50
PV	713	0	0	40
PV	714	20	0	0
PV	720	30	30	30
PV	722	0	10	10
PV	728	20	20	20
PV	730	20	20	20
PV	731	0	30	0
PV	733	30	30	0
PV	735	0	0	40
PV	737	50	0	0
PV	742	0	40	0
ES	702	50	50	50

The day-ahead and real-time price data are from PJM. Load forecast scenarios are generated from metered house-level load data extracted from the Pecan Street database[107]. Solar forecast scenarios are based on the one-minute resolution solar irradiance data is from NREL[108]. We adapt the ARIMA model in[109] to forecast locational marginal prices. The ARIMA model is selected for load forecasting, which yield comparable results as reference[11]. The Neural Network algorithm in[110] is picked up for photovoltaic power forecasting. We selected 122 days of data (June 1st to September 30th) for our case study. 20 day-ahead scenarios and 20 hourly-updated real-time scenarios of price, load and solar forecasts are conducted via the above-mentioned algorithms for each day based on historical data. The day-ahead forecast scenarios are statistically less accurate than the real-time forecast scenarios. Perturbations are included in the real-time solar irradiance realization to mimic unexpected solar irradiance variations. For example, the realized solar irradiance may suddenly drop to zero because of clouds moving in, which is not expected from solar forecasts made in previous hours. We also occasionally boost the real-time price to simulate the price spikes observed in our real-time locational marginal price data.

PJM publishes clearing prices for capacity markets, as well as rates for transmission services. The price of deviation is assumed to be a fixed rate of 0.05$/kWh.

122 rounds of simulations representing 122 days were performed to analyze how the streams of benefits are affected by various parameters. Each simulation consists of the following set of parameters: S_1 load and solar forecast scenarios at the day-ahead stage; 24 sets of real-time forecasts with horizons ranging from 24 hours to 1 hour, each set contains 20 scenarios. The S_2 scenarios of hour T_c resemble the forecast scenarios made at hour $T_c - 1$ with probabilistic perturbations to simulate sudden changes in solar irradiance and random noise added to represent forecast inaccuracies.

5.3.2 *The effectiveness of the two-stage model*

In this section, we consider the day-ahead formulation without regulation services. The wholesale day-ahead energy market requires the LSE to submit its hourly energy bid D_f^t , which we determine using our day-ahead formulation. Fig. 4.3 shows the hourly energy bids D_f^t , the solar outputs scenarios and the battery SoC trajectories under different scenarios for a typical day and a 3-hour battery energy/power ratio.

The hourly bids start to decrease from around 7 am when the solar power outputs begin to increase. In the afternoon the energy bids increase as solar irradiance declines. The daily peak demand arrives around 8 pm when the hourly bids reach their peak. The battery starts to charge around 5 am because of cheaper energy price. During the day time, the battery discharges to compensate for the drops in solar outputs. This ensures that the aggregated load follows the day-ahead bids and reduces the deviation costs. In the evening the battery discharges for peak shaving. Due to the uncertainties on the solar power forecast, it is difficult to determine the battery schedule on the day-ahead. This justifies the use of the additional real-time stage optimization.

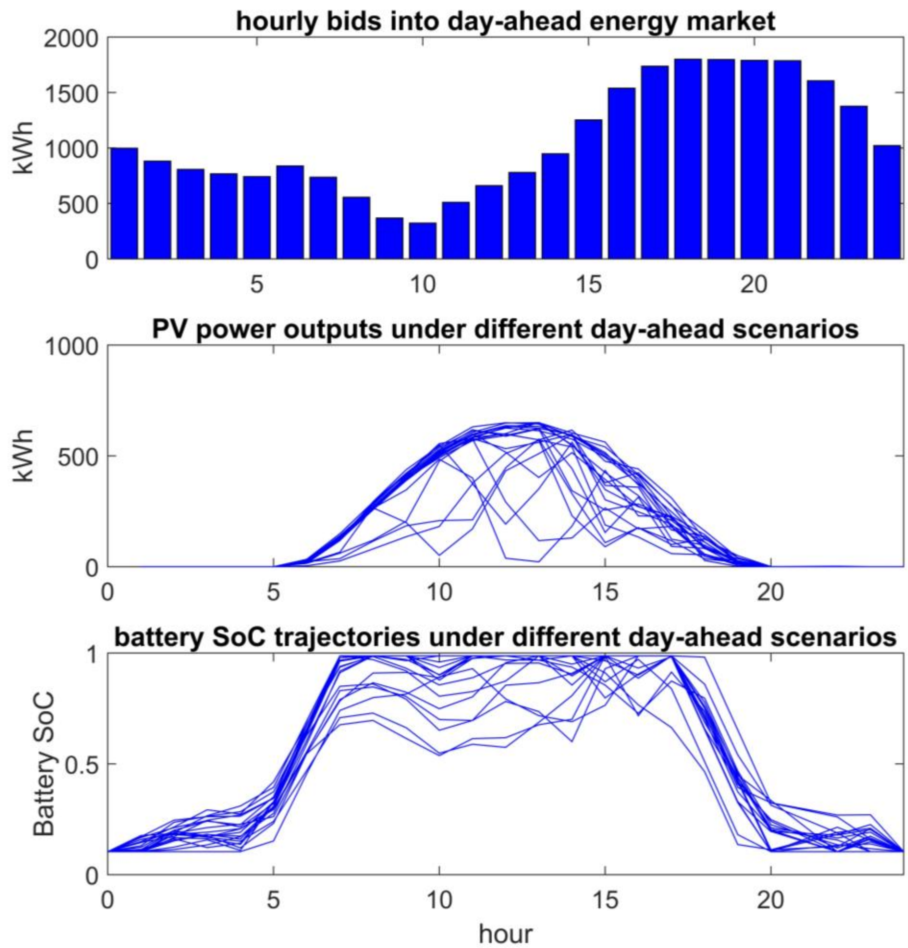

Figure 5-3: Hourly energy bids into the day-ahead energy market (top), solar outputs (middle) and battery SoC trajectories under different scenarios (bottom). Day No.45, 3-hour energy storage.

The real-time model utilizes the latest forecasts. Compared with earlier forecasts, these forecast are generally more accurate, which leads to increased savings from the use of energy storage. To quantify these savings, we consider the results from the day-ahead model and several real-time models. From each set of results that contains storage dispatch for S_1(S_2) scenarios, we pick the dispatch of the scenario with the highest probability. If we assume that the storage follows the most probable scenario dispatch, we can calculate the LSE's costs for energy, demand and deviation. For comparison, we calculate what these costs would be without energy storage. The differences between with the cases with storage and the reference case gives the storage benefits.

Table 5-2 lists these benefits by category. The columns RT 6h, RT 12h, RT 18h and RT 24h shows the storage benefits if the storage follows the dispatch results of the most probable scenario from the real-time optimization at 6h, 12h, 18h and 24h.

Table 5-2: Benefits ($) based on storage dispatch solutions of the most probable scenario

Benefit Category	DA	RT 6h	RT 12h	RT 18h	RT 24h
Energy Arbitrage	-0.34	1.56	1.34	3.65	4.54
Peak Shaving	35.00	36.76	36.34	49.40	52.36
Deviation	0.30	1.67	15.31	27.32	28.70
Total Benefit	34.96	39.98	52.99	80.37	85.60

Real-time storage schedules that utilize the latest forecast information achieve higher benefits compared with the earlier RT and DA schedules, especially in the deviation penalty category. The peak shaving benefit also increases with later demand forecasts. The results suggest that by adapting the two-stage model and making dispatch decisions every hour, the storage can achieve more benefits.

5.3.3 *Excluding regulation benefit*

In this section, we adapt the day-ahead model that excludes frequency regulation benefit. Different from the last section, we conduct simulations on all 122 days and 5 sizes of batteries. After each simulation, the cost of the reference case and the cost with the two-stage optimization for each of the energy storage sizes (1h, 2h, 3h, 4h and 5h) are recorded. The differences in cost between these 5 energy storage cases and the reference case are the benefits of energy storage.

Figure 5-4 is a box plot of the daily benefits distribution. The red line in the middle of each box is the median, the edges of the box indicate the 25th and 75th percentiles, and the whiskers extend to the 5th and 95th percentiles while the outliers are captured by plus marks. Figure 5-4 suggests that most of simulations result in significant positive benefits. However, the benefits are occasionally negative because sudden changes in demand and solar generation cause the daily peak to occur at an unexpected hour when energy storage is dispatched to charge. Instead of being shaved, the peak is then increased, leading to a higher demand charge, which outweighs the savings from energy arbitrage and deviation minimization.

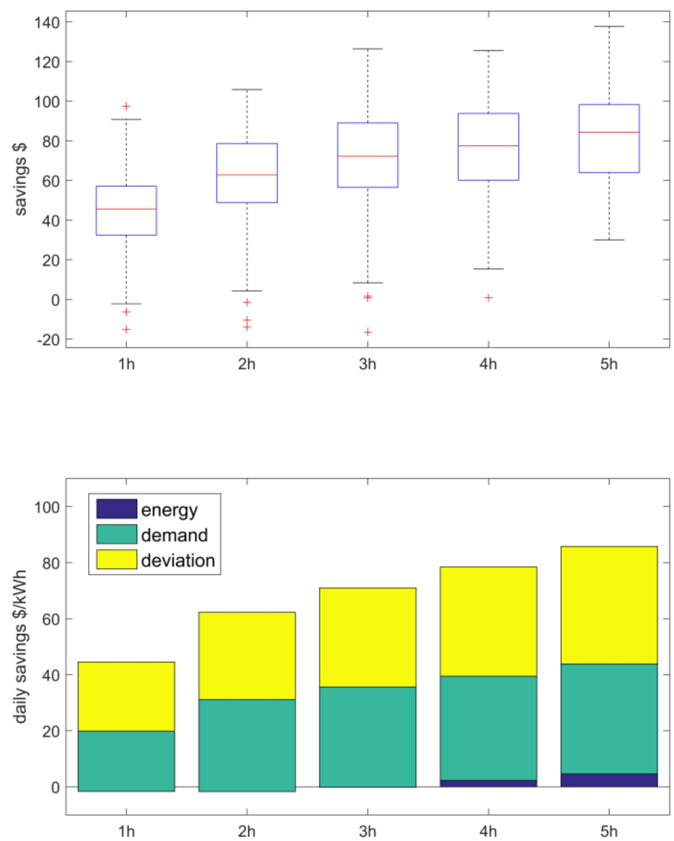

Figure 5-4: Top: energy storage daily benefits under five different energy ratings; Bottom: breakdown of average daily savings according to categories energy

Under the two-stage model the average total benefits gradually increase from $45 per day for a 1-hour energy storage to more than $80 per day for a 5-hour energy storage. Most of the benefits come from reduced demand and forecast-deviation charges. The energy storage is dispatched primarily for peak shaving and deviation minimization because these two are more lucrative than energy arbitrage. Since the demand and deviation benefits are more closely related to the capacity rating than the energy rating, these two benefits saturate for batteries with energy ratings greater than 2-hours.

5.3.4 *Including regulation benefit*

In this case, the LSE dispatches the energy storage units according to the model which considers simultaneously the energy, demand, deviation and regulation benefits. The regulation signal data is extracted with a 2-second resolution from PJM data. The 2-second signals are integrated to 1-hour the parameters $R^{s,t}$ which represent the impact of providing regulation on the battery SoC. The format of regulation forecasts is similar to load and solar forecasts: S_1 scenarios for the day-ahead and S_2 scenarios for each hour of the real-time stage.

The day-ahead model determines not only the hourly energy bids D_f^t , but also the hourly capacity allocated for regulation. As an example, let us consider storage with a 3-hour energy rating and one trial among the 122 rounds of simulations.

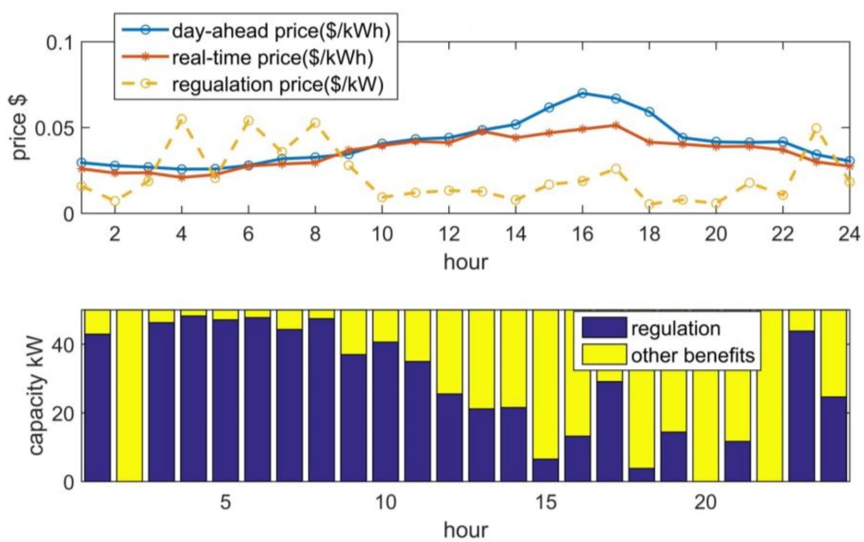

Figure 5-5: Top: the price data; Bottom: allocation of energy storage capacity plot. Day No.45, 3-hour energy storage

Figure 5-5 shows the day-ahead, real-time energy prices and frequency regulation prices for that specific day on the top subplot. The bottom subplot shows the allocation of storage capacity. The dark-colored bars indicate the capacity allocated for regulation, while the light-colored bars are capacities assigned for other benefits. From hour 12 to hour 22, most of the capacity is allocated for other benefits. During the rest of day more capacity is allocated for regulation benefits. Hour 2 is an exception where it is optimal to charge the energy storage for future discharge needs.

For the 3-hour energy rating storage, Figure 5-6 shows the average hourly savings from peak reduction, deviation minimization and regulation over 122 days. From around hour 22 to hour 10 in the next day, many businesses are not active and the solar irradiance is rather low, which makes forecasts of load and solar more accurate. These accurate forecasts result in less uncertainty and thus less forecast deviation benefits. The locational marginal prices are relatively flat which makes energy arbitrage less profitable. Based on the above analysis, the day-ahead optimization decides that for this period of day, most of the capacity should bid into the frequency regulation market, which is more lucrative.

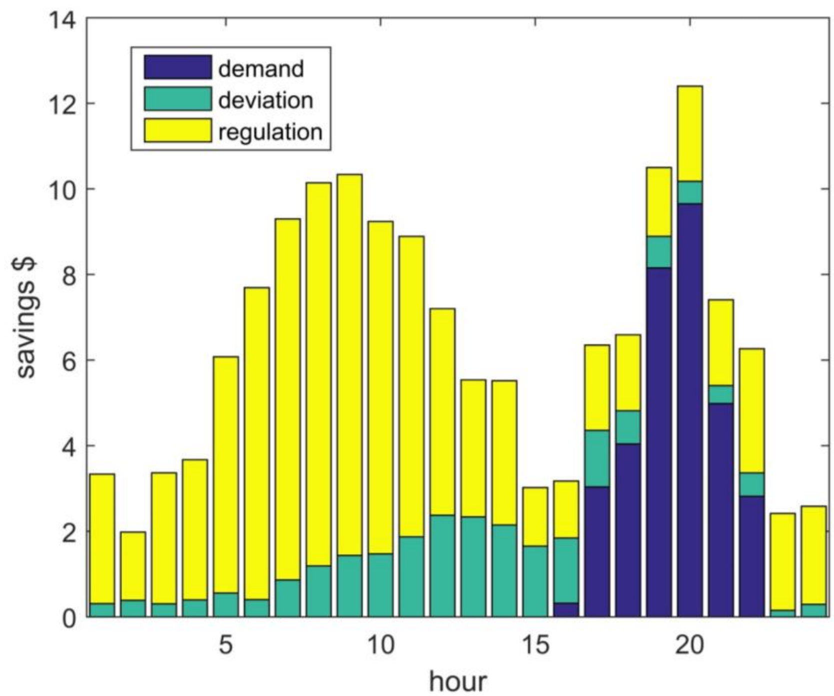

Figure 5-6: Average hourly savings of 3-hour energy storage

Summer peak demands usually occur during the late afternoon or early evening. Storage can provide peak shaving benefits by discharging for just a few hours when the daily peak load is likely to happen. During the rest of the day, the dispatch of energy storage has no impact over the daily peak demand. Thus, the demand reduction benefits are significant during hours 16 to 22. While deviations originate from both load and solar forecast errors, the larger part of these deviations is caused by the less accurate solar generation forecasts. Since PV forecasts errors are significant only during daylight hours, there is a greater potential for energy storage to minimize deviations during that time. The timing of demand and deviation benefits, together with the decrease in regulation prices from hours 10 to 22 result in less capacity reserved for regulation service. However, during the morning and late evening hours, more capacity is assigned for regulation due to increased regulation prices, reduced need for peak shaving and low forecast-deviation.

Figure 5-7 compares the average benefits over the 122 simulations, with (right) and without (left) regulation benefit. The total benefits with regulation are much higher than if regulation is excluded. Regulation accounts more than half of the total benefits for every energy storage size. Since the price of regulation is more closely linked to the capacity rating than to the energy rating, the latter has little impact on the regulation benefit. Although much of the energy storage capacity is reserved to provide regulation, the remaining capacity achieves comparable level of benefits through peak shaving and deviation minimization. The energy arbitrage benefits are almost negligible whether regulation is included or not.

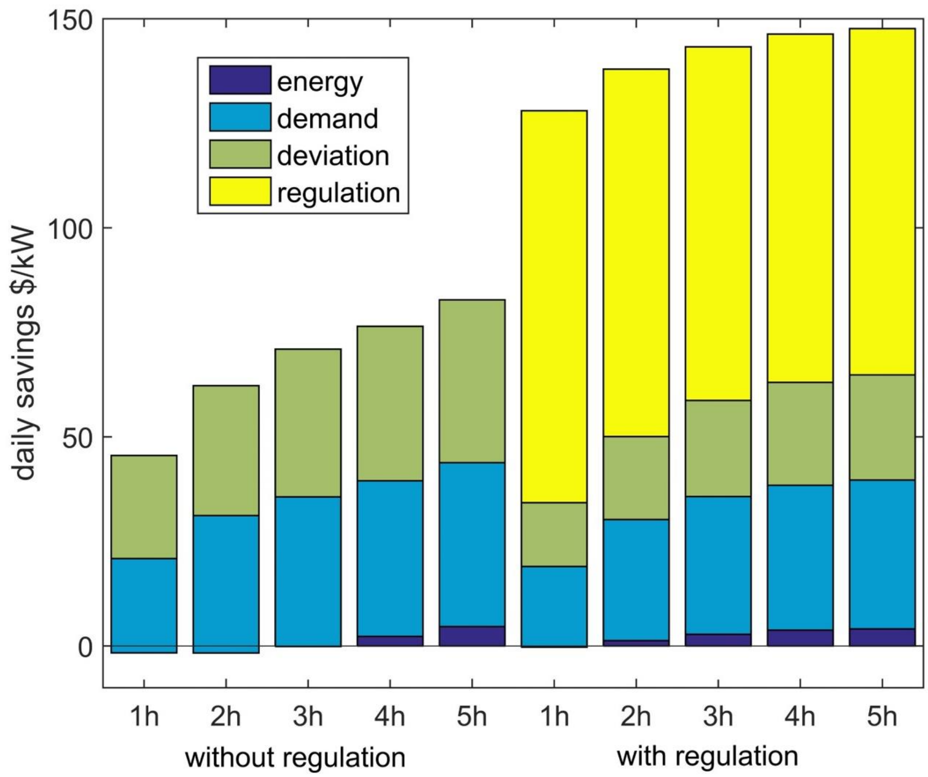

Figure 5-7: Average total benefits with and without regulation as a function of the energy rating of the energy storage

5.4 Conclusion

A two-stage, look-ahead optimization model is developed for daily scheduling of energy storage in a distribution network with a substantial photovoltaic penetration. The objective is to schedule energy storage to maximize the sum of multiple benefits: energy arbitrage, peak shaving, deviation minimization and frequency regulation.

With substantial photovoltaic penetration, the accuracy of solar irradiance forecast is a key factor. Day-ahead solar forecasts often yield inaccurate results but these results can be improved when real-time forecasts are updated throughout the day. The proposed two-stage model takes advantage of these updated forecasts by making a preliminary schedule at the day-ahead stage, then updating the schedule using a series of look-ahead optimizations with receding horizons at the real-time stage.

Regulation provides a significant benefit stream. The fast ramping capabilities of energy storage makes it ideal for providing regulation service. Results from the case study suggest that more than half of the total benefits come from regulation. Although a certain portion of hourly capacity is reserved for regulation, the remainder can still be dispatched to achieve peak-shaving and deviation minimization, which combined, provide benefits comparable to those achieved when the entire capacity is dedicated to non-regulation benefits.

Chapter 6. TWO-STAGE OPTIMAL SCHEDULING FOR AGGREGATORS OF BATTERIES OWNED BY COMMERCIAL CONSUMERS

6.1 INTRODUCTION

Case studies from the last chapter suggests that revenues from providing frequency regulation account for the majority share of battery's total revenue. However, the model has only one battery. In this chapter, we would like to propose an aggregator model that coordinates multiple batteries to provide frequency regulation service. In addition, the owners of the batteries are end-use consumers rather than the LSE. Thus, the aggregator considers both consumer level benefits as well as frequency regulation benefits. The aggregator model combines the tariff based methods with avoided cost based methods.

From a system perspective, storage facilitates the integration of variable renewable generation into the grid, helps address grid reliability challenges, and increases the utilization of the existing infrastructure[124]. From the perspective of individual participants in the electricity market place, storage can also provide several streams of monetary benefits. In this study, we consider batteries installed by end-use commercial consumers who are subject to typical commercial consumer tariffs that include $/kWh energy charges and $/kW demand charges. Storage can help these consumers reduce their electricity bills through energy arbitrage (i.e. charging the battery when the energy rate is lower and discharging it when this rate is higher), and through reducing demand charge by discharging the battery to shave the peak load. Besides these activities aimed at cost reduction, batteries could also be used to generate revenue by providing system services, such as frequency regulation. However, because batteries owned by individual consumers are likely to be too small to participate directly in the provision of frequency regulation services, their dispatches need to be coordinated by an aggregator.

The role of this aggregator is to maximize the sum of the benefits that consumers achieve from energy arbitrage, peak shaving and from the provision of frequency regulation. Figure 6-1 shows how this aggregator serves as an intermediary between the consumers, their load serving entity (LSE) and the independent system operator (ISO) running the frequency regulation market.

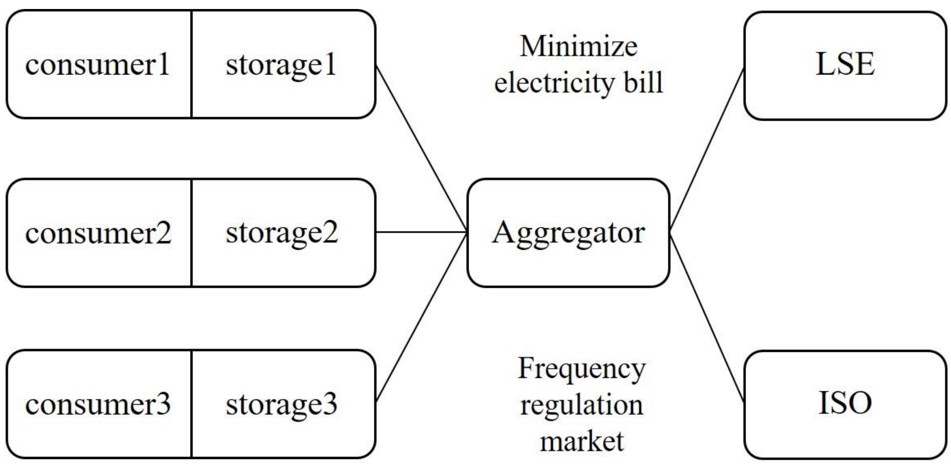

Figure 6-1: Interfaces between the consumers, the aggregator and the retail and frequency regulation markets

The contributions of this chapter can be summarized as follows:

- It proposes a method that enables the aggregator to maximize the benefits that consumer-owned batteries can achieve at the retail level and from participation in the system level frequency regulation market
- The model formulation adapts a two-stage approach. On the day-ahead, the aggregator determines energy consumption trajectories that minimize energy and demand charges, and the

spare battery capacity that can be bid into the frequency regulation market. In real-time, it dispatches the batteries to provide regulation while striving to follow the optimal trajectories.

- The formulation ensures that the real-time stage model can be solved sufficiently fast, even under cases that the aggregator coordinates a lot of consumer-owned batteries.

6.2 LITERATURE REVIEW

Several papers propose methods for dispatching batteries to maximize consumer benefits, such as energy arbitrage under either time-of-use pricing or real-time pricing. Van de Ven et al.[125] propose an optimal threshold-structured control policy for consumer-owned energy storage under dynamic pricing. The model is formulated as a Markov decision process, hence addressing the stochastic nature of demand and prices. Grillo et al.[126] present a method based on Markov decision processes that optimally schedules energy storage devices in power distribution networks with renewable generation. Erseghe et al.[127] investigate the use of energy storage units to reduce the average cost of supplying power. These authors apply dynamic programming to develop an optimal control policy for a single battery. They also propose a simple method to extend the optimal solution from a single battery to multiple batteries. Harsha and Dahleh[128] propose a dynamic programming approach to minimize the long-run cost of electricity and the cost of investing in energy storage. Tan et al.[129] study the optimal operation of a distributed battery energy storage system for energy arbitrage under dynamic pricing and propose a constrained stochastic shortest path model to balance the energy arbitrage benefits and the battery degradation cost.

Peak shaving provides another stream of benefit. Levron and Doron[130] describe an optimal peak shaving strategy and derive an analytic design method for attaining optimal peak shaving. Oudalov et al.[131] propose an energy storage sizing methodology that maximizes a consumer's economic benefit by reducing the power demand payments. Alam et al.[132] show how an electric vehicle battery could be used to shave the peak demand of residential consumers. Wang et al.[133] provide novel photovoltaic and load forecasting algorithms and dispatch energy storage to minimize consumer energy and demand charges based on these forecasts.

Several papers consider aggregators that dispatch the batteries of electric vehicles to provide regulation services. For example, Vagropoulos and Bakirtzis[134] develop an optimal bidding strategy for an electric vehicle aggregator participating in day-ahead energy and regulation markets. They also consider price deviations and statistical characteristics of regulation signals in their stochastic optimization. In[135], Vagropoulos et al. extend[134] to develop a framework for real-time charging management that the aggregator should use to meet day-ahead targets. Each vehicle is assigned a weight based on its SoC and departure time. Vehicles with lower weights have higher priorities to charge and provide regulation service. Vaya and Andersson[136] study the optimal bidding strategy of an electric vehicle aggregator in a day-ahead electricity markets and discuss the impact of such an aggregator on market clearing. These authors formulate a bi-level problem where the upper level problem minimizes the charging cost of the aggregator and the lower level clears the market. Donadee and Ilic[137] investigate the application of stochastic dynamic programming to determine the charging powers and frequency regulation capacities of electric vehicles. Their study accounts for Markov random prices and Markov random regulation signals.

6.3 Problem Formulation

We address this problem by dividing it into a day-ahead stage and a real-time stage. The day-ahead stage involves a hybrid of stochastic and robust optimizations to maximize the expected revenue for the next day. The values of the decision variables on the day-ahead become key inputs for the real-time stage. This real-time stage involves two steps: a rule-based preprocessor and a snapshot optimization. At both stages, we assume that the aggregator is a price taker and that its decisions do not affect the market clearing price.

6.3.1 *Day-ahead stage*

At the day-ahead stage, the objective of the aggregator is to minimize the sum of several quantities:

1) The consumers' payments for energy and demand charges

2) Minus the expected revenue from providing frequency regulation services

3) The cost of purchasing regulation capacity from alternative sources if the aggregator cannot meet its obligations using the batteries that it controls

4) The battery degradation costs.

To this end, the aggregator gathers demand profile forecasts, electricity tariffs and battery characteristics from the consumers and uses scenarios to represent the uncertainty on regulation market clearing prices and demand profiles. This optimization is carried out with a granularity of 15 minutes and a horizon of 24 hours, i.e. 96 time steps. In this study, the aggregator chooses to follow the dynamic regulation signal. This regulation signal is assumed to be energy neutral over a 15-minute time interval. Since customer's demand is also metered over 15-minute intervals, providing regulation should not impact the metered demand of the consumers nor the SoC of the batteries. The decision variables of this optimization problem include the hourly regulation capacity bids B_{agg}^{h}, the target energy level for each battery during each period $E_{tar}^{i,t}$ and the peak demand target for each consumer $D_{\max}^{i}$.

Mathematically, the objective is expressed as follows:

$$
\begin{aligned}
&Min: \ \frac{15\min}{1\text{h}} \sum_{\omega \in W} \theta^{\omega} \sum_{i \in I} \sum_{t \in T} \pi_e^{i,t} (P_{chg}^{i,\omega,t} - P_{dsg}^{i,\omega,t}) \\
&+ \sum_i \pi_d^i D_{\max}^i \\
&- \sum_{\omega \in W} \theta^{\omega} \sum_{h \in H} \lambda_r^{\omega,h} B_{agg}^h \\
&+ \frac{15\min}{1\text{h}} \sum_{\omega \in W} \theta^{\omega} \sum_{t \in T} \lambda_{pen}^{\omega,h} B_{alt}^{\omega,t} \\
&+ \sum_{\omega \in W} \theta^{\omega} \sum_i C_{cycle}^{i,\omega}
\end{aligned} \tag{6.1}
$$

where W is the set of scenarios, I is the set of consumers, T is the set of 15-minute time intervals, H is the set of 24 hours and θ^{ω} is the probability of scenario ω. The first term of this objective function is the sum of the energy payments over all consumers, where $\pi_e^{i,t}$ is the energy rate of consumer i's tariff, $P_{chg}^{i,\omega,t}$ and $P_{dsg}^{i,\omega,t}$ are the charging and discharging rates of the battery of consumer i for scenario ω during interval t. The second term is the sum of consumers' demand payments, where π_d^i is the demand rate of consumer i's tariff, and $D_{\max}^i$ is consumer i's peak demand target. The third term is the revenue from the provision of frequency regulation service, where $\lambda_r^{\omega,h}$ is the hourly regulation market clearing price under scenario ω, and B_{agg}^h describes the aggregator's regulation capacity bid for hour h. If the sum of the regulation capacities $B^{i,\omega,t}$ that can be obtained from the consumers' batteries is less than B_{agg}^h, the aggregator needs to buy regulation capacity from an alternative source $B_{alt}^{\omega,t}$. The fourth term therefore represents the cost of purchasing this regulation capacity, where $\lambda_{pen}^{\omega,h}$ is the price of regulation from the alternative source, which is set to be several times more expensive than market clearing price $\lambda_r^{\omega,h}$. The last term models the cost of battery degradation as a function of the cost of a daily charging/discharging cycle $C_{cycle}^{i,\omega}$, which is calculated as follows:

$$C_{cycle}^{i,\omega} = \frac{1}{\phi(DoD^{i,\omega})} C_B^i \ \ \forall i \in I, \omega \in \Omega \tag{6.2}$$

where C_B^i is the battery investment cost and $\phi(DoD^{i,\omega})$ is a function that calculates battery's cycle-life given a cycle's depth-of-discharge. $C_{cycle}^{i,\omega}$ can be modeled as a quadratic function on the depth-of-discharge variable $DoD^{i,\omega}$:

$$DoD^{i,\omega} = \frac{E_{hi}^{i,\omega} - E_{lo}^{i,\omega}}{E_{Cap}^i} \ \ \forall i \in I, \omega \in \Omega \tag{6.3}$$

$$E_{hi}^{i,\omega} \geq E^{i,\omega,t} \ \ \forall i \in I, t \in T, \omega \in \Omega \tag{6.4}$$

$$E_{lo}^{i,\omega} \leq E^{i,\omega,t} \ \ \forall i \in I, t \in T, \omega \in \Omega \tag{6.5}$$

where Eq. (6.3) defines the Depth of Discharge (DoD) of battery *i* under scenario ω, as the difference between the battery energy peak and the battery energy valley during the day, divided by the battery's energy rating. Equations (6.4) and (6.5) constrain the battery energy peak (resp. valley) to be greater (resp. less) or equal than the battery energy at any time interval. The degradation cost thus captures the largest cycle during daily operation. This term of the objective function makes the problem a quadratically constrained quadratic program.

This optimization is subject to a set of constraints.

1) The aggregator must ensure that, under each scenario ω and for every time interval *t*, the sum of the consumers' regulation capacities $B^{i,\omega,t}$ plus the regulation capacity from an alternative source $B_{alt}^{\omega,t}$ is greater or equal than the capacity that it bid into the market:

$$\sum_{i \in I} B^{i,\omega,t} + B_{alt}^{\omega,t} \geq B_{agg}^h \ \ \forall t \in h, \omega \in \Omega \tag{6.6}$$

where $B^{i,\omega,t}$ is the battery capacity reserved to provide frequency regulation.

2) The charging/discharging power and capacity reserved for regulation are positive:

$$P_{chg}^{i,\omega,t} \geq 0,\ P_{dsg}^{i,\omega,t} \geq 0,\ B^{i,\omega,t} \geq 0\ \forall i \in I, t \in T, \omega \in \Omega \tag{6.7}$$

3) For every battery, the sum of the capacity scheduled for charging or discharging and the capacity for provision of regulation service must be less than its power rating:

$$P_{chg}^{i,\omega,t} + B^{i,\omega,t} \leq P_{Cap}^{i}\ \ \forall i \in I, t \in T, \omega \in \Omega \tag{6.8}$$

$$P_{dsg}^{i,\omega,t} + B^{i,\omega,t} \leq P_{Cap}^{i}\ \ \forall i \in I, t \in T, \omega \in \Omega \tag{6.9}$$

4) Consumer i's peak demand target $D_{\max}^{i}$ is greater or equal than its grid power under any scenario for all time periods, where a consumer's grid power is defined as its consumption $\tilde{D}^{i,\omega,t}$ (unknown but bounded) plus charging power $P_{chg}^{i,\omega,t}$ minus discharging power $P_{dsg}^{i,\omega,t}$:

$$D_{\max}^{i} \geq \tilde{D}^{i,\omega,t} + P_{chg}^{i,\omega,t} - P_{dsg}^{i,\omega,t}\ \ \forall i \in I, t \in T, \omega \in \Omega \tag{6.10}$$

5) Assuming that the consumption $\tilde{D}^{i,\omega,t}$ can take any value between $[D_{f}^{i,\omega,t} - \Delta D_{f}^{i,\omega,t}, D_{f}^{i,\omega,t} + \Delta D_{f}^{i,\omega,t}]$, where $D_{f}^{i,\omega,t}$ is the consumption forecast of scenario ω and $\Delta D_{f}^{i,\omega,t}$ is the range of forecast error, we optimize the battery schedule against the worst case consumption profile.

$$D_{f}^{i,\omega,t} - \Delta D_{f}^{i,\omega,t} \leq \tilde{D}^{i,\omega,t} \leq D_{f}^{i,\omega,t} + \Delta D_{f}^{i,\omega,t} \tag{6.11}$$

6) In addition, the peak demand must be greater than the historical peak demand $D_{\max,hist}^{i}$, which is the maximum 15-minute interval demand since the beginning of the month till the present day.

$$D_{\max}^{i} \geq D_{\max,hist}^{i} \tag{6.12}$$

7) The evolution of the state of charge of the battery is:

$$E^{i,\omega,t} = E^{i,\omega,t-1} + \frac{15\min}{1\text{h}}(\eta_{chg}^{i} P_{chg}^{i,\omega,t} - P_{dsg}^{i,\omega,t} / \eta_{dsg}^{i})\ \ \forall i \in I, \omega \in \Omega, t \in T \tag{6.13}$$

where $E^{i,\omega,t}$ is the energy stored in the battery. The initial state of charge of the battery is:

$$E^{i,\omega,0} = E_{tar}^{i,0} = E_{\min}^{i} + \Delta E^{i} \;\; \forall i \in I, \omega \in \Omega \tag{6.14}$$

The day-ahead stage optimization determines the energy target trajectories $E_{tar}^{i,t}$. The scenarios represent the uncertainties of regulation price and consumer demand. To ensure that the stored energy $E^{i,\omega,t}$ under any scenario does not deviate too far from $E_{tar}^{i,t}$, we impose the following constraint:

$$E_{tar}^{i,t} - \Delta E^{i} \le E^{i,\omega,t} \le E_{tar}^{i,t} + \Delta E^{i} \;\; \forall i \in I, \omega \in \Omega, t \in T \tag{6.15}$$

where ΔE_i is the range of variation between $E^{i,\omega,t}$ and the target $E_{tar}^{i,t}$. In addition, the target trajectory of a battery $E_{tar}^{i,t}$ is constrained to ensure $E^{i,\omega,t}$ lies between the minimum and maximum energy ratings:

$$E_{\min}^{i} + \Delta E^{i} \le E_{tar}^{i,t} \le E_{\max}^{i} - \Delta E^{i} \;\; \forall i \in I, t \in T \tag{6.16}$$

Combining constraints (6.15) and (6.16), $E^{i,\omega,t}$ is bounded by the battery minimum and maximum energy ratings:

$$E_{\min}^{i} \le E^{i,\omega,t} \le E_{\max}^{i} \;\; \forall i \in I, \omega \in \Omega, t \in T \tag{6.17}$$

The difference of target trajectory between any two successive intervals $E_{tar}^{i,t}$ and $E_{tar}^{i,t+1}$ is bounded by the maximum charging and discharging powers:

$$E_{tar}^{i,t} - \frac{15\min}{1\text{h}} P_{\max}^{i} / \eta_{dsg}^{i} \le E_{tar}^{i,t+1} \le E_{tar}^{i,t} + \frac{15\min}{1\text{h}} \eta_{chg}^{i} P_{\max}^{i} \tag{6.18}$$

8) Finally, the aggregator needs to make sure that individual consumers are no worse off by participating in aggregation than they would be on their own. If a consumer utilizes its battery to minimize its own energy charge, demand charge and battery degradation cost and does not participate in regulation, its non-cooperative cost $\mathrm{C}^{i'}$ is:

$$Min: \; \mathrm{C}^{i'} = \frac{15\min}{1\mathrm{h}} \sum_{t} \pi_e^{i,t} (P_{chg}^{i,t} - P_{dsg}^{i,t}) + \pi_d^i D_{\max}^i + C_{cycle}^i \tag{6.19}$$

If this consumer decides to be aggregated and participate in frequency regulation, its share of the total cost is $C^{i,\omega}$:

$$\begin{aligned} \mathrm{C}^{i,\omega} &= \frac{15\min}{1\mathrm{h}} \sum_{t} \pi_e^{i,t} (P_{chg}^{i,\omega,t} - P_{dsg}^{i,\omega,t}) \\ &+ \pi_d^i D_{\max}^i \\ &- \sum_{h} \pi_r^{\omega,h} \frac{15\min}{1\mathrm{h}} \sum_{t \in h} B^{i,\omega,t} \\ &+ C_{cycle}^{i,\omega} \end{aligned} \tag{6.20}$$

To guarantee that this consumer is no worse off, its share of the cooperative cost should be no greater than its non-cooperative cost (which also means the benefit of cooperative is equal or greater than the benefit of on its own):

$$C^{i,\omega} \le C^{i'} \;\; \forall i \in I, \omega \in \Omega \tag{6.21}$$

6.3.2 *Real-time stage*

At the real-time stage, the aggregator carries out the following tasks:

1) It dispatches the batteries to satisfy its accepted regulation capacity bid B_{agg}^{h} and minimizes purchases from the alternative source $B_{alt}^{\omega,t}$.

2) It controls the charging/discharging of batteries to achieve no/minimal violations of the peak demand targets $D_{\max}^i$.

3) It makes sure that each battery follows its SoC trajectory $E_{tar}^{i,t}$ determined at the day-ahead stage as closely as possible, hence ensuring the battery can achieve its arbitrage and peak shaving goals.

The real-time stage involves two steps: 1) a rule-based pre-processing; 2) a real-time optimization. Both steps are executed every 15 minutes to determine the charging or discharging rates and the regulation capacity for the next 15-minute interval. To make sure the real-time model can be solved sufficiently fast, the horizon of model is just one single time-interval.

The aim of the rule-based preprocessing step is to prevent batteries from violating their minimum or maximum SoC constraints. The maximum and minimum SoCs are defined by equation (6.16), ensuring that the battery has enough energy to provide frequency regulation services for 15min, even under the most extreme regulation signals. If the SoC of a battery is higher than its upper bound, the aggregator forces the battery to discharge at maximum power. Conversely, if the SoC is less than the lower limit, the aggregator charges the battery at maximum power (or discharge at minimum power) without violating the peak demand target $D_{\max}^{i}$. Table 6-1 summarizes the rules used in this preprocessing step.

Table 6-1: Rule-based real-time preprocessor

(1): the energy is greater than $E^{i,t} > E_{\max}^{i} - \Delta E^{i}$
$P_{chg}^{i,t} = 0,\ P_{dsg}^{i,t} = P_{Cap}^{i},\ B^{i,t} = 0$
(2): the energy is less than $E^{i,t} > E_{\min}^{i} + \Delta E^{i}$
$if\ \ D_{f}^{i,t+1} \geq D_{i}^{\max} : P_{chg}^{i,t} = 0,$ $P_{dsg}^{i,t} = \min(P_{Cap}^{i}, D_{f}^{i,t+1} - D_{\max}^{i}),\ B^{i,t} = 0$ $else : P_{chg}^{i,t} = \min(P_{Cap}^{i}, D_{\max}^{i} - D^{i,t})$ $P_{dsg}^{i,t} = 0,\ B^{i,t} = 0$

The charging/discharging rates and regulation capacities of the batteries that are not affected by the preprocessing is determined by the real-time optimization, which considers only the next 15-minute interval and whose objective is:

$$\min : \sum_{i} \lambda_{dev} \left| \frac{E^{i,t+1} - E_{tar}^{i,t+1}}{E_{Cap}^{i}} \right|_{2}^{2} + \lambda_{pen}^{h} B_{alt}^{t} + \sum_{i} \pi_{d}^{i} \xi^{i} \tag{6.22}$$

Using λ_{dev} as a penalty factor, the first term penalizes batteries if their stored energy $E^{i,t+1}$ at the end of this 15-minute time window would deviate from the target $E_{tar}^{i,t+1}$. The second term is the cost of alternative regulation source. The third term is the cost of peak demand violation. ξ^i is a slack variable that describes violations of the peak demand. If the consumer's metered demand at the next interval does not exceed $D_{\max}^i$, ξ^i is zero. When the demand exceeds the peak demand target $D_{\max}^i$, ξ^i becomes positive and indicates the amount of demand violation (net demand minus $D_{\max}^i$). At the end of this interval, $D_{\max}^i$ is updated to reflect the new peak demand $D_{\max}^i \leftarrow D_{\max}^i + \xi^i$.

The total regulation capacity of the batteries plus the alternative source should be greater or equal than the aggregator's regulation capacity B_{agg}^h for the current hour:

$$\sum_i B^{i,t} + B_{alt}^t \geq B_{agg}^h \quad t \in h \tag{6.23}$$

The constraints on the charging/discharging rate and regulation capacities also apply:

$$P_{chg}^{i,t} \geq 0,\ P_{dsg}^{i,t} \geq 0,\ B^{i,t} \geq 0 \ \forall i \in I \tag{6.24}$$

$$P_{chg}^{i,t} + B^{i,t} \leq P_{Cap}^i \ \forall i \in I \tag{6.25}$$

$$P_{dsg}^{i,t} + B^{i,t} \leq P_{Cap}^i \ \forall i \in I \tag{6.26}$$

The energy at the end of this 15-minute interval is:

$$E^{i,t+1} = E^{i,t} + \eta_{chg}^i P_{chg}^{i,t} - P_{dsg}^{i,t} / \eta_{dsg}^i \ \forall i \in I \tag{6.27}$$

The demand over the 15-minute time window should not be greater than $D_{\max}^i$, plus the violation ξ^i:

$$D_{RT}^i + P_{chg}^{i,t} - P_{dsg}^{i,t} \leq D_{\max}^i + \xi^i \tag{6.28}$$

$$\xi^i \geq 0 \tag{6.29}$$

where D_{RT}^{i} represents the real-time metered consumption at the beginning of the 15-minute interval, which we assume reflects accurately the consumer's consumption during the next 15 minutes.

6.4 PROBLEM FORMULATION

6.4.1 *Data*

We selected 22 buildings on the campus of the University of Washington to represent consumers. These buildings include academic buildings, libraries, dormitories and a gym. We assume that a battery controlled by the aggregator has been installed in each building. The capital cost of the batteries is set at \$500/kWh. The power rating P_{Cap}^{i} of each battery is set at 20% of its building's annual peak demand, with an energy rating E_{Cap}^{i} of 4 hours. Table 6-2 summarizes the other battery parameters.

Table 6-2: Battery parameters

$E_{\max}^{i}$	$E_{\min}^{i}$	ΔE^{i}	η_{chg}^{i}	η_{dsg}^{i}
$0.95E_{Cap}^{i}$	$0.1E_{Cap}^{i}$	$15\,\text{min}\times P_{Cap}^{i}$	0.95	0.95

Regulation prices and regulation signal data are based on actual PJM data. At the real-time stage, the batteries dispatched to provide regulation service are assumed to follow the regulation signal accurately, giving them perfect performance scores. The regulation price is calculated based on the Regulation Market Capability Clearing Price and Regulation Market Performance Clearing Price under perfect performance score. The price of regulation from an alternative source $\lambda_{pen}^{\omega,h}$ is chosen as 5 times the regulation clearing price $\lambda_{r}^{\omega,h}$. At the day-ahead stage, 20 scenarios are chosen to represent the uncertainties in the regulation market clearing prices and consumer demand profiles. The range of forecast errors $\Delta D_f^{i,\omega,t}$ is set at 5% of the forecast value $D_f^{i,\omega,t}$. The penalty factor for deviation λ_{dev} is set at 100.

The two-stage model is developed on YALMIP integrated in MATLAB, with CPLEX as the solver on a desktop with Intel Xeon E3 1220-v, 3.1-GHz CPU and 16 GB RAM. The day-ahead stage model takes on average about 120 seconds to complete. Since the real-time stage model is deterministic and relatively simple, every round of real-time stage requires less than a second to solve.

6.4.2 *Day-ahead stage*

We consider a typical weekday in June, before the summer break, when most of the university buildings that house classrooms are occupied during working hours. The consumption profiles of these building are similar in that the daily peaks occur around noon. Other buildings (such as the dormitories, the library and the gym) have different consumption profiles. Figure 6-2 depicts the hourly aggregated consumption of the 22 buildings and the aggregator hourly regulation bids B_{agg}^h determined by the day-ahead optimization.

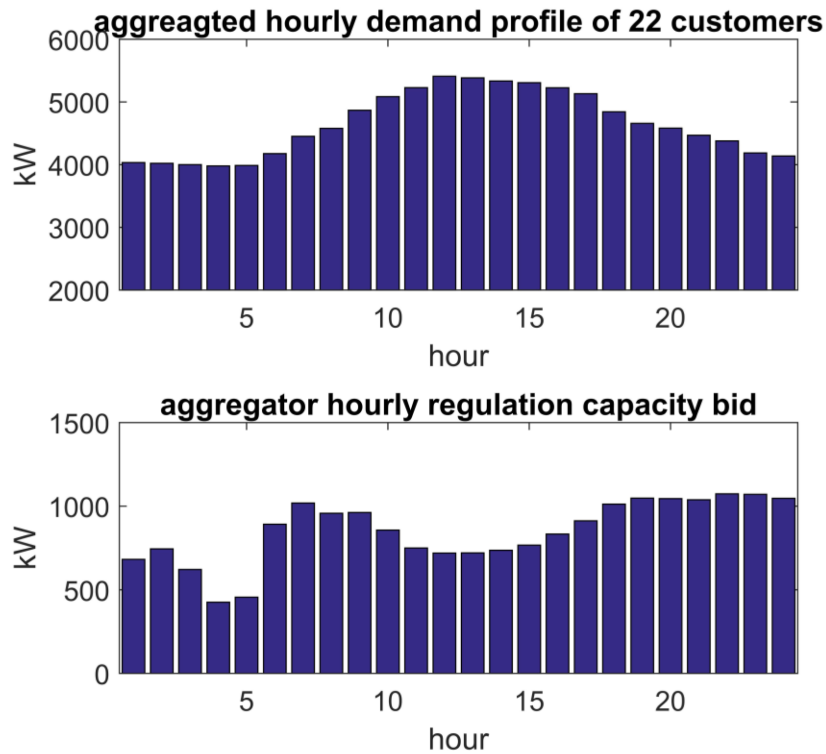

Figure 6-2: Hourly aggregated demand profiles and aggregator hourly regulation bids

As this figure shows, the aggregated demand profile peaks around noon. Batteries are therefore mostly discharging around that time for peak shaving and do not have much capacity available for frequency regulation. Correspondingly, the hourly regulation bids B_{agg}^{h} submitted by the aggregator are low around noon. These regulation bids are even lower from 1am to 3am when most batteries are scheduled to charge because 1) the energy rate is lower at that time; 2) the consumer demand profiles are also lower, allowing batteries to charge at higher rates without violating their peak demand targets $D_{\max}^{i}$.

Figure 6-3 illustrates the battery energy target trajectories. the target trajectories of all 22 batteries as determined by the day-ahead optimization. For each battery, its energy trajectory is divided by its energy rating that normalizes energy to SoC. During the early morning hours, the SoCs of most batteries increase rapidly to ensure that they have enough energy for future discharging purposes. From hour 4 to around hour 10, the SoC targets of many batteries stays high and flat because their power capacities are assigned to provide regulation. From around hour 11 to around hour 18, the SoCs decrease as batteries discharge to shave consumers' peak demands. From around hour 18 to around hour 22, the SoCs remain low and flat because the batteries are again participating in frequency regulation.

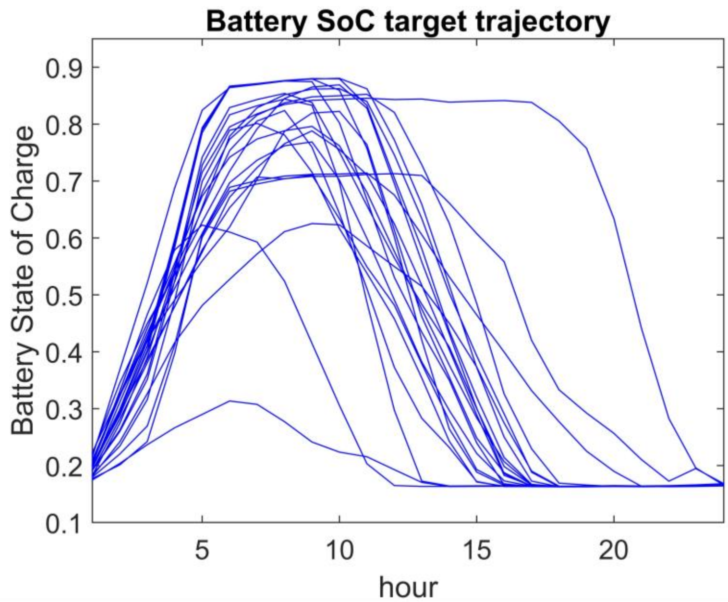

Figure 6-3: Normalized daily SoC target trajectories of all batteries

Because of the uncertainty on the regulation prices and demands, each battery's SoC follows different trajectories $E^{i,\omega,t}$ under different scenarios. Figure 6-4 shows the SoC trajectories of battery No.10 for all 20 scenarios, the target trajectory in the middle, and the SoC bounds. The constraint (6.15) ensures that all the trajectories remain within the bounds. This suggests a battery could have similar charging/discharging profiles under various scenarios of regulation prices and uncertain demand profiles.

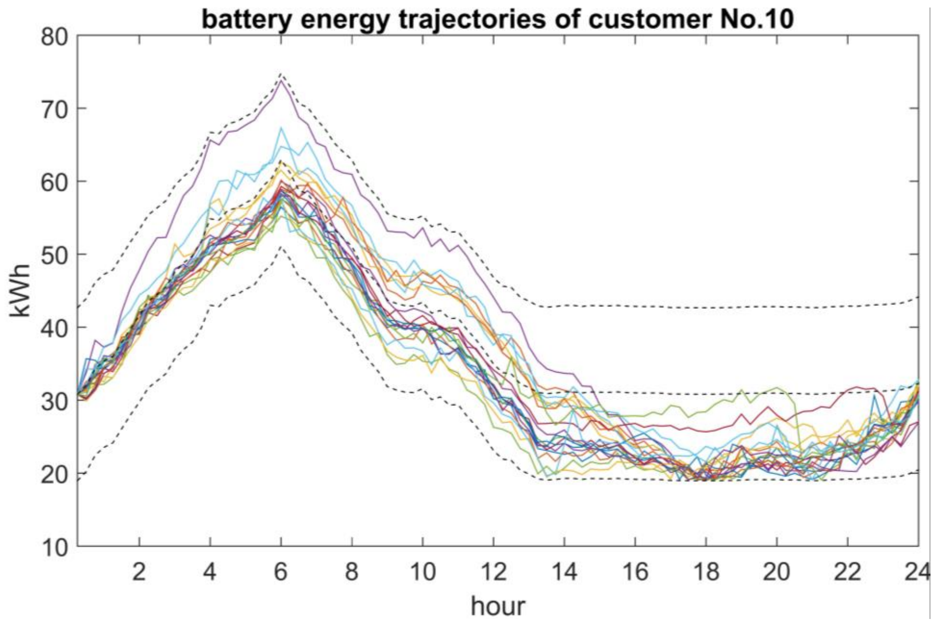

Figure 6-4: The SoC target trajectory (middle dashed line), the SoC upper and lower bands (upper and lower dashed lines), and the SoC trajectories under 20 scenarios (colored lines) for battery No. 10

6.4.3 *Real-time stage*

At the real-time stage, the two-step process is executed every 15 minutes. The realization of consumers' demand profiles may turn out to be different from what was anticipated on the day-ahead. The real-time stage handles the demand deviations and adjusts the dispatch of the batteries accordingly. The model also prevents the SoC of batteries deviate too far away from their targets. In addition, the aggregator dispatches the batteries to fulfill the hourly regulation bids.

Figure 6-5 illustrates the real-time stage for consumer No. 10 over the course of a typical day. The top two plots show that the building demand peaks around 3pm., the peak is shaved by discharging the battery. In return, the valley from midnight to 5am is filled by the charging of the battery.

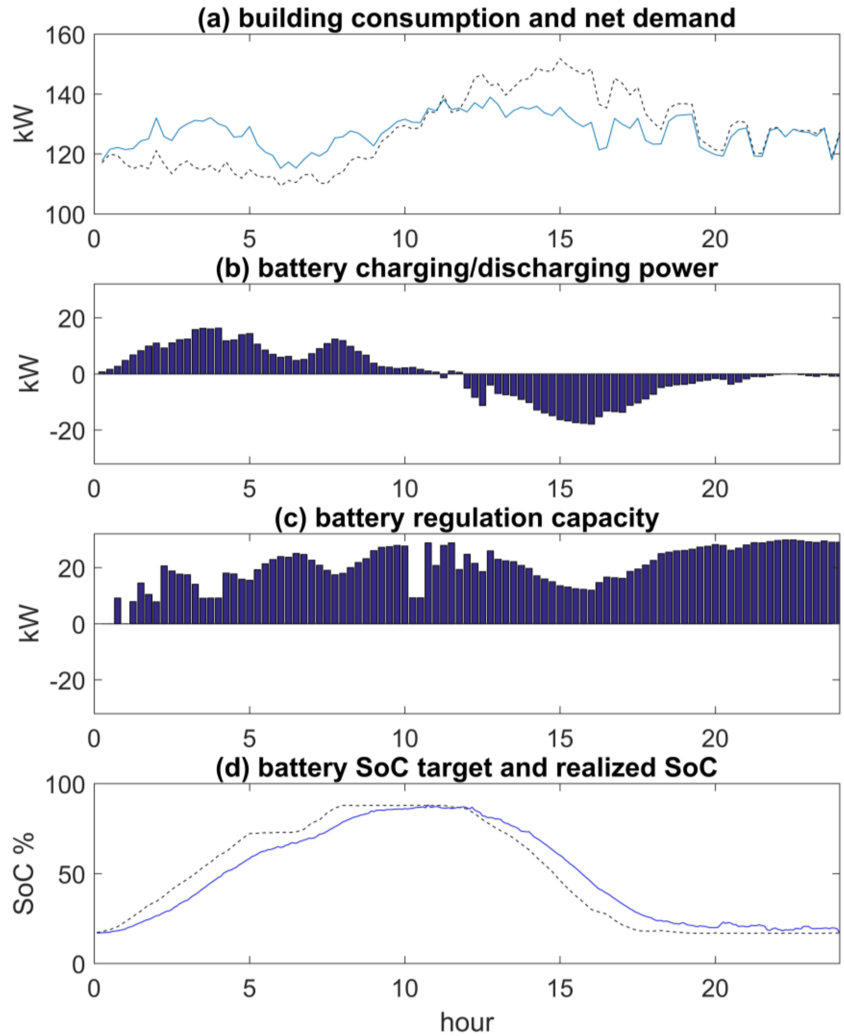

Figure 6-5: Real-time stage for Consumer No.10's over the course of a typical day. (a) Building load (dashed line) and grid power (solid line); (b) battery charging/discharging power; (c) battery regulation capacity; (d) battery SoC target (dashed line) and actual SoC (solid line)

The third plot shows the battery capacity that is used for regulation. Combining the second and third plots, we see that the capacity of battery is fully utilized either for energy shifting and for regulation during most of the day except for the first few hours after midnight. The fourth plot shows that the actual SoC profile follows quite well with the target profile. The difference between the target and realized SoCs is due to customer demand forecast errors. These forecast errors alter the charging and discharging powers of batteries as well as their capacity contributions to frequency regulation. Since the batteries are providing frequency regulation service collaboratively, the forecast error of one consumer may also impact the dispatch of other consumers' batteries.

The performance of the real-time stage can be assessed by comparing the day-ahead expected benefits with the real-time realized benefits. As in the day-ahead objective function (6.1), the benefits include energy arbitrage, peak shaving, frequency regulation, from which must be subtracted the cost of purchasing frequency regulation from alternative source and the battery degradation cost. Table 6-3 compares these various benefits and costs as optimally expected on the day-ahead vs. realized in real-time.

Table 6-3: Summary of day-ahead and real-time benefits and costs($)

	DA	RT		DA	RT
Energy Arbitrage	149.89	147.23	Reg. from Alt. Source	-4.09	-18.97
Peak Shaving	375.74	373.28	Battery Degradation	-188.48	-179.23
Frequency Regulation	850.58	850.58	Total	1183.64	1172.89

The real-time realizations of energy arbitrage and peak shaving benefits are close to their day-ahead expectations. Different from other cost/benefits, we rely on actual market clearing price to calculate frequency regulation benefit, so the day-ahead "expectation" and real-time realization should be the same. The deficit in battery regulation capacity is compensated by purchases from the alternative regulation source, which increases the overall actual cost compared to the day-ahead expected value. Overall, the real-time total benefit is quite close to what had been calculated on the day-ahead.

6.4.4 *Analysis on the penalty of SoC deviation* λ_{dev}

The penalty factor λ_{dev} associated with SoC deviations in the real-time objective function (6.22) balances consumer cost savings and revenues from frequency regulation. Setting λ_{dev} too high forces the SoC to follow closely the day-ahead target trajectory. Because day-ahead scenarios cannot predict the consumer demand perfectly, this restriction on battery SoC (stringent constraint on charging/discharging) causes a deficit in regulation capacity and force the aggregator to purchase more regulation capacity from the alternative source. On the other hand, choosing λ_{dev} too low lets the SoC deviate from the day-ahead target a lot, the benefits from energy arbitrage and peak shaving could be reduced. Table 6-4 summarizes the benefits for different values of λ_{dev}

Table 6-4: Summary of real-time benefits under different values of λ_{dev}

λ_{dev}	10	100	1000	10000
Energy Arbitrage	122.12	147.23	148.92	149.11
Peak Shaving	365.01	373.28	375.74	375.74
Frequency Regulation	850.58	850.58	850.58	850.58
Reg. from Alt. Source	0	-18.97	-57.76	-90.19
Battery Degradation	-167.38	-179.23	-184.23	-188.07
Total	1170.33	1172.89	1133.25	1097.17

Figure 6-6 illustrates the regulation capacities bought from the alternative source for different values of λ_{dev}. When $\lambda_{dev} = 10$, no capacity from the alternative source is required. As λ_{dev} increases, more and more capacity needs to bought from the alternative source. These purchases are highest from 3:00 am until 4:00 am, when most batteries are charging at high power.

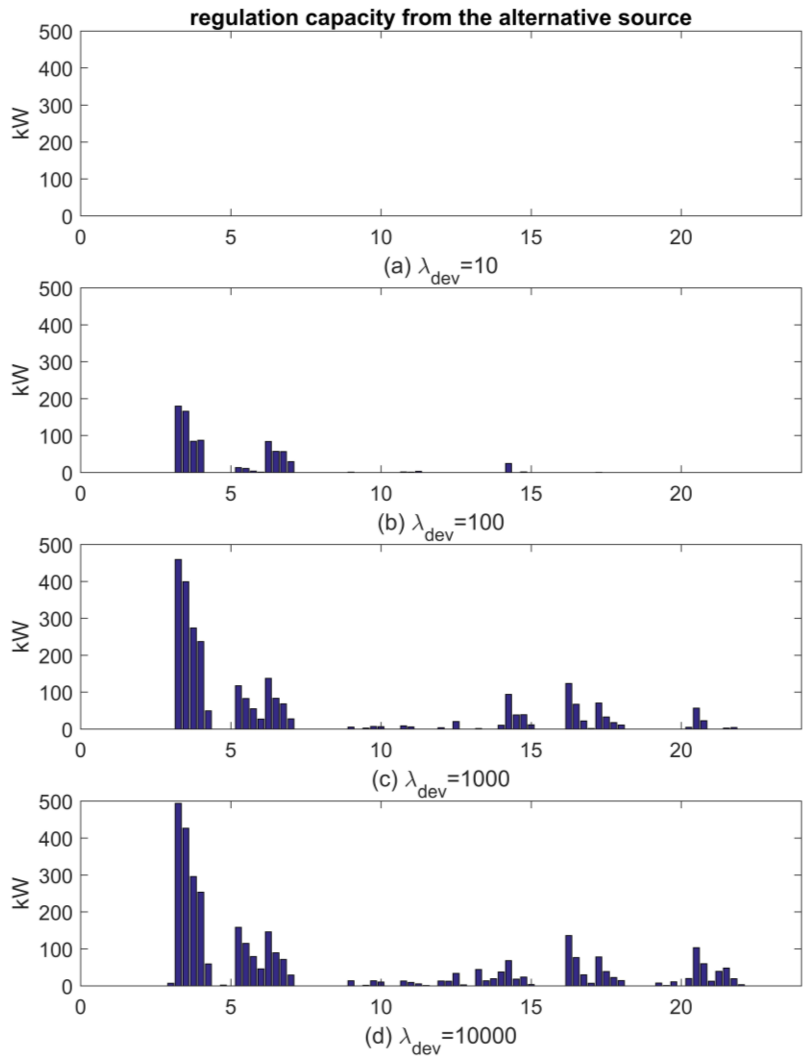

Figure 6-6: Regulation capacities bought from the alternative source with: (a) $\lambda_{dev} = 10$; (b) $\lambda_{dev} = 100$; (c) $\lambda_{dev} = 1000$; (d) $\lambda_{dev} = 10000$

6.4.5 *Performance of the model on different days*

We have described the results of the two-stage model on a single day. Here we examine the effectiveness of two-stage model by repeating the solution process on 30 different days with different demand profiles and regulation prices.

Following the procedures above, we keep λ_{dev} at 100 and calculate various benefits and costs as optimally expected on the day-ahead vs. realized in real-time. The difference between the benefit achieved in real-time and its day-ahead expectation is defined as "Realization Error":

$$\text{Realization Error} = \text{Benefit}_{\text{Real-time}} - \text{Benefit}_{\text{Day-ahead}} \tag{6.30}$$

Figure 6-7 shows the errors of each cost/benefit category:

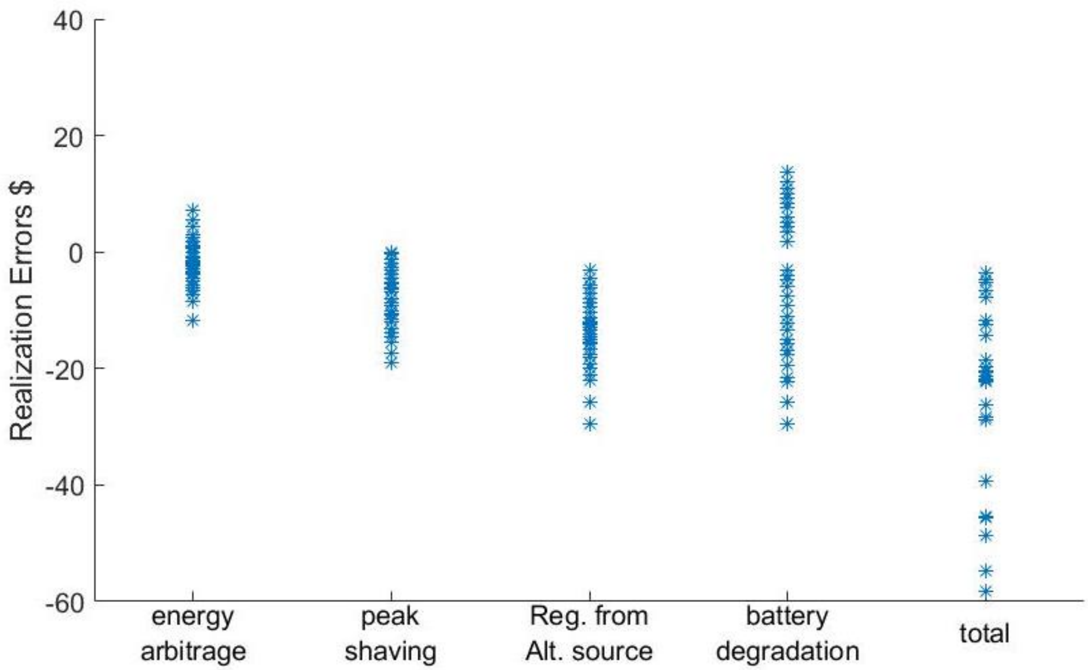

Figure 6-7: Realization errors for 30 days in each cost/benefit category

Overall, the total errors are relatively small compared with the total benefits. The errors in regulation from alternative source and peak shaving all have negative signs, showing that real-time realizations are a little less than day-ahead expectations. The reduction in benefits is due to demand forecast errors.

6.4.6 *Scalability of the proposed approach*

The results described so far are based on 22 consumers, which is a relatively small number. To evaluate the scalability of the proposed method, we consider two additional cases, one with 240 consumers and a second with 960 consumers. The consumer demand profiles of the two larger test cases come from the commercial customer demand profile database of NREL. Table 6-5 lists the solution time for the day-ahead and real-time models in the same simulation environment.

Table 6-5: Solution time for the day-ahead and real-time models

No. of consumers	DA Model Average Solution Time (s)	RT Model Average Solution Time (s)
22 Consumer	120s	Less than 1s
240 Consumer	2132s	3.5s
960 Consumer	15698s	25.1s

For the case with 960 consumers, the DA model takes more than 4 hours to solve. On the other hand, the RT stage, which needs to be solved every 15 minutes, requires considerably less computations because it is a deterministic optimization over a single time interval. The simplicity of RT stage model enables it be frequently executed.

6.5 CONCLUSIONS

In this chapter, we demonstrated a two-stage optimal scheduling method for an aggregator dispatching batteries owned by commercial consumers. This optimization combines several streams of benefits: consumer level benefits such as energy arbitrage and peak shaving, as well as system level benefits like frequency regulation.

The day-ahead stage maximizes the expected benefits considering uncertainties on regulation prices and consumer demand profiles It also considers the battery degradation cost. The real-time stage dispatches the batteries to follow the regulation capacity bids, to track the battery state of charge target trajectories and to ensure that the peak demand targets are not violated. Case studies demonstrate that this two-stage approach can effectively dispatch batteries to achieve both consumer and system level benefits.

Chapter 7. CONCLUSIONS, CONTRIBUTION AND FUTURE WORK

Distributed Energy Resources (DERs) comprise of three types of resources: distributed generation (DG), energy storage (ES) and demand response (DR). DERs are different from other resources because of their distinctive characteristics: they are located on the demand side and they have some flexibility. DERs bring many streams of benefits to different system participants. Various methods have been proposed to capture and quantify the benefits DERs bring and distribute them to DERs. In general, these methods can be put into two categories: avoided-cost based methods and tariff based methods. Both categories have disadvantages: the avoided-cost methods calculate the benefits indirectly making it complicated for DERs to be rewarded. The tariff based methods fail to represent some benefits while mispresent some other benefits.

The gaps between the benefits that DERs bring and fair methods to allocate the benefits motivate us to explore possibilities to improve the existing methods and develop new algorithms. This work evaluates the tariff based methods, avoided-cost based methods and develops methods that combine tariff based methods with avoided-cost based methods.

First, we analyze the financial impacts that the deployment of DERs by commercial customers would have on their LSE if the current tariff structure does not change. The result suggests:

A. The deployment of DERs by commercial customers would reduce the LSE’s revenues by a greater amount than its expenses for generation capacity and transmission charges.

B. In order for the LSE to accommodate DERs without losing money, the tariffs applied to commercial customers need to be redesigned.

The second part of this work aims to design tariffs for DERs that, compared with the current tariff, provide better economic incentives for both DERs customers and the LSE:

A. the energy charge component represents the variations in day-ahead locational marginal pricing, which betters indicates the time-varying costs of energy production.

B. the demand charge components are based not only on the customers' monthly peaks, but also on the customer's demand at hours coincident with the peaks in the LSE's aggregated demand.

C. case studies show both DERs customers and the LSE achieve more savings under the proposed DERs tariff.

Next, we switch our focus to the avoided-cost based methods. The third part proposes a model that optimally schedules the LSE owned battery energy storage to maximize multiple streams of benefits, the result shows:

A. Because different benefits are present at different hours of the day. The duration of a day can be split into several time slots. At each slot, the battery is primarily providing one stream of benefit. This increases the utilization of battery energy storage.

B. Frequency regulation benefit outweigh other benefits and accounts for the majority of battery revenue.

Frequency regulation benefit is difficult to integrate into the tariff. In the last part, we develop an aggregator model that controls consumer owned batteries and combine the tariff based benefits: energy arbitrage and peak shaving with the avoided-cost based frequency regulation benefit:

A. The model formulation adapts a two-stage approach. On the day-ahead, the aggregator determines energy consumption trajectories that minimize energy and demand charges, and the spare battery capacity that can be bid into the frequency regulation market. In real-time, it dispatches the batteries to provide regulation while striving to follow the optimal trajectories.

B. The formulation ensures that the real-time stage model can be solved sufficiently fast.

Building on this foundation, future work could further explore different streams of benefits that DERs provide. The benefits can be quantified and allocated to DERs through tariff based methods, avoided-cost based benefits or the combination of two methods. Studies that evaluate the benefits of DERs are mostly focus on long term/planning stage. The strategies to dispatch DERs in operational stage (day-ahead and real-time), especially for multiple streams of benefits have not been thoroughly studied.

DERs brings many local benefits to distribution systems. The outputs of DERs change the demand profiles of distribution systems which could relief the electrical stress on substation transformers, overhead wires and underground cables. With less electrical stress, these devices enjoy longer lifespans that the time to upgrade or replace them could be deferred. Methods need to be developed to quantify and allocate these investment deferral benefits.

DERs could also supply power to consumers through the formation of microgrids during outages when the primary supply from substation is cut off. The DERs could increase the reliability of power supply to some critical customers and be rewarded at appropriate rates.

Apart from evaluating the benefits of DERs, the costs associated with providing various benefits should be considered. Distributed generation, energy storage and demand response are very different resources. Studies that estimate the cost of DERs mostly focus on the longer time scale, life-cycle cost analysis. Further research could investigate the operational cost of DERs as a function of DERs dispatch. For example, the battery degradation cost associates with charging and discharging dispatches. With better understanding of the costs, we can better distinguish the various characteristics between DERs and find the suitable benefits/dispatch strategies for different DERs.

There are other possible directions for research. The contributions can come from identifying new streams of benefits, quantifying the cost and revenues DERs achieve for providing one/multiple streams of benefits and allocating the total economic savings to individual DERs. More researches are necessary to facilitate the economically competitive business models of DERs.

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