A MULTI-AGENT DEMAND RESPONSE PLANNING AND OPERATIONAL OPTIMIZATION FRAMEWORK

By

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To my mom and to the soul of my dad.

Abstract

A COMPREHENSIVE DEMAND RESPONSE PLANNING AND OPERATIONAL OPTIMIZATION FRAMEWORK USING MULTI-AGENT ADAPTIVE DYNAMIC PROGRAM

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This research describes a real-time optimization model for multi-agent demand response (DR) from a Load Serving Entity (LSE) perspective. We formulate two infinite horizon stochastic optimization models; specifically, an LSE model and a dynamic pricing customer model. The objective of these models is to minimize long-term cost and discomfort penalty of the LSE and dynamic pricing customers. We solve a deterministic finite horizon linear program as an approximation of the suggested stochastic model and provide computational experiments. In stochastic programming (SP), a wait-and-see solution is at least as good as an optimal policy. On the other hand, a policy that uses the expected value problem is never as good as an optimal policy. This is well established in SP when there is a single agent. A question arises whether bounds exist when we have two agents. The present study develops a research methodology to answer this question. Our experiments show that if we have two separate agents, and both agents get perfect information, this can be worse compared to both agents doing the mean value problem. Nevertheless, we have found that there are bounds when the first stage follows the same set of actions. A two-agent demand response problem has been used as a case study to show this claim.

Index Terms: Linear programming, Multi-agent demand response, Demand side management, Dynamic pricing customers, Stochastic bounds, Smart grid

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Chapter 1

INTRODUCTION

Energy needs were simpler when our current electric grid was created more than 100 years ago. Power generation was localized and built around communities, and electric energy systems were unidirectional and top-down oriented (Figure 1). Most homes had only small energy demands, such as a few light bulbs and a radio. The grid enabled utilities to deliver electricity to consumers' homes and invoice them monthly. Today, the number of large power plants that feed into the grid is still limited and is expected to keep demand and supply balanced at all times. In the operation of electric energy systems, this balance is critical. In today's world, stochastic renewable energy sources and electric vehicles are new challenges to this old balance, and require high-tech control techniques [1], [2]. The classic limited one-way interaction makes it difficult for the grid to respond to today's constantly changing and always increasing energy demands.

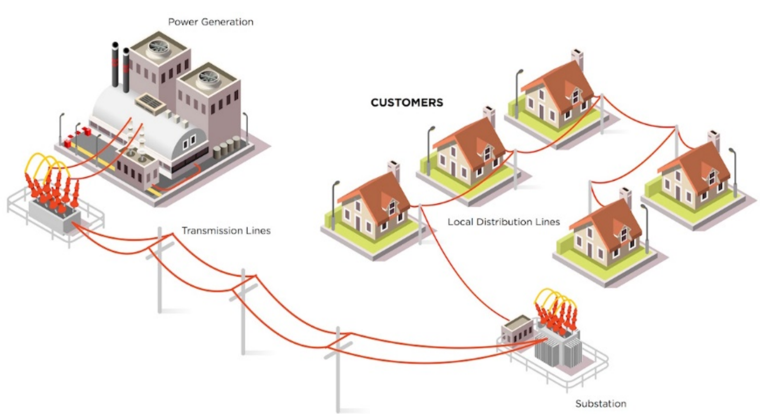

Figure 1. Classic electric grid[2]

The ***smart grid*** is a two-way dialogue through which electricity and information can be exchanged between a utility and its customers. It is an emerging network of communications, controls, computers,

[2] http://www.auburntransmissionproject.com

automation, and new technologies and tools working together to make the grid more efficient, more dependable, safer, and greener. It improves reliability performance and customers' responsiveness and encourages more capable decision making by both customers and utility provider. The smart grid enables newer technologies to be integrated, such as wind and solar energy production and plug-in electrical vehicle (PEV) charging. The smart grid will replace the ageing infrastructure of today's grid and utilities will be able to better communicate with customers to help manage their electricity needs [3]–[6]. Figure 2 shows a modern electric grid.

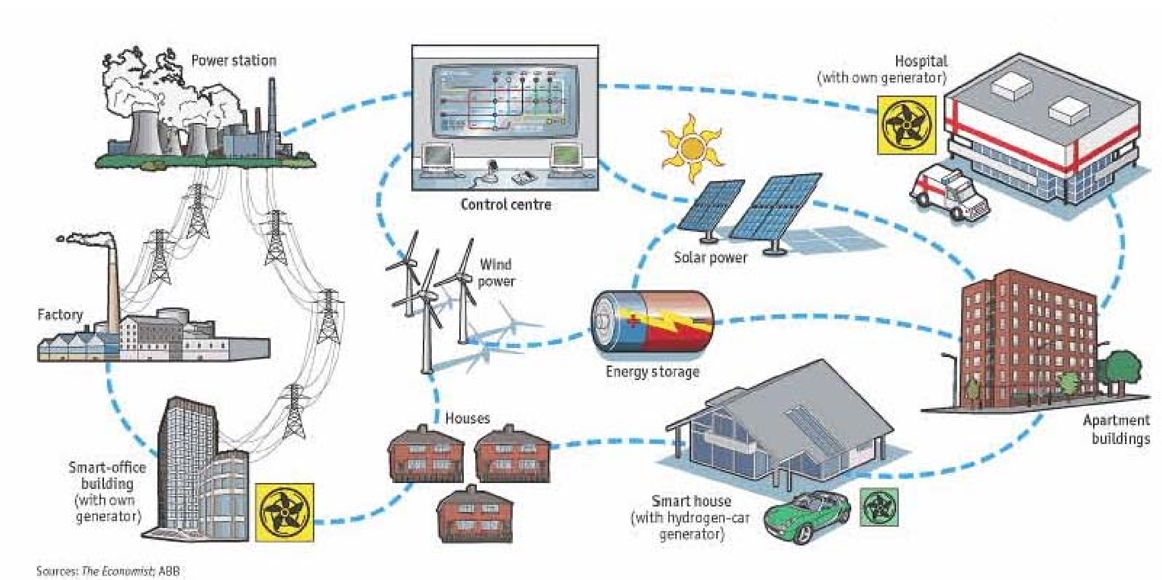

Figure 2. Modern electric grid[3]

Electricity companies are very experienced at optimizing energy generation and distribution, so the demand side receives the focus of attention by research and industry. ***Demand Side Management*** (DSM) includes everything the demand side of an energy system, from improving energy efficiency by using better materials, smart energy tariffs with incentives for favorable consumption patterns, to sophisticated real-time control of distributed energy resources. DSM programs are employed to utilize available energy more efficiently without installing new generation and transmission infrastructure [1], [7], [8].

[3] https://www.economist.com

Figure 3 shows that DSM consists of two major components: Energy Efficiency and Demand Response [9]–[12]. According to the "National Action Plan for Energy Efficiency", published by the U. S. Department of Energy and Environmental Protection Agency (EPA), Energy Efficiency refers to using less energy while affording the same or improved level of service to the energy consumer in an economically efficient way. The term Energy Efficiency as used here includes using less energy at any time, including at times of peak demand through Demand Response and peak shaving efforts [13]. Energy efficiency can be achieved among users by encouraging energy-aware consumption patterns and by constructing more energy efficient buildings. However, the need for practical solutions to shift high-power household appliances to off-peak hours to reduce the peak-to-average ratio in load demand also exists. Appropriate load-shifting is expected to become even more crucial as plug-in hybrid electric vehicles become popular [7], [14]. DSM's greatest advantage is that it is less costly to influence a load intelligently, than to build a new power plant or install an electric storage device [1].

Ridde et al. [15] analyzes the business impacts of DSM. Four business models are evaluated and a district of 300 households with three different types of electric household devices are simulated: loads with storage (e.g., boiler), shiftable loads (e.g., dishwasher), and real electric storages (e.g., batteries). They found that the variation in load flow decreases proportionally to the fraction of smart controlled power. In addition, they studied the implications for retailers and end users of three billing types: a fixed tariff, a two-tariff structure, and an hourly real-time tariff structure. Compared to the fixed tariff, the incentive to use smart devices is small in the double tariff. In a real-time tariff, income rises, and risk decreases for the retailer, while end users have the potential to decrease costs [15].

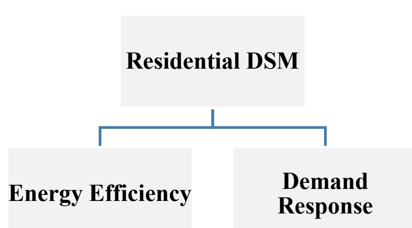

Figure 3. Components of DSM [16]

One goal of Smart Grid development is to create technologies, tools, and techniques to optimize grid operations and resources dynamically, while building in demand response and consumer involvement. ***Demand Response*** (DR), which is sometimes referred to as the "virtual power plant" is a key component of the emerging smart grid paradigm and the focus of this research (Figure 4). According to U.S. Dept. Energy [17], demand response is "changes in electric usage by end use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [17]. Demand response is a term for programs designed to encourage end users to reduce short-term energy demand in response to a price signal from the electricity hourly market, or a trigger from the electricity grid operator. Typically, DR actions would be in the range of 1 to 4 hours and include turning off or dimming banks of lighting, adjusting heating, ventilation, and air conditioning levels, or shutting down a portion of a manufacturing process. Alternatively, onsite generation can displace load drawn from the electricity power grid. By improving the reliability of the power system and, in the long term, lowering peak demand, DR reduces overall plant and capital cost investments and postpones the need for network upgrades [4].

Several initiatives are promoting the role of demand response under the smart grid and energy market paradigms. To provide an incentive for end users to develop DR capability, most utilities and power regulators across North America have developed suites of DR programs. Federal Energy Regulatory Commission (FERC) Order 719, aiming to improve wholesale markets by establishing a more forceful role for demand response, and the American Recovery and Reinvestment Act (ARRA), allocating significant levels of funding for smart grid activities, are the most remarkable [18].

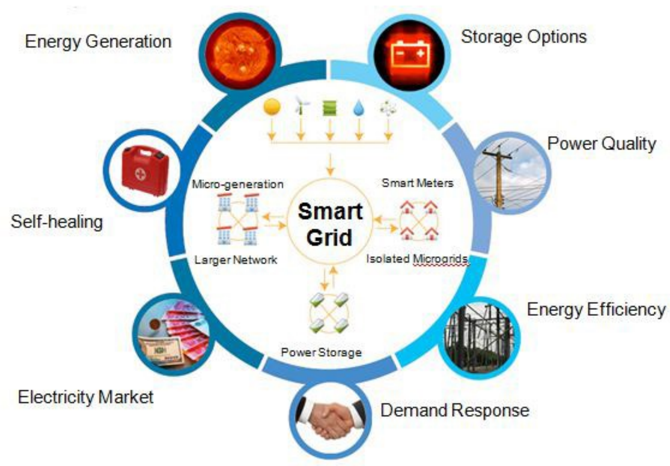

Figure 4. Smart grid components[4]

Independent System Operator (ISO) is an organization formed at the direction or recommendation of the Federal Energy Regulatory Commission (FERC). Figure 5 shows existing ISOs in the United States: New York ISO (NYISO), Pennsylvania-Jersey-Maryland (PJM), ISO New England (ISO-NE), Midwest ISO (MISO), California ISO (CAISO), Electric Reliability Council of Texas (ERCOT), and Southwest Power Pool (SPP) [18].

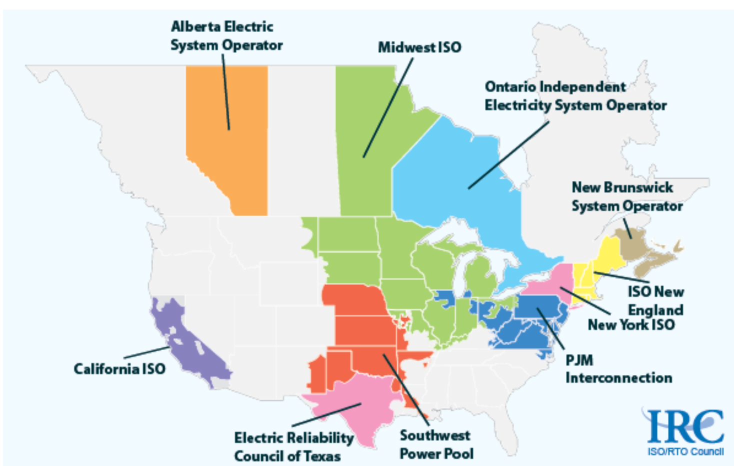

Figure 5.Regional transmission organization (North America)[5]

[4] http://electronicsbeliever.com
[5] https://isorto.org/

The case study of this research is a part of the Texas ISO, ***ERCOT***. ERCOT operates the electric grid and manages the deregulated market for 75% of Texas (Figure 6) and 90% of Texas' load. There are 24 million consumers in the ERCOT region. The record peak demand occurred when demand reached 71110 MW on August 11, 2016 [19].

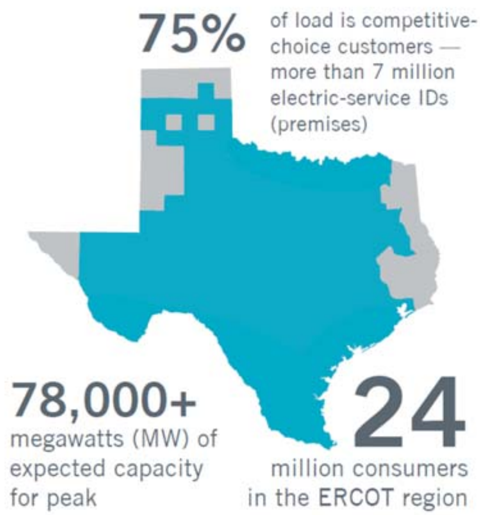

Figure 6. ERCOT region [19]

Figure 7 shows the ERCOT market relationship. Load serving entity (***LSE)*** provides electric service to individual and wholesale customers. Qualified scheduling entities (***QSE***s) submit bids on behalf of resource entities (REs) or LSEs, such as retail electric providers (REPs). Transmission/distribution service providers (***TDSP***s) own or operate for compensation the equipment or facilities to transmit and/or distribute electricity in Texas. TDSPs are regulated by the Public Utility Commission of Texas (PUCT) and are required to provide nondiscriminatory access to the grid. LSE and Aggregator are the entities that we will talk about in the case study of this research. Customers can have the LSE directly, or can go through the aggregator. They always bill and make contract with LSE.

Demand response is usually provided at commercial, industrial, and residential customers. DR for residential customers is the focus of this research. Often DR at the residential level must be "aggregated" to be eligible as wholesale market products [18]. These small companies are called ***aggregators***. This research describes a real-time optimization model for multi-agent DR from an aggregator or LSE perspective.

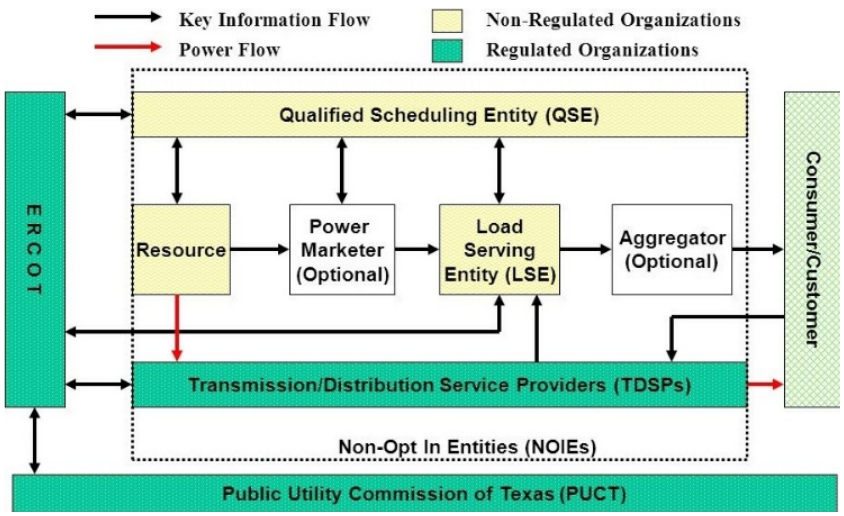

Figure 7. ERCOT market relationship[6]

We organize the remainder of this research as follows. Chapter 2 summarizes background and literature on demand response programs and our contributions. Also included is information on approximate dynamic programming background. Chapter 3 includes mathematical formulation of the LSE and dynamic pricing customer models. In addition, this chapter describes computational experiments for a deterministic problem of the suggested model. It ends with conclusions and future work.

[6] http://www.ercot.com/

Chapter 2

LITERATURE REVIEW

We recognize smart grids for their competencies and related advantages. However, we require a great deal more to transform smart grids into actuality [20]. With the development of technology and communications, advanced metering systems and energy management provide more active participation of customer demand in power systems. Based upon these advancements, demand response is proposed to deal with this relationship between customers and the power system. These DR programs are different from the current electricity usage situation, since most customers pay only a flat electricity price and have no incentive to change their electric usage in response to prices [17]. Therefore, the main objective of DR programs is to offer incentives to customers who will reduce energy usage at peak demand times [21]. With this, DR will help mitigate market power generation, reduce electricity prices, resolve transmission lines congestion, enhance resilience of the power system, and improve market liquidity [22]. Classification of DR and its benefits and costs are included in this chapter. Next, a literature review in utility-based and customer-based DR is provided. Approximate dynamic programming is concisely described. Finally, future challenges in DR and our contributions will end the chapter.

2.1 CLASSIFICATION OF DEMAND RESPONSE PROGRAMS

Demand response programs have been classified into two categories: ***Incentive-based programs*** (IBP) and ***Price-based programs*** (PBP) (Table 1). In IBP, if a participating customer reduces its electricity consumption, it will be given financial incentives such as a bill credit or a discount rate. Many utilities in North America and worldwide have experiences with IBP. As an example, NYISO IBP paid out $27.2 in incentives to more than 14,000 program participants to release 700MW peak capacity in the summer of 2003. The load curtailment programs were estimated to have generated reliability benefits of more than $50 million on August 15, 2003. In general, it was reported that the benefits of these programs exceeded their cost by a factor of 7:1 [23].

Alternatively, in ***Price-Based Programs*** (PBP), the price is the control that convinces participants to manage their demands during critical conditions, e.g., by reducing their consumption at peak hours. Time-of-use pricing (TOU), critical-peak pricing (CPP), and real-time pricing (RTP) are popular PBP programs [7], [24]–[27]. ***TOU*** is a rate for which usage unit prices vary by more than one time period within a 24-hour day. Daily pricing blocks might include an on-peak, partial-peak, and off-peak price for non-holiday weekdays, with the on-peak price as the highest price, and the off-peak price as the lowest price [1], [13]. ***CPP*** rates typically charge a much higher price during a few hours per day on critical peak days. Participating customer can reduce his electricity usage during critical peak periods when prices are high without changing consumption pattern during other periods. An example is when thermostat setting of heaters or air conditioners are temporary changed [27]. In ***RTP***, also known as dynamic pricing programs, electricity prices fluctuate, reflecting the real-time cost of electricity in the wholesale market. The objective is to flatten the demand curve by offering high prices during peak periods and lower prices during off-peak periods [27]. RTP programs have been adopted in some places in North America, e.g., by the Illinois Power Company in Chicago [7]. Many economists are convinced that RTP programs are the most efficient and direct DR programs suitable for competitive electricity markets and should be the focus of policymakers [28]. On the other hand, one weakness of RTP programs is that they are usually confusing and difficult for customers to respond manually to changing prices [29], [30]. Another issue is load synchronization, where a large portion of load is shifted from a typical peak hour to a typical off-peak hour [7], [31].

Table 1. Classification of demand response programs

Incentive-Based Programs (IBP)	Classical	Direct Load Control [32]
		Interruptible/Curtailable Programs [22]
	Market Based	Demand Bidding [33]
		Emergency DR [34]
		Capacity Market [35]
		Ancillary Services Market [36]
Price-Based Programs (PBP)	Time of Use (TOU) [37]	
	Critical Peak Pricing (CPP) [24]	
	Real-Time Pricing (RTP) [38]	

In this research, we consider three major residential customer groups: fixed-pricing, direct load control, and dynamic pricing customers. A summarized discussion of each is next.

A. Fixed-Pricing Customers (FPC)

In fixed-pricing programs, the utility offers electricity at a fixed rate regardless of the day-ahead or real-time market prices. It means that the price remains stable throughout the length of the contract [39]. We expect that these kinds of customers remain a considerable portion of the customers, and we will need to consider them in future demand response decisions.

B. Direct Load Control Customers (DLC)

DLC programs reduce load during extreme events, such as high production costs or amid system reliability issues. In direct load control programs, the LSE or aggregator has remote control over certain appliances of the customers based on the agreement. For example, they may turn off and on the air conditioner, dishwasher, PEV, and pumps. [7], [27]. The LSE awards participants with sizable credits for reducing load when the LSE initiates an event. There is much research focusing on direct load control customers, such as [40]–[43].

C. Dynamic Pricing Customers (DPC)

As mentioned earlier, in dynamic pricing programs, sometimes referred to as real-time pricing or time-varying programs, we assume that each customer has access to the real-time wholesale market price and responds individually to the time-differentiated prices by shifting its load [24], [25], [44]. We assume that residential customers have smart meters in their houses that simply control their consumptions by an algorithm. It can have the current price and the forecasted trajectory of the price. Based upon this information, it might delay some level of operation of appliances such as an air conditioner or dishwasher. The question is how sophisticated that forecast could be. There can be some level of communication between the smart meter and the cloud. They can do some sophisticated optimization on the cloud and then send the signal over to the device. Alternatively, we could have some component of the device. The smart meter sends messages to devices, which have pre-programs enabling them to do something smart like a heuristic.

As a promising solution to achieve dynamic supply-demand balance, demand response with dynamic pricing signals attracts great interest. It can shift peak consumption and allow higher flexibility to account for uncertainties in the energy market. Palensky and Dietrich [1] note that the existing demand response programs focus mainly on a small number of industrial and large commercial customers using direct load control and interruptible loads. Some researchers have conducted studies on residential DR with dynamic electricity pricing in recent years [45]–[47]. However, the current studies mostly target some specific subproblems with a very restricted type of customer, control mechanisms, and pricing strategies. The less dynamic time-varying pricing structures have mostly adopted, for example, time of using pricing, critical peak pricing, and peak time rebates. These price structures define different electricity prices at different fixed periods of the day or year. High stochastic real-time dynamic pricing structures need both more study and future investigations to enable their great potential. Overall, the current DR management studies and methods are generally limited and cannot be scaled up to handle future large numbers of small commercial and residential customers with different control and operation types, including direct load control, real-time dynamic pricing, and fixed price customers. To the best of our knowledge, at present, no DR management research simultaneously considers all three major categories of customers in achieving efficient real-time optimal DR decision making for large-scale end users in the highly dynamic and stochastic future energy market. This emerging problem of large-scale residential DR programs with the introduction of dynamic electricity pricing structures mixed with other traditional pricing types is extremely difficult, and currently less studied. It is believed that demand response management in the future would be very different from today's. The next generation of real-time demand response (DR) management of large-scale residential end users is an urgent need yet unsolved to achieve highly coordinated energy use and generation using market forces of dynamic power price signals in the face of future high penetration of renewable energies and DERs. This research aims at developing a comprehensive DR planning and operational optimization model. The LSE will use the developed optimization model to determine optimal DR control signals dynamically, based on forecasted market prices, renewable energy generation, storage, and aggregated demand flexibility. The proposed modeling and optimization architecture will influence the overall smart power system and its participants, particularly the LSE, customers, and system operators.

2.2 DEMAND RESPONSE BENEFITS AND COSTS

This section summarizes potential benefits and associated cost of demand response. Table 2 categorizes the benefits in four main categories: participant, market wide, reliability, and market performance benefits [27]. Customers participating in DR programs can expect savings on their electricity bills if they reduce their electricity usage during peak periods. In fact, some participants might experience savings even if without reducing their consumption pattern. To achieve this, their normal consumption during high price peak periods must be lower than their class average [23]. Some customers might be able to increase their total energy consumption by operating more off-peak equipment without paying more. Moreover, participants in classical IBP are entitled to receive incentive payments for their participation, while market-based IBP will receive payments based on their performance.

Benefits of DR programs are not exclusive to program participants; in fact, some benefits are market-wide. An overall electricity price reduction is expected eventually, a result of more efficient utilization of the available infrastructure. An example would be the reduction of demand from expensive electricity generating units. Moreover, DR programs can increase short-term capacity via market-based programs. This in turn results in an avoided or deferred capacity costs. The cascaded impact of DR programs includes avoided or deferred need for distribution and transmission infrastructure enforcements and upgrades. All avoided or deferred costs will be reflected in the price of electricity for all electricity consumers.

Reliability benefits can be considered a market-wide benefit because they affect all market participants. Because of their importance, reliability benefits have been considered as a category unto itself. By having a well-designed DR program, participants have the opportunity to help reduce the risk of outages. Simultaneously and consequently, participants reduce their own risk of being exposed to forced outages and electricity interruptions. On the other hand, the operator will have more options and resources to maintain system reliability, thus reducing forced outages and their consequences.

The last category of DR programs benefits is improving electricity market performance. DR program participants have more choices in the market, even when retail competition is unavailable. Consumers can manage their consumption since they can affect the market; this is true especially for market-based programs and dynamic pricing programs. Actually, this drove many utilities to offer DR programs, especially for large consumers [48]. Reduction of price volatility in the spot market also improved the market. Demand responsiveness reduces the ability of main market players to exercise power in the market. During the California electricity crisis of 2000-2001, a 5% reduction of demand could have resulted in a 50% price reduction [49], because generation cost increases exponentially near maximum generation capacity. A small reduction in demand will result in a large reduction in generation cost and in turn a reduction in the price of electricity.

Although some might argue about the environmental benefits associated with DR programs, their benefits are evident [3]. Environmental benefits of DR programs are many, including better land utilization from avoided/deferred new electricity infrastructure, including generation units and transmission/distribution lines, and air and water quality improvement from efficient use of resources, and reduction of natural resources depletion.

Table 2. Demand Response Benefits

<table>
<tr><td rowspan="2">Participant</td><td>Incentive payments</td><td rowspan="3">Market-Wide</td><td>Price reduction</td></tr>
<tr><td>Bill savings</td><td>Capacity increase</td></tr>
<tr><td rowspan="4">Reliability</td><td>Reduced outages</td><td>Avoided/deferred infrastructure costs</td></tr>
<tr><td>Customer participation</td><td rowspan="3">Market performance</td><td>Reduces market power</td></tr>
<tr><td rowspan="2">Diversified resources</td><td>Options to customers</td></tr>
<tr><td>Reduces price volatility</td></tr>
</table>

Any DR program involves various costs. Table 3 categorizes the costs of DR programs in two main categories: participant and program owner. Both DR programs owners and participants incur initial and ongoing costs. The program participant might be required to install some enabling technologies to participate in a DR program. Enabling technologies can include smart thermostats, peak load control, energy management system, and onsite generation units. A response plan needs to be established so that it can be implemented in case of an adverse event. These initial costs are usually paid by the participant; however, technical assistance should be provided by the program. Other event-relevant costs are easier to quantify, such as lost business or rescheduling industrial processes or activities. If a participating customer decides to use a backup onsite generation unit (customer-owned distributed generation), fuel and maintenance costs need to be worked into the plan [27].

The program owner must absorb initial and running system-wide costs. Most DR programs involve metering and communication costs as initial costs. Utilities need to install advanced metering systems to measure, store, and transmit energy usage at required intervals, e.g., hourly readings for real-time pricings. Running costs of DR programs include administration and management cost of the program. Incentive payments are considered part of the IBP's running costs. Upgrading the billing system is a must before deploying most DR programs, especially PBP, to enable the system to deal with the time-varying cost of electricity. Another important component before deploying any DR program is educating eligible customers about the potential program benefits. Different DR program choices must be explained to potential participants and possible demand response strategies must be defined. The success of a DR program depends highly on customer education. Continuous marketing is important to attract new participants. A continuous evaluation and assessment of DR programs is important to develop a better approach to reach the ultimate objectives of the programs [27].

Table 3. Classification of Demand Response costs

Participant	**Program owner**
Enabling technology	Metering & Communication
Response plan	Billing system
Inconvenience	Customer education
Lost business	Marketing
Rescheduling	Incentive payments
Onsite	Evaluation

2.3 UTILITY BASED DR RESEARCH

To improve the usage of DR programs, utilities should create more flexible DR resources to make these programs more attractive to customers; they should, for example, focus more on price reduction and not just on system reliability [50]. So far, people in demand response have conducted many research projects such as [9], [14], [31], [51]-[56]. In this section, we will review a few that pertain to utility based research. Li *et al*. [39] propose a demand response model based on utility maximization. They assume households with different kinds of usage like PEVs and batteries. They consider dynamic pricing and claim that they can align individual optimality with social optimality. They suggest a joint algorithm for utility and residential customers. They also mention that by increasing the number of customers, the benefit of their algorithm increases but finally will saturate. Pipattanasomporn *et al*. [57] propose another intelligent home energy management (HEM) algorithm to manage power consumption of household appliances with demand response analysis. Its simulation results demonstrate that this algorithm can control appliance operation and limit household power consumption below a certain demand.

In [58], the demand response relationship is directly between the power system and its customers. However, in practice it is difficult to control and adjust a customer's electricity usage directly from market level since the individual customer's electricity usage has little effect on the overall power market, and the transaction cost of such direct control is excessive. In 2008, Belhomme *et al*. [59] describe the ADDRESS European project ("Active Distribution networks with integration of Demand and distributed energy RESourceS") as building a comprehensive and commercial smart grid framework for the development of the "active demand" of residential customers. In this project, they introduce a new intermediary between the power system and local customers, called an *aggregator*. As the name suggests, the aggregator is a larger cluster, which groups together the small-scale consumer services, controls and adjusts the consumers' energy usage to help them save money without forfeiting their lifestyle, and then trades with grid companies to generate revenue [58]. This definition indicates that an aggregator is a company that earns income by trading with power markets and end users. In addition, the consumers in a cluster ideally share similar energy usage characteristics, which include their habits and geographical regions. An aggregator will provide better opportunities for customers to take advantage of their potential flexibility. In our research, the aggregator has the same meaning as the ADDRESS project. It groups the small-scale consumer services together and has two kinds of customers, FPC and DLC.

In [60], aggregators work with domestic small-scale customers by aggregating flexible demand and generation of equipment such as electrical appliances, including air conditioners and washing machines, energy storage such as batteries, and distributed generation including solar panels and micro wind turbines, which are installed at the customers' premises. Angentis et al. [61] focus on the aggregator trying to maximize profit. Two terms compose the objective function: the first, to sell the energy on the market to earn income, and the second, the price paid to the consumers for their participation in this service. A mixed-integer linear programming (MILP) algorithm achieves the best outcome. Furthermore, to consider the customers' energy usage, Angentis *et al*. [62] develop a model that optimally schedules appliances at the end users' premises. They describe three goals in the objective function, namely overall cost, climate comfort level, and timeliness. They also assign weights to each of these three terms according to customer preferences. They also solve this problem with an MILP algorithm, and the results show that this model can solve such problems efficiently. Parvania *et al*. [63] continue researching optimal demand response aggregation in a wholesale energy market. In their proposed framework, DR aggregators optimize the bids submitted to the wholesale market based on specific DR contracts for local customers in order to reduce the energy usage, and then it uses a price-based self-scheduling model to determine an optimal schedule for the day-ahead energy markets. Ahmadi *et al.* [64] develop a linear program for optimizing direct control of a micro grid. They introduce an approach wherein consumer behavior shifts from passive customers to active customers and gives a suitable and dynamic system of load rescheduling hinging on customer's precedence and load characteristics. They also define a controllability index to measure the performance of a micro grid on different levels of consumer flexibility. They conclude that the proposed framework determines the optimal load control strategy to balance electricity consumption, demand rescheduling, and selling electricity to the main grid.

Incentive-based DR given the hierarchical electricity market is explained by [65]. The model in this article takes the grid operator's view, and spans three hierarchical levels of the operator, multiple service providers, and corresponding customers. A unique Stackelberg equilibrium exists among the actors when the grid operator first posts incentive to the service providers, who then through subprograms give their customers incentives according to their load reduction in the DR program. The grid operator after collecting the load reduction from all service providers calculates the total cost, consisting of incentive payments to the service providers and the running cost of the generators. The process would be executed repeatedly until the system cost reaches a minimum. The DR model thus is based on an incentive model aimed at helping the grid operator procure resources from the generator and demand side at a minimum cost. From the results, it is seen that there is a reduction of 47% in the total cost by using the proposed model when compared to the model providing resource only to running generators. The truthfulness of the players participating in this case was also analyzed, concluding that profits of the service providers will decrease if other incentives are chosen. The utility of each customer also decreases on choosing other incentives. Thus, it was concluded that each player cannot increase its own utility by choosing a different strategy and a unique Stackelberg equilibrium provides an optimal solution.

Dynamic price optimization models for managing time-of-day electricity usage is explained by [66]. A day-ahead optimization approach using dynamic pricing incentives for an electric utility is presented to manage the residential electricity load profile. The approach is based on prediction of customer's response to price incentives to shift electricity usage from peak to off-peak periods. For estimating the intra-day hourly loads, a multinomial logit consumer-choice model is used, and the resulting nonlinear optimization problem is solved using a series of transformations, which include the reformulation-linearization technique, to obtain a mixed-integer programming model. The main contribution of this article is to propose an optimization model that optimizes time-of-day prices in such a way that the resultant customer response to pricing incentives does not cause the existing peak demand simply to migrate to another time of day. Moreover, the article also focuses on maximization of profit of the utility company by reshaping the intra-day demand profile while not affecting the customer's electricity bill. From the results, it was concluded that cost reductions were attainable by shifting peak loads, thus decreasing spot-market electricity usage. Near-optimal solutions were also achieved, indicating that the proposed methodology can be used in decision support systems for practical intra-day load management and day-ahead pricing.

2.4 CUSTOMER BASED DR

Some research, such as those following, has been conducted demand response for single or multiple households evaluating a pricing policy. Conejo *et al*. [20] built a real-time demand response model to adjust the hourly load level of a given consumer by considering hourly electricity price. They use a simple LP algorithm to solve this model, and the case study results demonstrate that it is possible to achieve maximum utility for customers to use this proposed model. Pedrasa et al. [53] suggest a customer-based model in order to schedule available distributed energy resources. The objective is to maximize the profits of the household in a day-ahead market. Mohsenian-Rad et al. [31] propose a residential load scheduling framework by evaluating a real-time pricing tariff. They predict the price and try to make a tradeoff between minimizing the household electricity bill and minimizing the delay time of the appliance in the house. In another article, Mohsenian-Rad et al. [7] presents an incentive-based autonomous and distributed demand-side energy management system among households with a shared energy source. They used game theory in which customers are the players and daily schedule of their appliances are the strategies. The purpose is to minimize the energy cost and balance the total residential load. Utilizing some assumptions, they showed that the Nash equilibrium globally minimizes energy costs.

Modelling DR using utility theory and model predictive control is explained by [67]. The article focuses on developing an agent-based simulation in which the household makes a suitable decision over a 24-hour cycle and selects optimal set points to maximize utility. The article is motivated by two factors. Thermostatically Controlled Loads (TCL) are the primary contributors of residential energy consumption. Second, residents' decisions on energy consumption are not only based on profit maximization but also on comfort/convenience maximization. The change in energy consumption behavior in terms of thermostatic loads was studied and Model Predictive Control was used to model consumers' decision on consuming TCL's. From the results, it was concluded that different pricing structures had a strong effect on households, with equal importance for cost and convenience. Households with higher weight for either attribute exhibited lower shift in behavior since they were harder to influence.

Optimizing load control in a collaborative residential micro grid environment is explained in [64]. An analytical model was developed for a Residential Micro Grid (RMG) under a social agreement environment. Priority was assigned by customers for appliances consuming residential load and the RMG notified the customer about the real-time consumption and economic benefits at a particular time. This allows customers to analyze and choose an alternative based on profit maximization. This article introduces an approach through which consumer behavior shifts from passive to active and yields a suitable and dynamic system of load rescheduling based on customer preference and load characteristics. A controllability index to measure the performance of micro grid on different levels of consumer flexibility is also defined. From results, it was concluded that the proposed framework determines the optimal load control strategy to balance electricity consumption, demand rescheduling and selling electricity to the main grid while residential loads have been prioritized by the customers. Significant financial benefits can be attained by allowing a controller to schedule loads and sell electricity to the main grid.

Dynamic demand response in smart buildings using an intelligent residential load management system is explained by [68]. In this article, an Intelligent Residential Load Management System (IRLMS) is proposed for customers to reduce electricity bill and availing more incentives from utility by responding to their DSM schemes. The IRLMS aims to reduce electricity bill and maintain the load under maximum limit by scheduling the schedulable loads while considering the operating dynamics of non-schedulable loads. Priority-based scheduling algorithm and optimization-based scheduling algorithm are used by the scheduler for flat rate tariff and real-time pricing, respectively. The proposed method updates change in utility's conditions such as fluctuations in electricity price, maximum demand limit, and changes in customer's operating time of load. This article focuses on developing a scheduling algorithm for schedulable loads to minimize electricity bill by considering the operational dynamics of non-schedulable loads, desire and comfort of the user, variation in electricity price of utility, and operational limits such as the maximum demand load. From the results it was concluded that the proposed IRLMS achieves substantial savings while reducing peak demand and keeping the total household demand below the maximum load limit. It was also inferred that considering the dynamics of non-schedulable loads has a notable impact on reduction in electricity bill.

Decentralized neighborhood energy management with coordinated smart home energy sharing is explained by [69]. The article focuses on a day-ahead decentralized coordination method with appliance scheduling and energy sharing to minimize electricity costs. Emphasis is placed on improving the utilization of renewable sources. Optimization is solved via a genetic algorithm. Two decentralized coordination models are presented in the study and the impact of sequence (group-based vs. turn-based) on coordination is analyzed by comparing the performance of two decentralized approaches. From the results, it was concluded that the turn-based algorithm gives better results than the group-based algorithm.

2.4.1 DYNAMIC PRICING DR RESEARCH

One of the main focal points of this research is considering the dynamic pricing customer as an agent. A brief review of research in this area follows.

A real-time demand response model to adjust the hourly load level of a given consumer in response to hourly electricity prices is explained in [20]. The objective of the model is to increase the customer profitability by considering the daily load consumptions, and maximum and minimum load levels. A simple linear programming algorithm is developed and integrated into the energy management system via a bidirectional communication device. The model makes use of real-time information about electricity prices with the help of smart grid technology. The price uncertainty following 24 hours is modeled using robust optimization. The hourly price uncertainty was modeled using a forecast value with a confidence interval about that value. The study was conducted both with smart grids and without using smart grids. The use of the smart grid model allows achieving a daily utility for the consumer that is 15.86% higher than that obtained in the absence of a smart grid. The weekly average utility is 16.22% higher with the robust model than that obtained with price forecasts.

Optimal residential appliance scheduling under dynamic pricing scheme is explained by [70]. Research shows that the lack of effective home automation systems and lack of awareness among end users to respond to time-varying prices are two obstacles to utilizing completely the advantages of dynamic pricing schemes. The article provides a solution to tackle these problems by proposing an automatic and optimal residential consumption scheduling technique. They try to achieve a trade-off between minimizing energy costs and the inconvenience of operating both electrical and thermal in a smart home environment. The study considers the environmental data, such as outdoor temperature and sun irradiation, and aims to present a smart home that is also capable of generating and storing energy by means of its own units. A home energy management scheduling problem with energy sources and controllable appliances such as a plug-in hybrid electric vehicle, washing machine, dishwasher, and spin dryer models is modeled as a mixed-integer nonlinear programming problem over a finite horizon of time. The results show that scheduling controllable electrical appliances and controllable thermal appliances can be reached simultaneously by using the proposed formulation. The results also suggest that considerable reduction in energy costs can be achieved through a conscientiously designed energy billing model and by appropriately scheduling load consumption.

Hubert *et al.* [71] focus on energy scheduling and optimization algorithms for residential electricity consumption in a dynamic pricing environment. The proposed modeling framework is based on mixed-integer linear programming and is presented from a consumer's perspective. The home energy controller derived from this formulation was used to control the various home grid components to optimize the household energy use based on the consumer's preferences. This leads to significant economic savings for the consumer.

Predictive control of buildings for DR with dynamic day-ahead and real-time prices is explained by [72]. The article focuses on a Model Predictive Control (MPC) scheme to control residential buildings having space heating/cooling loads, an electric water heater, photovoltaics, and battery storage in a time-varying electricity price environment. In models for system components as well as future disturbances such as weather conditions, electricity prices are used by the MPC controller to obtain operation that minimizes electricity costs given comfort constraints of the customer. Three scenarios are considered for building operations, a simple day-night tariff for end-customers, a day-ahead dynamic tariff reflecting the wholesale market, and marginal costs and a real-time dynamic tariff. This article also provides a sensitivity analysis of building response with respect to day-ahead and real-time price signals. Furthermore, evaluation of potential DR schemes where real-time price signals are superimposed on top of day-ahead price profiles are analyzed.

Real-time energy management optimization for the smart household is explained by [73]. The article focuses on energy management problem of a smart home consisting of a renewable energy source (RES), an energy storage system (ESS), a set of schedulable home appliances, and a dynamic electricity tariff. The objective is to find the load scheduling problem of home appliances and the energy dispatch problem of a utility grid under a single optimization framework by using a mixed-integer linear programming formulation. The proposed energy management system minimizes the energy cost without violating the operating constraints of a smart home and the convenience level of users. The proposed home energy management system minimizes the cost by prioritizing the use of self-generated PV power and energy stored in ESS and optimizes the electricity drawn from utility grid to satisfy load demands.

Bahrami *et al.* [74] describe employing smart meters in a modified approach for residential load scheduling. The article concentrates on a practical method directed to optimize the consumer's electricity bill cost and satisfaction by considering generation capacity limitation and dynamic electricity price in different time slots of a day. The proposed optimization algorithm is compared with Particle Swarm Optimization (PSO) algorithm to demonstrate the potential usage of the proposed algorithm as a practical tool for peak load saving. The article focuses on developing an incentive-based program considering user satisfaction, dynamic electricity prices, and constraints regarding electricity generation capacity. The algorithm allows users to shift their utility consumption to periods in which the electricity cost is more economical. From the results, it is concluded that the new proposed method introduces a management strategy based on modified cost function that reduces peak load, while regarding the impacts of capacity and load rates on the price. The accuracy and speed are concluded to be better than the PSO method and the controlling parameters can be used to adjust the scheduling algorithm of utilities. A trade-off between the customer's satisfaction maximization and energy consumption cost minimization can be reached using the proposed approach.

Effective load scheduling of residential consumers based on dynamic pricing with price prediction capabilities is explained by [75]. The article focuses on an automatic load control approach with dynamic pricing models for residential customers. Linear prediction model and artificial neural network are implemented for predicting the prices. Binary linear programming computations are used for optimization purposes. Real time pricing (RTP) is considered as the DR policy and residential load model, price prediction model and load control problem are developed. The main objective is to deploy a day-ahead RTP with a linear prediction model and an artificial neural network. The next goal is to develop an automatic load control algorithm to achieve optimal scheduling of residential consumers and to improve energy efficiency. The RTP pricing models with price prediction were combined to design a price-based demand response model.

Roy et al. [76] explains optimization in load scheduling of a residential community using dynamic pricing. The article presents a study of a residential community of three houses with different electrical appliances. The study is based on comparative genetic algorithm and dynamic programming. Three types of houses are compared under an energy management benchmark problem. The optimization performance of control approaches is validated with different priority optimization in load scheduling of a residential community using dynamic pricing. The main objective of the study was to examine comparatively three optimization approaches, genetic algorithm, aggressive dynamic programming (designed based on comfort of the user), and conservative dynamic programming (designed based on energy cost saving) in terms of cost minimization for the utility. From the results, the conservative dynamic approach showed the smallest energy cost, the genetic algorithm optimizes the energy consumption, and the aggressive dynamic approach reduces the computational complexity as well as decreases the energy cost. Thus, the aggressive dynamic approach is recommended as the best choice for real-life application.

2.5 APROXIMATE DYNAMIC PROGRAMMING (ADP)

In 1957, Bellman originated dynamic programming (DP), a mathematical programming method solving multistage decision problems. DP cuts a complicated problem down into a collection of simpler subproblems and solves each just once. Solutions are maintained in a memory-based data structure [77]. The first Bellman equation can be written as:

$$V_t(s_t) = \min_{u_t}(c_t(s_t, u_t) + V_{t+1}(s_{t+1})) \qquad (2.1)$$

s_t State space
u_t Decision variable
c_t Cost function
V_t Future value function

In classical DP, the state space is assumed to comprise a finite number of states and is assumed to be known. Equation (2.1) can be used to solve a deterministic finite-horizon problem.

A stochastic DP (SDP) considers randomness when making decisions, and its goal is to minimize an expected cost. A typical recursive SDP formulation for a finite-horizon problem with a continuous state space can be written as

$$V_t(s_t) = \min_{\mathrm{u_t}} E\{c_t(s_t, u_t, \varepsilon_t) + V_{t+1}(s_{t+1})\} \tag{2.2}$$

$$\begin{aligned} s.t. \qquad & s_{t+1} = f_t(s_t, u_t, \varepsilon_t) && t = 1, \dots T \\ & u_t \epsilon \Gamma_t && t = 1, \dots T \\ & V_T(s_T) = \min_{u_T} E\{c_T(s_T, u_T, \varepsilon_T)\} \end{aligned}$$

T	Time horizon
ε_t	Stochastic variable
Γ_t	Constraint space for the state and decision variables
f	State transition function

An infinite horizon problem differs from the finite horizon problem. For an infinite horizon problem, the future value function formulation is written as follows:

$$V(s_t) = \min_{u \in \Gamma} E\{c(s_t, u_t, \xi_t) + \gamma V(f(s_t, u_t, \xi_t))\} \tag{2.3}$$

ξ	Stochastic variable
γ	Discount factor

Bellman's classical DP method can be used only to solve a small problem or problems under certain restrictions by optimizing the system over time [78]. Typically, Markov decision processes have either many discrete states and decisions or continuous state spaces. Due to the large number of possible state variables and the number of possible outcomes from the stochastic variables, computational obstacles can arise, commonly referred to as the "curse of dimensionality." Powell [79] summarizes the three main reasons that cause the curse of dimensionality, namely, increasing the dimensions of the state variables, the decision variables, and exogenous information variables. The curse of dimensionality renders impractical the traditional DP solution approach that relies upon exhaustive search. With advances in computational power, a new family of dynamic programming, approximate dynamic programming (ADP), has emerged. A real-world DP problem is often high-dimensional and stochastic with continuous state variables. To address this problem, ADP methods discretize/sample the continuous state space and approximate the future value function by statistical modeling techniques. The earliest strategies used full finite grid discretization with multilinear or spline interpolation. From a statistical standpoint, more efficient design of experiments' methods, such as orthogonal arrays (OAs), Latin hypercube, and number-theoretic methods (NTMs), combined with flexible statistical modeling methods, including multivariate adaptive regression splines (MARS) and neural networks (NNs), enabled approximate solutions to higher-dimensional problems [79]. Chen et al. [81] proposed discretizing the state space using an orthogonal array. This approach is able to overcome the sampling drawbacks that exist in the other discretization methods.

The value iteration version of ADP approximates the value function based on data instead of using the true value function, and iteratively employs approximation to numerically solve the problem. Consequently, ADP attempts to find a converged *approximate FVF* ($\hat{V}$) using the following formulation.

$$\hat{V}(x) \approx \tilde{V}(x) = \min_{u \in \Gamma} E\{c(x,u,\xi) + \gamma \hat{V}\big(f(x,u,\xi)\big)\} \ . \qquad (2.4)$$

The proposed two-agent demand response model is an infinite horizon problem. The design and analysis of computer experiments (DACE) based approach is one of the infinite horizon ADP approaches in literature. Originally developed by Chen et al. [81], it replaces the time physical experiments such as full grid design. DACE makes the best of DOE to discretize the state space and utilize the statistical learning method to build the surrogate model based on inputs and calculated objective values. In applying DACE, fewer points are needed to represent the state space, tremendously reducing computational time. Chen et al. [82] stated that a "space-filling" sampling technique including OAs and NTM is appropriate for DACE-based ADP. Original DACE-based ADP focused on solving finite horizon DP problems over continuous spaces. In 2013, Chen et al. [83] proposed the DACE-based infinite horizon ADP algorithm based on adaptive value function approximation (AVFA). The DACE-based infinite horizon ADP algorithm is flexible and able to overcome the curse of dimensionality.

The only research using DP for demand response in the literature is by Liu et al. [84]. They develop a dynamic programming approach that can manage the nonlinearity and non-convexity in a DR problem in order to find the optimal operating sequence. Their proposed formulation explicitly accounts for the dynamic behavior of the transition between operating modes, time-varying electricity prices, and varying energy generation profiles. Their formulation is then applied to a continuously stirred tank reactor example, in which they assert that energy consumption is proportional to the material flow, and the process must meet hourly varying product demand. They claim that their proposed methodology resulted a 12.9% operating cost saving in a continuously stirred tank reactor model.

2.6 FUTURE CHALLENGES IN DR

Two big challenges await DR programs in the near future, large scale renewable energy supply and large numbers of electric vehicles. Figure 8, known as duck curve, shows how projected increases in renewable energy generation might affect the net load in California. It shows the actual and projected hourly net load profile over the years 2012-2020. It reveals large shares of renewable energy, especially solar, during the day, creating ramping-up problems in the late afternoon. Moreover, renewable energy supply is highly variable because it is weather dependent.

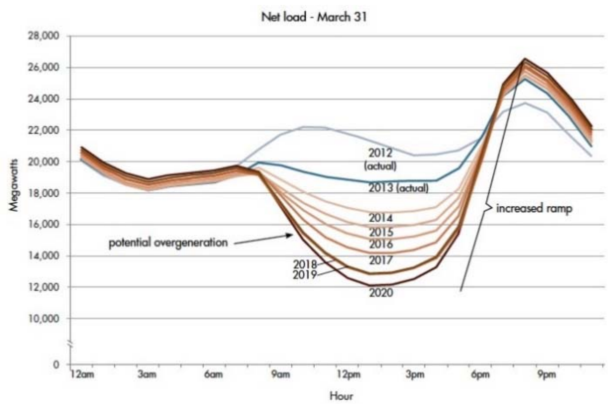

Figure 8. Duck curve[7]

In addition, the large number of electric vehicles in the future will change the current demand profile. Thus, we believe that demand response in the future would be different from today.

2.7 CONTRIBUTIONS

Although the current electric distribution and management system has been relatively constant and stable for many decades, factors are at play that may fundamentally change the design and operation of the electric system. A number of significant transformations have been occurring that create new challenges to the existing power supply management. The transformations include more renewable energy resources in the

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[7] http://www.greentechmedia.com/

bulk power system, proliferation of distributed energy resources (DERs) of various capacities in both transmission and distribution systems, increased installations of local renewable resources at end-use points, and rapid growth of transportation electrification (e.g., Plug-in Electric Vehicles-PEVs) at end users [85]–[97]. Of particular concern is rapid growth in the use of intermittent renewable energy resources in both the bulk power system and at end-use points served by distribution systems [98]. According to the U.S. Department of Energy (DOE) forecast, renewable energy will provide at least 20% of the U.S. electricity market by 2030 [99]. Due to the fast progress of the renewable energy revolution with rapidly falling cost, most recent clean energy initiatives aim to achieve a much higher share of renewable energy in strategic plans, like the Clean Energy Act of California, which aims to achieve 50% penetration of renewable energy by 2030 [100], introducing high stochasticity in the future energy market. We expect the potential high penetration of wind and solar resources, as well as customer-installed generation and storage operated autonomously, to cause serious problems of intermittent shortage or overproduction that far exceed the capability of the current electric distribution systems [93]–[97]. This emerging issue of intermittent shortage or overproduction is critical mainly because the key differentiator of the electricity system compared to other commodities is that we must balance supply and demand across the entire grid in real time [97].

Even though many groups have widely studied residential demand response, most of the current approaches and solutions actually target certain DR sub problems restricted to some specific types of customers, specific types of control mechanisms, price strategies, or forecasting of demand response and energy market price. To the best of our knowledge, at present, no DR management research simultaneously considers all three major categories of customers in achieving efficient real-time optimal DR decision making for large-scale end users in highly dynamic and stochastic future energy markets. This emerging problem of large-scale residential DR programs with the introduction of dynamic electricity pricing structures mixed with other traditional pricing types is extremely difficult, and currently less studied. The next generation of real-time demand response (DR) management of large-scale residential end users is an urgent need and yet unsolved to achieve highly coordinated energy use and generation using market forces of dynamic power price signals in the face of future high penetration of renewable energy and DERs. This research aims at developing a comprehensive DR planning and operational optimization model. The LSE will use the developed two-agent stochastic optimization model to determine optimal DR control signals dynamically, based on forecasted market prices, renewable energy generation, storage, and aggregated demand flexibility. The proposed modeling and optimization architecture will influence the overall smart power system and its participants, particularly the LSEs, customers, and system operators. It could potentially optimize energy management at homes, businesses, and improve the control of distributed energy resources.

Solving this two-agent stochastic model has great importance. We find the lower and upper bounds for the aforementioned problem using the expected value problem and the wait-and-see solution. They provide minimum and maximum operational costs that the LSE can use for its financial planning. Experiments analyzing the stochastic gap in the Dallas-Fort Worth metroplex (DFW) are also presented. Because of electricity market prices and high penetration of renewable generations, this system is highly dynamic and stochastic. Hence, the proposed research is important to tackle emerging challenges and develop new advanced modeling, simulation, and optimization tools. To our knowledge, this is the first paper that provides stochastic bounds for a two-agent stochastic optimization model.

Chapter 3

FIRST PAPER

Linear Programming for Multi-Agent Demand Response

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***Abstract* -This research describes a real-time optimization model for multi-agent demand response (DR) from a Load Serving Entity (LSE) perspective. We formulate two infinite horizon stochastic optimization models; specifically, an LSE model and a dynamic pricing customer model. The objective of these models is to minimize long-term cost and discomfort penalty of the LSE and dynamic pricing customers. We solve a deterministic finite horizon linear program as an approximation of the suggested stochastic model and provide computational experiments.**

***Index Terms:* Linear programming, multi-agent demand response, demand side management, dynamic pricing customers, smart grid**

1. INTRODUCTION

Although the current electric distribution and management system has been relatively constant and stable for many decades, recent advancements may fundamentally change the design and operation of the electric system and create new challenges to the existing power supply management. These transformations include more renewable energy resources in the bulk power system, proliferation of distributed energy resources (DERs) of various capacities in both transmission and distribution systems, increased installations of local renewable resources at end-use points, and rapid growth of transportation electrification (e.g., Electric Vehicles-EVs) at end users [1]–[13]. Of particular concern is rapid growth in the use of intermittent renewable energy resources in both the bulk power system and at end-use points served by distribution systems [14]. According to the U.S. Department of Energy (DOE) forecast, renewable energy will provide at least 20% of the U.S. electricity market by 2030 [15]. Because of the current trends with renewables with rapidly falling cost, most recent clean energy initiatives aim to achieve a much higher share of renewable energy in strategic plans, like the Clean Energy Act of California, which aims to achieve 50% penetration of renewable energy by 2030 [16], introducing high stochasticity in the future energy market. We expect the potential high penetration of wind and solar resources, as well as customer-installed generation and storage operated autonomously, to cause serious problems of intermittent shortage or overproduction that far exceed the capability of the current electric distribution systems [9], [11], [17]–[19]. This emerging issue of intermittent shortage or overproduction is critical mainly because the key differentiator of the electricity system compared to other commodities is that electricity distributors must balance supply and demand across the entire grid in real time [13].

Although many groups have widely studied residential demand response, most of the current approaches and solutions actually target certain DR sub-problems restricted to some specific types of customers, specific types of control mechanisms, price strategies, or forecasting of demand response and energy market price. Some studies have focused on an integrated and complete functioning platform for residential DR LSEs to handle massive market and customer information and build optimal decision making. They have strived for a realistic operating scenario in which DR LSEs will most likely meet in the future smart grid market. We particularly design this research to bridge the knowledge gap and to develop a model for residential DR LSEs. Our approach incorporates a complete portfolio of future potential end-user customers, including all three major customer groups: fixed-pricing, direct load control, and dynamic pricing customers. A summarized discussion of each is next.

A. Fixed-Pricing Customers (FPC)

In fixed-pricing programs, the utility offers electricity at a fixed rate regardless of the day-ahead or real-time market prices, so the price remains stable throughout the length of the contract [45]. We expect that these kinds of customers remain a considerable portion of the customers, and we will need to consider them in future demand response decisions.

B. Direct Load Control Customers (DLC)

In direct load control programs, the LSE or aggregator has remote control over certain appliances of the customers based on the agreement. For example, they may turn off and on the air conditioner, dishwasher, EV charger, and pumps [20], [21]. There is much research focusing on DLCs, such as [22]–[25].

C. Dynamic Pricing Customers (DPC)

In dynamic pricing programs, also known as real-time pricing or time-varying programs, we assume that each customer has access to the real-time wholesale market price and responds individually to the time-differentiated prices by shifting his load [26]–[28]. We assume that residential customers have smart meters in their houses that simply control their consumptions by an algorithm. It can have the current price and the forecasted trajectory of the price. Based upon this information, it might delay some level of operation of appliances such as an air conditioner or dishwasher. The question is how sophisticated that forecast could be. There can be some level of communication between the smart meter and the cloud. They can do some sophisticated optimization in the cloud and then send the signal over to the device. Alternatively, they could have some component of the device. The smart meter sends messages to devices that have pre-programs enabling them to do something smart like a heuristic.

We organize the remainder of this paper as follows. Section 2 summarizes background and literature on demand response programs and our contributions. Section 3 reviews energy resources for both LSE and DPCs. Section 4 includes mathematical formulations of the LSE and DPC models. Section 5 describes computational experiments for a deterministic problem of the suggested model. Finally, Section 6 derives the conclusions and future work.

2. LITERATURE REVIEW

We recognize smart grids for their competencies and related advantages. However, we require a great deal more to transform smart grids into actuality [29]. With the development of technology and communications, advanced metering systems and energy management provide a more active participation of customer demand in power systems. Based upon these advancements, demand response (DR) is proposed to deal with this relationship between customers and the power system. These DR programs are different from the current electricity usage situation, since most customers pay only a flat electricity price and have no incentive to change their electric usage in response to prices [30]. Therefore, the main objective of DR programs is to offer incentives to customers who reduce energy usage at peak demand times [31]. With this, DR mitigates market power generation, reduce electricity prices, resolve transmission lines congestion, enhance resilience of the power system, and improve market liquidity [32]. To improve the usage of DR programs, utilities should create more flexible DR resources to make these programs more attractive to customers; for example, they should focus more on price reduction and not just on system reliability [33].

So far, researchers in the demand response field have conducted many research projects such as [34]–[44]. We will review a few that pertain to our work. Li *et al.* [45] propose a demand response model based on utility maximization. They assume households with different kinds of usage like EVs and batteries. They consider dynamic pricing and claim that they can align individual optimality with social optimality. They suggest a joint algorithm for utility and residential customers. They also mention that by increasing the number of customers, the benefit of their algorithm increases but finally will saturate. Conejo *et al*. [46] built a real-time demand response model to adjust the hourly load level of a given consumer by considering hourly electricity price. They use a simple LP algorithm to solve this model, and the case study results demonstrate that it is possible to achieve maximum utility for customers to use this proposed model. Pipattanasomporn *et al*. [47] propose another intelligent home energy management algorithm to manage power consumption of household appliances with demand response analysis. Their simulation results demonstrate that this algorithm can control appliance operation and limit household power consumption below a certain demand.

In these four research papers, the DR relationship is directly between the power system and its customers. However, in practice it is difficult to control and adjust a customer's electricity usage directly from market level since the individual customer's electricity usage has little effect on the overall power market, and the transaction cost of such direct control is excessive [48]. In 2008, Belhomme *et al*. [49] describe the ADDRESS European project ("Active Distribution networks with integration of Demand and distributed energy RESourceS") as building a comprehensive and commercial smart grid framework for the development of the "active demand" of residential customers. In this project, they introduce a new intermediary between the power system and local customers, called an *aggregator* [48].

In Evens *et al.* [50], aggregators work with domestic small-scale customers by aggregating flexible demand and generation of equipment such as electrical appliances, including air conditioners and washing machines, energy storage such as batteries, and distributed generation including solar panels and micro wind turbines, which they install on the customers' premises. Angentis *et al.* [51] focus on the aggregator trying to maximize profit. Two terms compose the objective function: the first, to sell the energy on the market to earn income, and the second, the price paid to the consumers for their participation in this service. A mixed integer linear programming (MILP) algorithm achieves the best outcome. Furthermore, to consider the customers' energy usage, Angentis *et al*. [52] develop a model that optimally schedules appliances at the end users' premises. They describe three goals in the objective function: overall cost, climate comfort level, and timeliness. They also assign weights to each of these three terms according to customer preferences. They solve this problem with an MILP algorithm, and the results show that this model can solve such problems efficiently. Parvania *et al*. [53] continue researching optimal demand response aggregation in a wholesale energy market. In their proposed framework, DR aggregators optimize the bids submitted to the wholesale market based on specific DR contracts for local customers in order to reduce energy usage, and then it uses a price-based self-scheduling model to determine an optimal schedule for the day-ahead energy markets. Ahmadi *et al.* [54] develop a linear program for optimizing direct control of a micro grid. They introduce an approach wherein consumer behavior shifts from passive customers to active customers and gives a suitable and dynamic system of load rescheduling hinging on customers' precedence and load characteristics. They also define a controllability index to measure the performance of a micro grid on different levels of consumer flexibility. They conclude that the proposed framework determines an optimal load control strategy to balance electricity consumption, demand rescheduling, and selling electricity to the main grid.

As a promising solution to achieve dynamic supply-demand balance, DR with dynamic pricing signals attracts great interest. It can shift peak consumption and allow higher flexibility to account for uncertainties in the energy market. Palensky and Dietrich [55] note that the existing demand response programs focus mainly on a small number of industrial and large commercial customers using DLC and interruptible loads. Some researchers have conducted studies on residential DR with dynamic electricity pricing in recent years [56]–[58]. However, the current studies mostly target some specific sub-problems with a very restricted type of customer, control mechanisms, and pricing strategies. The less dynamic time-varying pricing structures have mostly adopted, for example, time of using pricing, critical peak pricing, and peak time rebates. These price structures define different electricity prices at different fixed periods of the day or year. High stochastic real-time dynamic pricing structures need more investigation to enable their great potential. Overall, the current DR management studies and methods are generally limited and are difficult to scale to handle future large numbers of small commercial and residential customers with different control and operation types, including DLC, real-time dynamic pricing, and FPCs.

3. CONTRIBUTION

To the best of our knowledge, at present, no DR management research simultaneously considers all three major categories of customers in achieving efficient real-time optimal DR decision making for large-scale end users in highly dynamic and stochastic future energy markets. This emerging problem of large-scale residential DR programs with the introduction of dynamic electricity pricing structures mixed with other traditional pricing types is extremely difficult, and currently less studied. The next generation of real-time demand response (DR) management of large-scale residential end users is an urgent need and yet unsolved to achieve highly coordinated energy use and generation using market forces of dynamic power price signals in the face of future high penetration of renewable energy and DERs. This research aims at developing a comprehensive DR planning and operational optimization model. The LSE will use the developed optimization model to determine optimal DR control signals dynamically, based on forecasted market prices, renewable energy generation, storage, and aggregated demand flexibility. The proposed modeling and optimization architecture will influence the overall smart power system and its participants, particularly the LSEs, customers, and system operators. It could potentially optimize energy management at homes, businesses, and improve the control of distributed energy resources.

4. ENERGY RESOURCES

We consider five types of energy resources for the LSE and three types for DPCs. Pre-purchased electricity, wind, solar, battery inventory, and the main grid are LSE's resources. They are solar, battery inventory, and the grid for DPCs.

The LSE has the ability to purchase the electricity in a day-ahead market or through a long-term contract. We call it pre-purchased electricity resource. In this research, we assume that it is the difference between a forecasted demand profile and renewable energy generation. Note that DPCs do not receive pre-purchased electricity.

In October 2017, the installed capacity of wind farms in Texas surpassed 20,000 megawatts, the highest installed wind power capacity in the US, according to Electric Reliability Council of Texas (ERCOT). Texas achieved the Wind Penetration record of 54% on October 27, 2017. Approximately 17.4% of the energy used in ERCOT came from wind in 2017. We assume that the LSE has a contract with a wind farm (e.g., 30% of its wind energy production). We choose a nearby wind farm in Oklahoma with a 74.25 MW capacity for this research. We also assume that DPCs lack access to a wind farm. ERCOT provides our 15-min wind power data.

Installed solar capacity in Texas exceeded 1,000 megawatts in October 2017, according to ERCOT. We assume that both the LSE and DPCs have solar energy resources. The LSE can access a solar park, and DPCs can have top roof solar panels.

Given [62], we estimate battery capacity to be 3.6 MWh per battery slot. We choose battery capacity and other battery specifications such as charging and discharging rates like [62]. The other assumption is that the LSE has ten battery slots and DPCs have a cumulative five battery slots.

Finally, the main grid is the other source of energy for both LSE and DPCs. They have the ability to buy electricity from the grid as needed. They also can sell the electricity to the grid when it is expensive or surplus.

5. FORECASTING METHODS

In this research, we use methods described in [63]–[65] for forecasting market price, wind generation, and solar photovoltaic (PV) generation. They use support vector regression to make predictions in the deregulated market. In addition, they take advantage of Martingale Model Forecast Evolution (MMFE) to investigate the characteristics of forecast uncertainty.

For wind generation, our methods take into consideration factors including wind generation, wind speed, and relevant weather parameters, such as gusty wind, wind direction, and temperature as the input parameters. The final model that we use in this research consists of three predictors. They are wind generation at 15 and 30 min before prediction time and wind speed at 15 min before the prediction. Fig. 1 shows the forecasted wind generation for the LSE in a one-day deterministic problem.

For PV generation, these methods utilize factors as predictors, including historical PV generation, humidity, temperature, cloud rating, wind speed, and the previous day of sunshine. Their final model consists of three predictors: historical PV generation at 15 and 30 min before the prediction time and the previous day of sunshine. Fig. 1 shows the forecasted solar generation for an assumed LSE in a one-day deterministic problem.

For market price, the final model consists of historical market price, temperature, and load profile at 15 and 30 min before the prediction time.

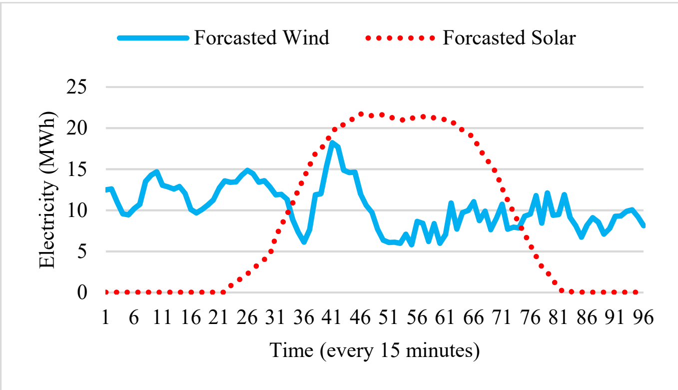

Fig. 1. Forecasted renewable energy

6. PROBLEM FORMULATION

In this section, we present two infinite horizon stochastic programming models for LSE and DPCs. We use three terms to explain the model in a simpler way: recaptured demand, lost demand, and spilled demand. *Recaptured demand* is the deferred demand that we satisfy later. Examples are dishwasher and dryer loads. *Lost demand* is the eliminated demand that the customer no longer needs in future periods. An example is air conditioner load. *Spilled demand* is the summation of the recaptured and lost demand.

The first multi-stage model is the LSE's stochastic optimization program for the real-time market. Table 1 lists the notation of the model parameters that we use throughout the article. Tilda denotes the uncertain stochastic parameters.

Table 4. Model parameters

r	Renewable energy generation
g	The main energy grid
b	Battery storage
d_1	Load demand from DLCs
d_2	Load demand from DPCs
d_3	Load demand from FPCs
t	Index for the time period, in which $t = 0$ is the current time period
T	A fixed set of time periods for which loads may be deferred for DLCs
$\tilde{c}_t$	Random variable for the real-time market price in time period t
$\tilde{r}_t$	Random variable for the LSE's renewable generation in time period t
p_t	Pre-purchased electricity for time t
γ	Discount factor
$\tilde{r}_{tDPC}$	Random variable for the DPC's renewable generation in time period t
$\tilde{d}_{t1}$	Random variable for the load demand from the DLCs in time period t
$\tilde{d}_{t3}$	Random variable for the load demand from the FPCs in time period t
d_{t2}	The load demand from the DPCs, which is a function of $\tilde{r}, \tilde{c}$, as well as previous DPC load $\tilde{d}_2$
e_c	Battery charging efficiency rate
e_d	Battery discharging efficiency rate
u_{tc}	Upper limit on charging the battery in a period
u_{to}	Upper limit on discharging the battery in a period
l_b	Lower limit on the battery storage
u_b	Upper limit on the battery storage
l_{td}	Lower limit on energy supplied to the DLCs in a period
u_{td}	Upper limit on energy supplied to the DLCs in a period
p_i	The amount of previously purchased energy
Δ_t	The electricity exchange between the LSE and the DPCs at time t
a_t	The recapture rate
$z_{t\bar{t}}$	A discomfort penalty for recapturing load from time period t to time period $\bar{t}$, for each $\bar{t} = t, \dots, t+T$

Transferred electricity, battery inventory level, and recaptured demand are decision variables. Table 2 shows the notation description of these variables.

Table 5. Decision variables

x_{tgd}	The amount of electricity transferred from the grid to demand at time t
x_{tgb}	The amount of electricity transferred from the grid to battery storage at time t
x_{tgDPC}	The amount of electricity transferred from the grid to the DPCs at time t
x_{trd}	The amount of electricity transferred from renewable generation to demand at time t
x_{trb}	The amount of electricity transferred from renewable generation to battery storage at time t
x_{trg}	The amount of electricity transferred from renewable generation to the grid at time t
x_{trDPC}	The amount of electricity transferred from renewable generation to DPCs at time t
x_{tbg}	The amount of electricity transferred from battery storage to the grid at time t
x_{tbd}	The amount of electricity transferred from battery storage to demand at time t
x_{tbDPC}	The amount of electricity transferred from battery storage to DPCs at time t
x_{tpg}	The amount of pre-purchased electricity transferred to the grid at time t
x_{tpb}	The amount of pre-purchased electricity transferred to the battery at time t
x_{tpd}	The amount of pre-purchased electricity transferred to demand at time t
x_{tpDPC}	The amount of pre-purchased electricity transferred to the DPCs at time t
I_t	The battery inventory level at the beginning of time period t
$d_{t\bar{t}1}$	Recaptured demand from time period t to time period $\bar{t}$ for the DLCs, for each time period $\bar{t} = t, \dots, t+T$
$d_{\bar{t}t1}$	Recaptured demand from time period $\bar{t}$ to time period t for the DLCs, for each time period $\bar{t} = t-T, \dots, t$
d_{tt1}	Satisfied demand for the DLCs at time t

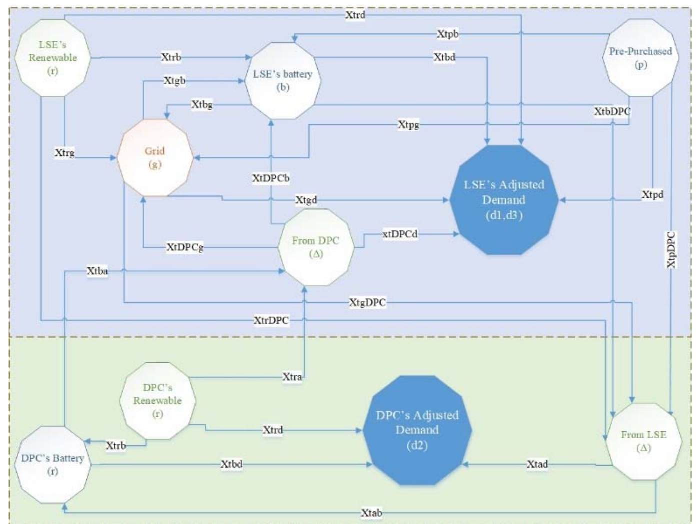

Fig. 2. Demand-supply flow chart

Fig. 2 presents a flow chart showing demand, supply and their relationships for both the LSE and the DPCs. Because we have market price information every 15 min, we observe 15-min intervals. In each interval, the state variable is the expected value. The objective is to minimize the long-term operational cost of the LSE and the discomfort penalty. The first part is the cost of buying from the grid for demand and battery storage, minus the revenue from selling back to the grid from renewable generation and battery storage. The second part of the following linear objective function shows the penalty function.

$$\min \sum_{t=0}^{\infty} \gamma \Bigg(\tilde{c}_t \left(x_{tgd}^a + x_{tgb}^a + x_{tgDPC}^a - x_{trg}^a - x_{tbg}^a - x_{tpg}^a - x_{tDPCg}^a \right) + \sum_{t=0}^{\infty} \sum_{\bar{t}=t-T}^{t} z_{t\bar{t}}^a \, d_{\bar{t}t1} \Bigg) \quad (1)$$

One of the model parameters in the objective function (1) that shows customer flexibility is the *waiting cost function*, symbolized by $z_{t\bar{t}}^a$. Costs relative to rescheduling loads rise over time; consumers can bear short delays more readily than longer ones. Naturally, consumer frustration increases with waiting time. The waiting cost's upper limit should reflect market price. Note that rescheduling is detrimental if the waiting cost is too large. No low market price can compensate for an excessive waiting cost, and in such circumstances, rescheduling is not beneficial. There is a critical point within the waiting cost function at which rescheduling stops for all waiting costs above this point.

In this example, no economic benefit can be found for load rescheduling when waiting costs exceed $M = 4$ (\$/MWh). In this research, we choose a logarithmic function (2) through which the waiting cost function increases rapidly in early periods. We can easily substitute other kinds of cost functions, such as linear and exponential. For more information about different cost functions, refer to [54].

$$z^a_{t\bar t} = ln\left(\frac{t-\bar t}{T}e^M + 1 - \frac{t-\bar t}{T}\right) \qquad \bar t = t-T, \dots, t \tag{2}$$

Fig. 3 presents an example of a waiting cost curve in our research. If we defer load for 15 min, it costs \$0.44 per MWh. It is \$1.70 for 2 hours' deferral.

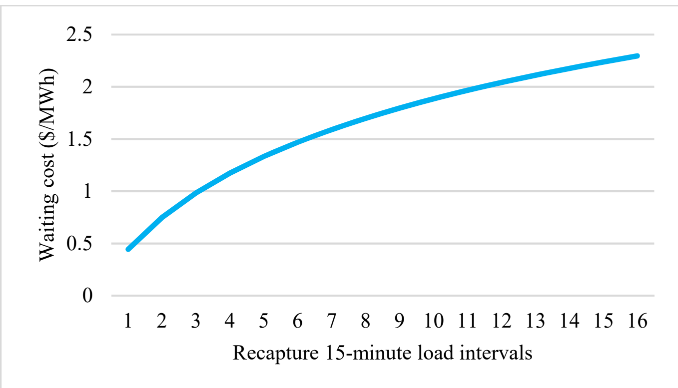

Fig. 3. Waiting cost function

Energy storage is the first constraint set (3). It calculates the battery storage in time period *t+1* considering the previous storage, inputs, and outputs to the battery. The assumed charging and discharging efficiency rates are 79.8% in the computational experiments [59].

$$I^a_{t+1} = I^a_t - \frac{x^a_{tbg} + x^a_{tbd} + x^a_{tbDPC}}{e^a_d} + e^a_c\left(x_{trb}\, x^a_{trb} + x^a_{tgb} + x^a_{tpb} + x^a_{tDOCb}\right) \quad \forall t = 0, \dots \tag{3}$$

Renewable generation balance is the second constraint set (4). It is included to ensure that LSE renewable generation ($\tilde r^a_t$) is equal to the transferred renewable generation to the grid, battery storage, demand, and the DPCs. In addition, *Pre-purchased balance* is the third constraint set (5).

$$\tilde r^a_t = x^a_{trg} + x^a_{trb} + x^a_{trd} + x^a_{trDPC} \quad \forall t = 0, \dots \tag{4}$$

$$p^a_t = x^a_{tpb} + x^a_{tpg} + x^a_{tpd} + x^a_{tpDPC} \quad \forall t = 0, \dots \tag{5}$$

The fourth set of constraints (6) is for *load supply-demand balance*. The left side of the equation shows the total demand for the LSE. It is the demand of two kinds of customers, respectively, the DLCs, and the FPCs. The right side shows the electricity transmitted to demand from renewable generation, the grid, battery storage, pre-purchased electricity, and the DPCs' surplus.

$$\sum_{\bar t = t-T}^{t} d_{\bar t t1} + \tilde d_{t3} = x^a_{trd} + x^a_{tgd} + x^a_{tbd} + x^a_{tpd} + x^a_{tDPCd} \quad \forall t = 0, \dots \tag{6}$$

The fifth set of constraints shows the transferred electricity from the LSE to the DPCs, Δ^+_t, and the transferred surplus electricity from the DPCs to the LSE, Δ^-_t.

$$\Delta_t = \Delta^+_t - \Delta^-_t \quad \forall t = 0, \dots \tag{7}$$

$$\Delta^+_t = max(\Delta_t, 0) \quad \forall t = 0, \dots \tag{8}$$

$$\Delta^-_t = -\min(\Delta_t, 0) \quad \forall t = 0, \dots \tag{9}$$

$$\Delta^+_t(\tilde c, \tilde d_2, \tilde r) = x^a_{tpDPC} + x^a_{tbDPC} + x^a_{tgDPC} + x^a_{trDPC} \quad \forall t = 0, \dots \tag{10}$$

$$\Delta^-_t(\tilde c, \tilde d_2, \tilde r) = x^a_{tDPCg} + x^a_{tDPCb} + x^a_{tDPCd} \quad \forall t = 0, \dots \tag{11}$$

Recaptured *demand balance* is the sixth set of constraints (12). It says that a fraction (a^a_t) of the amount of demand that is unsatisfied now, must satisfy in future periods. We call it the recapture rate. We assume that the recapture rate is 75% in the computational experiments.

$$\sum_{\bar t = t+1}^{t+T} d_{t\bar t 1} = a^a_t\left(\tilde d_{t1} - d_{tt1}\right) \quad \forall t = -T, \dots \tag{12}$$

Discharge rate limit and charge rate limit are the seventh set of constraints (13) and (14). Constraint set (13) ensures that the discharge of the battery in a period is limited to u^a_{to}. Constraint set (14) ensures that the charge of the battery in a period is limited to u^a_{tc}.

$$x^a_{tbg} + x^a_{tbd} + x^a_{tbDPC} \le u^a_{to} \quad \forall t = 0, \dots \tag{13}$$

$$x^a_{trb} + x^a_{tgb} + x^a_{tDPCb} + x^a_{tpb} \le u^a_{tc} \quad \forall t = 0, \dots \tag{14}$$

Storage limits constraints (15) enforce bounds on the battery storage.

$$l^a_b \le I^a_t \le u^a_b \quad \forall t = 0, \dots \tag{15}$$

Constraint (16) shows that we assume the storage level at the last stage is the same as the storage level at the first stage.

$$I^a_T = I^a_0 \tag{16}$$

Constraint sets (17) and (18) support nonnegative supply and nonnegative recaptured load for the DLCs.

$$x^a_t, \Delta^+_t, \Delta^-_t \ge 0 \quad \forall t = 0, \dots \tag{17}$$

$$d_{t\bar t 1} \ge 0 \quad \forall \bar t = t, \dots, t+T\,;\ \forall t = 0, \dots \tag{18}$$

The second multi-stage model, shown in Table 3, is the DPC's stochastic optimization program for the real-time market. For simplicity, we choose the parameters and decision variables of this model similar to the LSE's model. Two new parameters are $\bar d_{t2}$ and $\bar z_t$. The first is the lost demand, and the second is a penalty for reducing load at time *t*.

Table 6. The stochastic optimization model to estimate load demand for the DPCs

Minimize long-term cost and discomfort penalty	$\min \sum_{t=0}^{\infty} \gamma \tilde{c}_t (x_{tad}^d + x_{tab}^d - x_{tra}^d - x_{tba}^d) + \sum_{t=0}^{\infty} \sum_{\bar{t}=t-T}^{t} z_{t\bar{t}}^d \, d_{\bar{t}t2} + \sum_{t=0}^{\infty} \bar{z}_t^d \bar{d}_{t2}$	
Energy storage	$I_{t+1}^d = I_t^d - \frac{x_{tba}^d + x_{tbd}^d}{e_d^d} + e_c^d \, (x_{trb}^d + x_{tab}^d)$	$\forall t = 0, \ldots$
Renewable generation	$\tilde{r}_t^d = x_{tra}^d + x_{trb}^d + x_{trd}^d$	$\forall t = 0, \ldots$
Load supply-demand balance	$\sum_{\bar{t}=t-T}^{t} d_{\bar{t}t2} = x_{trd}^d + x_{tad}^d + x_{tbd}^d$	$\forall t = 0, \ldots$
Transferred From the LSE	$-\Delta_t^- = x_{tad}^d + x_{tab}^d$	$\forall t = 0, \ldots$
Transfer to the LSE	$\Delta_t^+ = x_{tba}^d + x_{tra}^d$	$\forall t = 0, \ldots$
Recaptured load demand	$\sum_{\bar{t}=t}^{t+T} d_{t\bar{t}2} = \tilde{d}_{t2} - \bar{d}_{t2}$	$\forall t = -T, \ldots$
Discharge rate limit	$x_{tba}^d + x_{tbd}^d \leq u_{to}^d$	$\forall t = 0, \ldots$
Charge rate limit	$x_{trb}^d + x_{tab}^d \leq u_{tc}^d$	$\forall t = 0, \ldots$
Storage limits	$l_b^d \leq I_t^d \leq u_b^d$	$\forall t = 0, \ldots$
Nonnegative supply and reduced load	$\bar{d}_{t2}, x_t^d \geq 0$	$\forall t = 0, \ldots$
Nonnegative recaptured loads	$d_{t\bar{t}2} \geq 0$	$\forall \bar{t} = t, \ldots, t+T$ $\forall t = 0, \ldots$

Like the LSE's model, the objective function and all constraints are linear. We link the LSE's model and the DPCs through the electricity exchange. The LSE's model uses the electricity exchange, Δ_t, from the DPCs as a parameter. Consequently, the DPCs' optimization model is solved first.

If this two-agent model is separable, we can solve each agent separately and then combine the results. However, we believe that the LSE and the DPCs preferences are different. Consequently, the DPCs actions are different from each other's and the LSE. Therefore, the two agents are not going to have same demand profile. In that case, this two-agent problem is not separable. You may find a detailed discussion of this in [60]. While solving this two-agent stochastic programming model as described is certainly difficult and beyond the scope of this paper, in the next section, we solve a deterministic problem to provide insight into the behavior of the system.

7. COMPUTATIONAL EXPERIMENTS

In this section, we present results for solving the suggested model for one day (96 intervals; every 15 min) using MATLAB. Fig. 4 shows demand and the adjusted demand profile for an assumed LSE in the Dallas/Fort Worth area for every 15 minutes. The difference between adjusted demand and demand is the spilled demand. We assume that we divide the total demand evenly for each type of customer, 33% each.

Fig. 5 shows the electricity that transfers to the demand from the grid, renewable generation, battery storage, the pre-purchased electricity, and the DPCs for a one-day deterministic problem. As we expect, pre-purchased electricity supplies most of the demand. It also shows that the grid supplies part of the demand when it is either really necessary or is inexpensive. Renewable generation and battery inventory are two other sources.

We use the retail electricity market price on January 2012 in Texas [61], [62]. Fig. 6 presents the market price for one day of a deterministic problem.

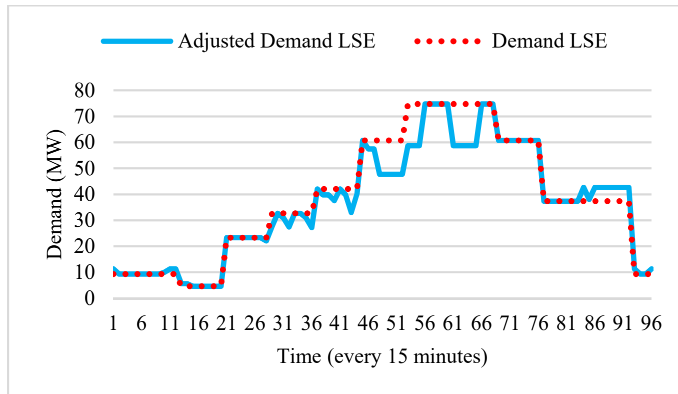

Fig. 4. Demand profile

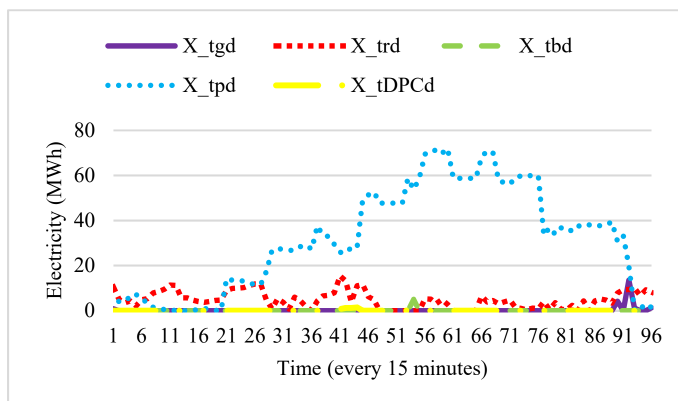

Fig. 5. Demand pulled from different sources

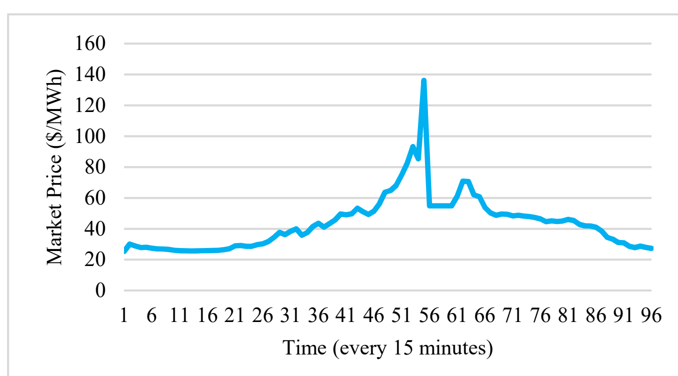

Fig. 6. Electricity market price

Fig. 7 shows the battery level for the LSE for one day of a deterministic problem. At t=12, 4:00 a.m., when the market price is low, it starts charging, and it reaches its highest capacity. Then, the system starts using the battery from t=12:45 p.m. when the market price is at its peak. Finally the battery storage starts charging at t=91, 10:45 pm, when the electricity price is low.

Four sources transfer load to the battery: the grid, renewable generation, and pre-purchased electricity. Fig. 8 shows how much load transfers from each of these sources to the battery. It uses the grid when the market price is low, mostly at the end of the day and early morning. It uses wind energy in early morning. In addition, it sometimes uses pre-purchased electricity to charge the battery. On the other side, battery storage transfers electricity to the grid, demand, and the DPCs. Fig. 9 shows that some of the battery inventory goes to demand, but in this specific example, most of it goes to the grid when market price is high.

We see similar results for the DPCs. The difference is that there is no pre-purchased electricity for these customers. There is also no wind energy, so the only source for renewable is rooftop solar panels.

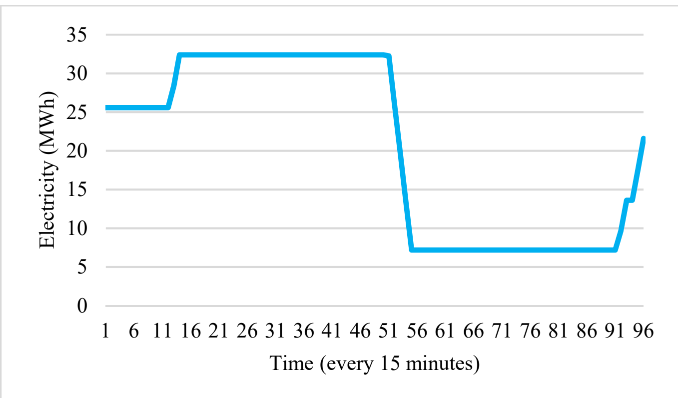

Fig. 7. Battery level for the LSE

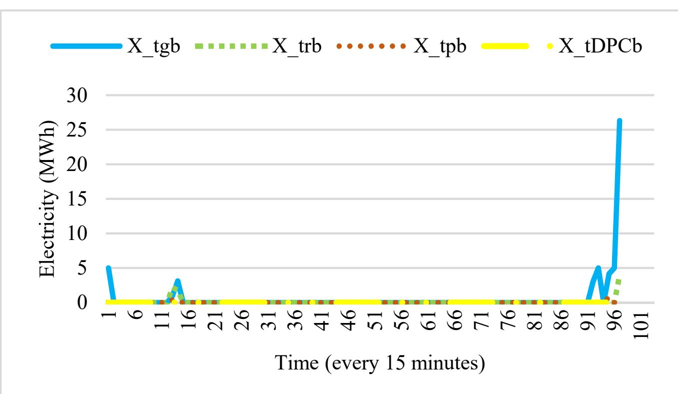

Fig. 8. Load transferred from multiple sources to the battery storage

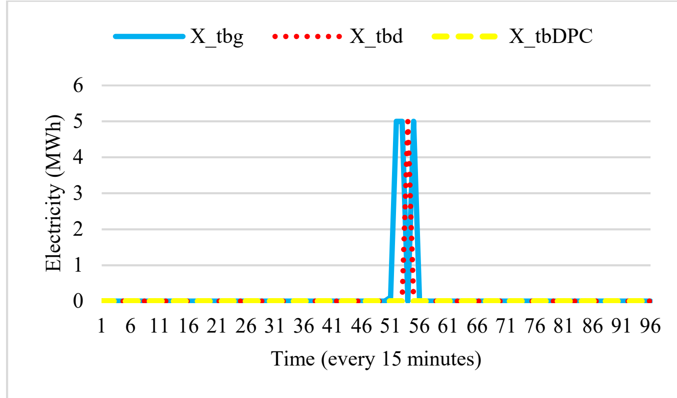

Fig. 9. Load transferred from battery storage to the grid and demand

The other source of energy for the LSE is pre-purchased electricity. Fig. 10 shows the pre-purchased electricity that transfers to the grid, battery storage, demand, and the DPCs. As we expect, most of it transfers to demand and the DPCs. However, some of it transfers to the grid when the market price is high. In addition, small portions transfer to the battery for storage.

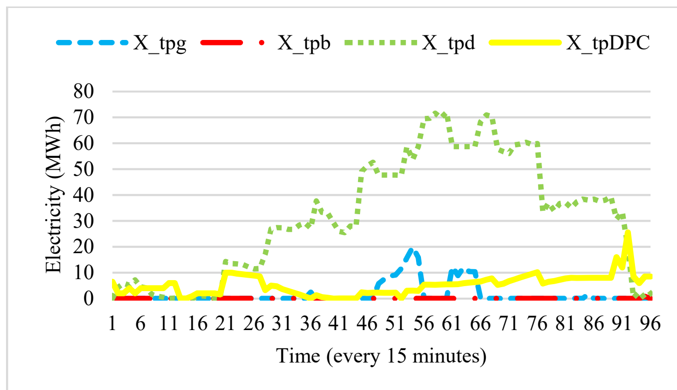

Fig. 10. Load transferred from pre-purchased electricity

Renewably generated electricity transfers to demand, battery storage, the grid, or the DPCs. Fig. 11 shows that the LSE sells back to the grid most of the renewable generation, especially in the middle of the days when we have more solar generation. Some of it satisfies demand and transfers to the DPCs, and a little of it charges the battery.

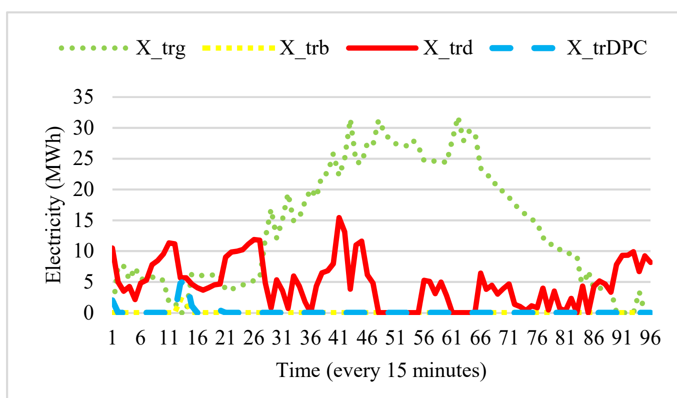

Fig. 11. Transferred electricity from renewable

Fig. 12 displays the electricity sold back to the grid from renewable generation, battery storage, the pre-purchased electricity, and the DPCs in order to minimize the operational cost of the LSE. It shows that the transferred electricity to the grid is highest when the market price is high. As Fig. 13 shows, the other side might also happen. We might transfer electricity from the grid to demand, battery storage, or the DPCs when the market price is low or when the other sources do not satisfy demand. The deterministic example shows that most electricity transfers from the grid to demand at the end of the day, because load transfers from previous hours. In fact, adjusted demand is relatively high at day's end.

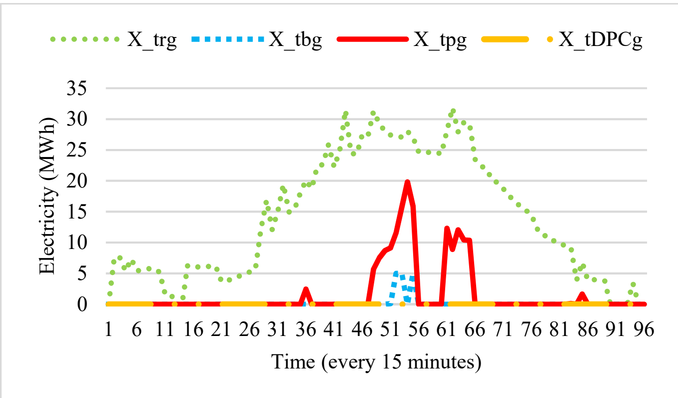

Fig. 12. Electricity transferred to the grid

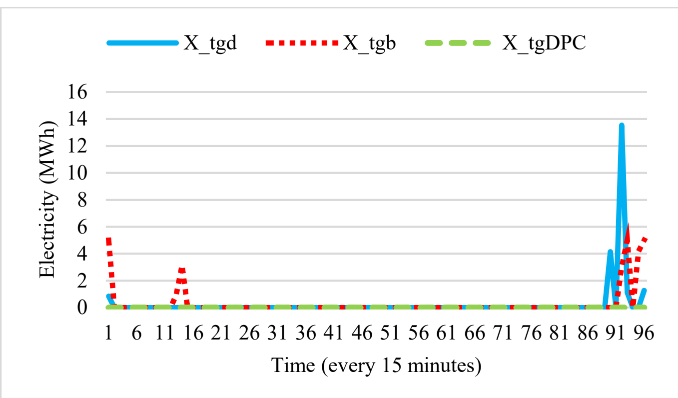

Fig. 13. Electricity transferred from the grid

8. CONCLUSION AND FUTURE WORK

In this research, we propose a comprehensive optimization model for demand response in the future electricity market. We formulate two linear programming stochastic models for both the LSE and DPCs. The objective of the models is to minimize long-term cost and discomfort penalty. Computational experiments of a one-day deterministic problem show the behavior of the system. It suggests that buying from the grid for the purpose of storage or satisfying demand when market price is low or when there is a shortage of supply. It also suggests selling back to the grid when market price is high in order to make a profit. Note that in this paper, we use 15-min time intervals from Settlement Point Price (SPP) calculations; however, the model is flexible and adjustable for 5-min intervals based on Locational Marginal Price (LMP). In the next step, we suggest solving this problem as an infinite horizon stochastic optimization system to make it more realistic.

ACKNOWLEDGMENT

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Chapter 4

SECOND PAPER

Stochastic Bounds on Real-Time Multi-Agent Demand Response

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ABSTRACT

In stochastic programming (SP), a wait-and-see solution is at least as good as an optimal policy. On the other hand, a policy that uses the expected value problem is never as good as an optimal policy. This is well established in SP when there is a single agent. A question arises whether bounds exist when we have two agents. The present study develops a research methodology to answer this question. Our experiments show that if we have two separate agents, and both agents get perfect information, this can be worse compared to both agents following a mean value problem policy. Nevertheless, we have found that there are bounds when the first stage follows the same set of actions. A two-agent demand response problem has been used as a case study to show this claim.

Keywords: Multi-agent demand response, Stochastic bounds, Demand side management, Dynamic pricing customers, Smart grid

1. INTRODUCTION

Stochastic programs are known to be computationally difficult to solve. Because of this, many professionals faced with real-world problems are naturally inclined to use simpler solution approaches. Frequently used simpler solution approaches are, for example, to solve the deterministic program obtained by replacing all random variables with their expected values. Other approaches solve several deterministic programs, each corresponding to one particular scenario, and then combine these different solutions by some heuristic rule [1].

This paper develops, analyzes, and computationally tests stochastic bounds for a two-agent problem under some assumptions. The case study is the emerging problem of large-scale residential demand response (DR) programs with the introduction of real-time dynamic electricity pricing structures mixed with other traditional pricing types. The problem is extremely difficult yet less studied. Three major customer groups are included as main residential customers: fixed pricing customers (FPC), direct load control customers (DLC), and dynamic pricing customers (DPC) [2]. The objective is to minimize the long-term cost and discomfort penalty of a load serving entity (LSE) and DPCs. With traditional FPC, the utility offers electricity at a fixed rate; the price remains constant throughout the length of the contract [3]. A considerable portion of the customers are expected to remain and need to be considered in future DR decisions. In DLC programs, customers enroll voluntarily in certain incentive-based programs that allow the LSE control over certain appliances (air conditioners, heaters, dryers, etc.) to directly shift load during peak or emergency situations [4], [5]. As the proportion of renewables and self-generated electricity increases, direct control is becoming more difficult given the current operation and power management system. Market operators cannot control fluctuations caused by weather and generally must take all of the power produced by wind and solar resources. As a promising solution to achieve dynamic supply-demand balance, DPC programs, also known as real-time or time-varying pricing, have been studied and developed. In DPC programs, customers receive real-time wholesale electricity price signals and manage their electricity consumption individually by shifting their load [6]–[8]. We assume that each customer is equipped with a smart meter that runs a distributed algorithm and schedules household energy consumption. A detailed discussion of these three kinds of customers is provided in [2].

With customers producing their own electricity and high penetration of stochastic renewable energy sources, power distributors must respond to an extremely dynamic, complex, and challenging real-time supply-demand balancing problem, which will likely lead to an intensely different energy market in the near future. The traditional bell-shaped demand curve that is representative in most current markets is soon to be replaced with a “duck curve”: the duck belly corresponds to the middle of the solar day when solar generation is highest, but the net load exits to a very narrow and sharp peak as the sun sets. This leads to a challenging new operating condition in which the current power distribution system dramatically increases power generation flexibility to meet the higher-than-ever short-time peak-load changes in the near-future energy market.

This research is particularly designed to bridge the knowledge gap and to develop the next generation real-time DR management for large-scale residential end-users to achieve highly coordinated energy use and generation for a highly stochastic and dynamic energy market in the near future. Reaching the objectives and exploiting the results of the proposed research can help the development of the future Smart Grid Platform vision to become a reality.

The balance of this paper has five sections. Section 2 reviews recent literature on stochastic bounds. Section 3 explains a two-agent infinite horizon stochastic programming model. Theory on stochastic bounds for a two-agent stochastic model is provided in Section 4. Section 5 discusses computational experiments of a demand response problem. Conclusions are detailed in Section 6.

2. LITERATURE REVIEW

Many real world problems are stochastic and complex. Finding an exact solution for these problems is very complicated and sometimes impossible. Consequently, many research projects focus on finding bounds using the expected value of perfect information. These bounds have a wide variety of applications, including economic load dispatching [9], sums of dependent risks [10], present value functions [11], execution times of parallel programs [12], portfolio analysis [13], network flow [14], facility location problems [15], generation and transmission expansion under risk [16], and two-stage adjustable optimization for unit commitment [17]. A two-agent optimization problem arose when we consider three major categories of customers simultaneously for realistic future electricity markets. However, to our knowledge, no research has found bounds for a two-agent stochastic problem. A review of related literature follows.

Some research projects have focused on the value of a stochastic solution, that is, a measure of the benefit received from solving the stochastic program over solving a deterministic program in which expected values have replaced random parameters. Birge [18] has conducted such research. He also presented the relationship and distinctions between this quantity and the expected value of perfect information for stochastic linear programs. Moreover, he found bounds for the value of the stochastic solutions by computing a series of sub problems. In addition, Birge and Louveaux [1] provided a detailed description of the value of stochastic solution using examples.

Some researchers use Monte Carlo versions of lower bounds obtained in adaptations of deterministic cutting-plane algorithms. Dantzig *et al.* [19] estimated the coefficients and right-hand sides of cutting planes using Monte Carlo sampling for a two-stage stochastic linear program in the framework of Benders decomposition. They suggested a theory for estimating a lower bound for the objective value. Higle and Sen [20] used randomly generated observations of random variables to construct statistical estimates of supports of the objective function.

Finding lower and upper bounds for different stochastic problems is also investigated in the literature. Norkin *et al.* [15] used pessimistic and optimistic bounds within a stochastic version of the branch-and-bound algorithm for stochastic global optimization. They discussed convergence of their method and the random accuracy estimates derived. They also demonstrated the theoretical considerations with an example of a facility location problem. Mak *et al.* [21] showed that the solution value to a standard approximating problem for a two-stage stochastic program (SP) yields a lower bound, in expectation, on the solution value of SP. A sampling procedure based on common random numbers ensures nonnegative gap estimates and provides significant variance reduction over naive sampling on four test problems. Their result has been exploited, in a batch-means approach, to develop confidence intervals on the optimality gap with respect to any candidate solution to SP. They also indicated that confidence intervals may be obtained for two-stage stochastic programs with general structure. They claim that the lower-bounding result extends to multi-stage stochastic programs. Birge and Louveaux [1] provided a detailed description of lower and upper bounds for stochastic optimization problems. They proved that the expectation of the expected value problem, and the wait-and-see solution are upper and lower bounds for a stochastic minimization problem. Sarikprueck *et al.* [22] developed bounds for optimal control of a system of electric vehicle charging stations using linear programming and simulation. They evaluated bounds with two stochastic measures, which can be solved using the expected value problem and the wait-and-see solution. They found that the largest uncertainty in the system occurs during weekdays in the summer when market price forecasting error is greatest.

3. CONTRIBUTION

The purpose of this research project is to incorporate a portfolio of potential residential customers. We study three major customer groups including direct load control, dynamic pricing, and fixed pricing customers. The current demand response models are generally limited and have ignored such a mix of customers. In the previous step of the project, we developed a mathematical stochastic optimization model. We consider first two types of customers as one agent and the dynamic pricing customers as the second agent of the model. A stochastic optimization formulation for this problem is provided in [2]. Solving this two-agent stochastic model has great importance. In this paper, we find the lower and upper bounds for the aforementioned problem using the expected value problem and the wait-and-see solution. These bounds provide minimum and maximum operational costs that the LSE can use for its financial planning. Experiments analyzing the stochastic gap in the Dallas-Fort Worth metroplex (DFW) are also presented. Because of electricity market prices and high penetration of renewable generation, this system is highly dynamic and stochastic. Hence, the proposed research is important to mitigate emerging challenges and to develop new advanced modeling, simulation, and optimization tools. To our knowledge, this is the first paper that provides stochastic bounds for a two-agent stochastic optimization model.

4. TWO-AGENT MODEL

Here, we present two infinite horizon stochastic programming models for the LSE and DPCs. [2] provides a detailed explanation of these models. *Recaptured demand* is the deferred demand that we will satisfy later. *Lost demand* is the eliminated demand, in other words, the electricity that the customer no longer needs in future periods. *Spilled demand* is the sum of the recaptured and lost demand. The first multi-stage model is the LSE's stochastic optimization program for the real-time market. Table 1 lists our model parameters. Tilda denotes the uncertain stochastic parameters.

Table 7. Model parameters

r	Renewable energy generation
g	The main energy grid
b	Battery storage
d_1	Load demand from DLCs
d_2	Load demand from DPCs
d_3	Load demand from FPCs
t	Index for the time period, in which $t = 0$ is the current time period
T	A fixed set of time periods for which loads may be deferred for DLCs
$\tilde{c}_t$	Random variable for the real-time market price in time period t
$\tilde{r}_t$	Random variable for the LSE's renewable generation in time
p_t	Pre-purchased electricity for time t
γ	Discount factor
$\tilde{r}_{tDPC}$	Random variable for the DPC's renewable generation in time
$\tilde{d}_{t1}$	Random variable for the load demand from the DLCs in time
$\tilde{d}_{t3}$	Random variable for the load demand from the FPCs in time
d_{t2}	The load demand from the DPCs, which is a function of $\tilde{r}$, $\tilde{c}$, as well as previous DPC load $\tilde{d}_2$
e_c	Battery charging efficiency rate
e_d	Battery discharging efficiency rate
u_{tc}	Upper limit on charging the battery in a period
u_{to}	Upper limit on discharging the battery in a period
l_b	Lower limit on the battery storage
u_b	Upper limit on the battery storage
l_{td}	Lower limit on energy supplied to the DLCs in a period
u_{td}	Upper limit on energy supplied to the DLCs in a period
p_t	The amount of previously purchased energy
Δ_t	The electricity exchange between the LSE and the DPCs at time t
a_t	The recapture rate
$z_{t\bar{t}}$	A discomfort penalty for recapturing load from time period t to time period $\bar{t}$, for each $\bar{t} = t,\ldots, t+T$

Decision variables are transferred electricity, battery inventory level, and recaptured demand. Table 2 shows the notation description of these variables.

Table 8. Decision variables

x_{tgd}	Electricity transferred from the grid to demand at time t
x_{tgb}	Electricity transferred from the grid to battery storage at time t
x_{tgDPC}	Electricity transferred from the grid to the DPCs at time t
x_{trd}	Electricity transferred from renewable generation to demand at time t
x_{trb}	Electricity transferred from renewable generation to battery storage at time t
x_{trg}	Electricity transferred from renewable generation to the grid at time t
x_{trDPC}	Electricity transferred from renewable generation to DPCs at time t
x_{tbg}	Electricity transferred from battery storage to the grid at time t
x_{tbd}	Electricity transferred from battery storage to demand at time t
x_{tbDPC}	Electricity transferred from battery storage to DPCs at time t
x_{tpg}	Pre-purchased electricity transferred to the grid at time t
x_{tpb}	Pre-purchased electricity transferred to the battery at time t
x_{tpd}	Pre-purchased electricity transferred to demand at time t
x_{tpDPC}	Pre-purchased electricity transferred to the DPCs at time t
I_t	The battery inventory level at the beginning of time period t
$d_{t\bar{t}1}$	Recaptured demand from time period t to time period $\bar{t}$ for the DLCs, for each time period $\bar{t} = t,\ldots, t+T$
$d_{\bar{t}t1}$	Recaptured demand from time period $\bar{t}$ to time period t for the DLCs, for each time period $\bar{t} = t\text{-}T,\ldots, t$
d_{tt1}	Satisfied demand for the DLCs at time t

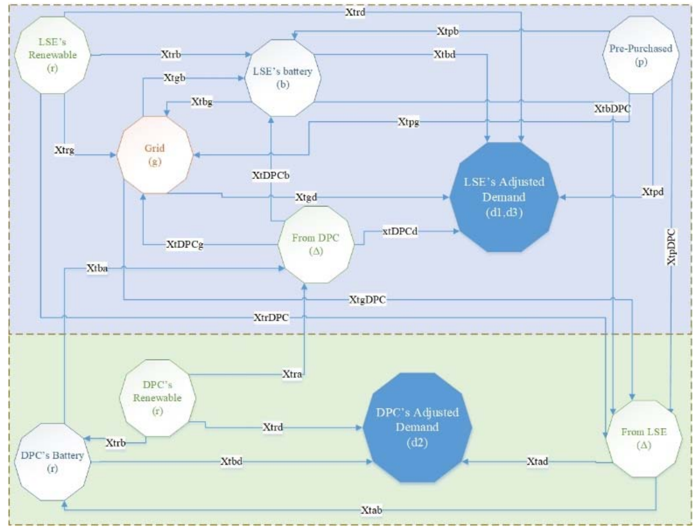

Fig. 1. Demand-supply flow chart

Fig.1 presents a flowchart showing demand, supply, and their relationships for both the LSE and the DPCs. Market price information is available over 15-minute intervals. In each interval, the state variable is the expected value. The objective is to minimize the long-term operational cost of the LSE and the discomfort penalty. The first part of the following linear objective function is the difference between the cost of buying from the grid for demand and battery storage and the revenue from selling back to the grid from renewable generation and battery storage. The second part of the objective function shows the penalty function.

$$min \sum_{t=0}^{\infty} \gamma \Bigg(\tilde{c}_t \big(x_{tgd}^a + x_{tgb}^a + x_{tgDPC}^a - x_{trg}^a - x_{tbg}^a - x_{tpg}^a - x_{tDPCg}^a \big) + \sum_{t=0}^{\infty} \sum_{\bar{t}=t-T}^{t} z_{t\bar{t}}^a \, d_{\bar{t}t1} \Bigg) \quad (1)$$

Energy storage is the first constraint set (2). It calculates the battery storage in time period t+1 considering the previous storage, inputs, and outputs to the battery.

$$I_{t+1}^a = I_t^a - \frac{x_{tbg}^a + x_{tbd}^a + x_{tbDPC}^a}{e_d^a} + e_c^a \big(x_{trb} + x_{trb}^a + x_{tgb}^a + x_{tpb}^a + x_{tDPCb}^a \big) \quad \forall t = 0, \ldots \quad (2)$$

Renewable generation balance is the second constraint set (3). Its inclusion ensures that LSE renewable generation ($\tilde{r}_t^a$) is equal to the transferred renewable generation to the grid, battery storage, demand, and the DPCs.

Pre-purchased balance is the third constraint set (4). The LSE has pre-purchased electricity in the day-ahead market to meet most of the demand. The main energy market grid supplies only part of the demand from the intra-day market when it is necessary or the price is low.

$$\tilde{r}_t^a = x_{trg}^a + x_{trb}^a + x_{trd}^a + x_{trDPC}^a \quad \forall t = 0, \ldots \quad (3)$$

$$p_t^a = x_{tpb}^a + x_{tpg}^a + x_{tpd}^a + x_{tpDPC}^a \quad \forall t = 0, \ldots \tag{4}$$

The fourth set of constraints (5) is for *load supply-demand balance*. The left side of the equation shows the total demand for the LSE, which is the demand of two kinds of customers, the DLCs, and the FPCs. The righthand side of the equation shows the electricity transmitted to demand from renewable generation, the grid, battery storage, pre-purchased electricity, and the DPCs' surplus.

$$\sum_{\bar{t}=t-T}^{t} d_{\bar{t}t1} + \tilde{d}_{t3} = x_{trd}^a + x_{tgd}^a + x_{tbd}^a + x_{tpd}^a + x_{tDPCd}^a \quad \forall t = 0, \ldots \tag{5}$$

The fifth set of constraints shows the transferred electricity from the LSE to the DPCs, Δ_t^+, and the transferred surplus electricity from the DPCs to the LSE, Δ_t^-.

$$\Delta_t = \Delta_t^+ - \Delta_t^- \quad \forall t = 0, \ldots \tag{6}$$

$$\Delta_t^+ = \max(\Delta_t, 0) \quad \forall t = 0, \ldots \tag{7}$$

$$\Delta_t^- = -\min(\Delta_t, 0) \quad \forall t = 0, \ldots \tag{8}$$

$$\Delta_t^+(\tilde{c}, \tilde{d}_2, \tilde{r}) = x_{tpDPC}^a + x_{tbDPC}^a + x_{tgDPC}^a + x_{trDPC}^a \quad \forall t = 0, \ldots \tag{9}$$

$$\Delta_t^-(\tilde{c}, \tilde{d}_2, \tilde{r}) = x_{tDPCg}^a + x_{tDPCb}^a + x_{tDPCd}^a \quad \forall t = 0, \ldots \tag{10}$$

Recaptured demand balance is the sixth set of constraints (11). This shows that a fraction (a_t^a) of the amount of demand currently unsatisfied which must satisfy in future periods. We define this as the recapture rate. We assume that the recapture rate is 75% in the computational experiments.

$$\sum_{\bar{t}=t+1}^{t+T} d_{t\bar{t}1} = a_t^a(\tilde{d}_{t1} - d_{tt1}) \quad \forall t = -T, \ldots \tag{11}$$

Discharge rate limit and *charge rate limit* are the seventh set of constraints (12) and (13). The constraint set (12) ensures that battery discharge in a period is limited to u_{to}^a. Constraint set (13) guarantees that the charge of the battery in a period is limited to at most u_{tc}^a.

$$x_{tbg}^a + x_{tbd}^a + x_{tbDPC}^a \leq u_{to}^a \quad \forall t = 0, \ldots \tag{12}$$

$$x_{trb}^a + x_{tgb}^a + x_{tDPCb}^a + x_{tpb}^a \leq u_{tc}^a \quad \forall t = 0, \ldots \tag{13}$$

Storage limits constraints (14) apply bounds on battery storage.

$$l_b^a \leq I_t^a \leq u_b^a \quad \forall t = 0, \ldots \tag{14}$$

Constraint (15) shows that we assume the storage level at the last stage equals the storage level with that of the first stage.

$$I_T^a = I_0^a \tag{15}$$

Constraint sets (16) and (17) show nonnegative supply and nonnegative recaptured load for the DLCs.

$$x_t^a, \Delta_t^+, \Delta_t^- \geq 0 \quad \forall t = 0, \ldots \tag{16}$$

$$d_{t\bar{t}1} \geq 0 \quad \forall \bar{t} = t, \ldots, t+T \,;\, \forall t = 0, \ldots \tag{17}$$

The second multi-stage model, shown in Table 3, is the DPC's stochastic optimization program for the real-time market. To reduce complexity, we choose the parameters and decision variables of this model similar to that of the LSE's model. Two new parameters are $\bar{d}_{t2}$ and $\bar{z}_t$. The first is the lost demand and the second is a penalty for reducing load at time *t*.

Table 9. The stochastic optimization model to estimate load demand for DPCs

Minimize long-term cost and discomfort penalty:
$\min \sum_{t=0}^{\infty} \gamma \tilde{c}_t(x_{tad}^d + x_{tab}^d - x_{tra}^d - x_{tba}^d) + \sum_{t=0}^{\infty} \sum_{\bar{t}=t-T}^{t} z_{t\bar{t}}^d\, d_{\bar{t}t2} + \sum_{t=0}^{\infty} \bar{z}_t^d \bar{d}_{t2}$
Energy storage: $I_{t+1}^d = I_t^d - \frac{x_{tba}^d + x_{tbd}^d}{e_d^d} + e_c^d\,(x_{trb}^d + x_{tab}^d)$
Renewable generation: $\tilde{r}_t^d = x_{tra}^d + x_{trb}^d + x_{trd}^d$
Load supply-demand balance: $\sum_{\bar{t}=t-T}^{t} d_{\bar{t}t2} = x_{trd}^d + x_{tad}^d + x_{tbd}^d$
Transferred From the LSE: $-\Delta_t^- = x_{tad}^d + x_{tab}^d$
Transfer to the LSE: $\Delta_t^+ = x_{tba}^d + x_{tra}^d$
Recaptured load demand: $\sum_{\bar{t}=t}^{t+T} d_{t\bar{t}2} = \tilde{d}_{t2} - \bar{d}_{t2}$ (*)
Discharge rate limit: $x_{tba}^d + x_{tbd}^d \leq u_{to}^d$
Charge rate limit: $x_{trb}^d + x_{tab}^d \leq u_{tc}^d$
Storage limits: $l_b^d \leq I_t^d \leq u_b^d$
Nonnegative supply and reduced load: $\bar{d}_{t2}, x_t^d \geq 0$
Nonnegative recaptured loads: $d_{t\bar{t}2} \geq 0 \quad \forall \bar{t} = t, \ldots, t+T$
$\forall t = 0, \ldots$ (*) $\forall t = -T, \ldots$

Like the LSE's model, the objective function and all constraints are linear. We link the LSE's model and the DPCs through the electricity exchange. The LSE's model uses the electricity exchange, Δ_t, from the DPCs as a parameter. Consequently, the DPCs' optimization model is solved first.

Solving this two-agent stochastic programming model as described is certainly difficult and beyond the scope of this paper. In the next section though, we derive stochastic bounds.

5. STOCHASTIC BOUNDS

[1] and [23] have established stochastic bounds for traditional stochastic programming. However, they always assumes a single agent problem. For a two-agent problem, if agents are separable, then there would be two separate stochastic programming problems, and the traditional stochastic bounds of the objective function are still bounds in the separable case. In our case study though, DPC customers do behave dynamically, suggesting that traditional stochastic bounds are

no longer applicable, and the problem is not separable. To our knowledge, no research has been done in two-agent stochastic programming in which one agent makes decisions before a second agent. The optimization problem of the first agent, DPC, has the following form

$$\min_{x_1} z_1(x_1, \xi) \tag{18}$$

where z_1 is a real-valued function, x_1 is a vector of DPC decision variables, and ξ is a vector of random variables whose realizations correspond to various scenarios. Traditional stochastic bounds for the objective function of this problem are applicable because they are indifferent to the decisions of the LSE. However, finding bounds for the second agent, which is the focus of this paper is quite difficult and sometimes impossible. Since the LSE's stochastic program depends upon the decisions of the DPCs, it is optimized based upon market price, generation, and past load. More specifically, the two stochastic programs are linked through the electricity exchange, Δ_t. Consequently, the decision-making policies of the LSE and the DPCs are based upon a more broadly defined formulation for a new two-agent continuous-state infinite-horizon stochastic dynamic programming problem. Consider the following notation

$$\min_{x_2} z_2(\tilde{x}_1, x_2, \xi)$$

$$\text{s.t.} \quad \tilde{x}_1 \in \operatorname{argmin} z_1(x_1, \xi) \tag{19}$$

where z_2 is a real-valued function, x_2 is a vector of decision variables for the LSE, and ξ is a vector of uncertain influences, such as the market price, wind and solar generation. Under some assumptions for the first agent, we can gather bounds for the second agent's optimal solution. Definitions of an expected value problem (*EV*), expectation of the expected value problem (*EEV*), the expected value of the wait-and-see solutions (*WS*), and recourse problem (*RP*) for the second agent of a two-agent problem are next.

The second agent problem is a minimization problem; therefore, the evaluation of any policy is an upper bound on the evaluation of the optimal policy. One type of policy that is not only used in the literature but also frequently used in the real world is an expected (mean) value policy. There, we determine policy by replacing all random variables by their expected values, defined for a two-agent problem as

$$EV = \min_{x_2} z_2(\tilde{x}_1, x_2, \bar{\xi})$$

$$\text{s.t.} \quad \tilde{x}_1 \in \operatorname{argmin} z_1(x_1, \bar{\xi}) \tag{20}$$

where $\bar{\xi} = E(\xi)$ expresses the expectation of ξ. We will denote an optimal solution to (20) by $\bar{x}(\bar{\xi})$. This is the expected value solution. We will define the expected result of using the *EV* solution to be the expectation of the expected value problem (*EEV*)

$$EEV(\tilde{x}_1) = E_{\xi}\left[z_2\left(\tilde{x}_1, \bar{x}_2, \bar{\xi}\right), \boldsymbol{\xi}\right]$$

$$s.t. \quad \bar{x}_2 \in \operatorname*{argmin}_{x_2} z_2(\tilde{x}_1, x_2, \bar{\xi}) \tag{21}$$

which is an upper bound for the objective value of (19). With the expected value policy, one can typically model the situation farther into the future, since there is no scenario tree that grows exponentially as more stages are considered. In addition, if forecasts are accurate with minimal uncertainty, the mean value policy are near optimal. However, it typically fails when uncertainty is significant.

Another idea is to determine a provable lower bound on the evaluation of the optimal policy. The most common lower bound on the evaluation of the optimal policy is the expected value of wait-and-see solutions (WS). In a WS solution, the decision maker can wait until the uncertainty is resolved. We can think of this as simulating an omniscient optimizer. Here's how it works: suppose an evaluation consists of N scenarios (realizations of the random variables). For each of these scenarios N, we calculate a provable optimal policy assuming the data for these scenarios are deterministic. In other words, for each scenario, we simply determine policy by using the values in the scenario instead of the random variables. Then we take the average of these values over N, and this is a lower bound on the evaluation of the optimal policy. Here, we assume that we have perfect information $\tilde{x}_1(\boldsymbol{\xi})$ and their objective values $z_1(\tilde{x}_1, \boldsymbol{\xi})$ for the first agent and define the *wait-and-see* solution as

$$WS' = E_{\xi}[\min z_2(x_1^*, x_2, \boldsymbol{\xi})] \tag{22}$$

$$x_1^* \in \operatorname*{argmin}_{x_1} z_1(x_1, \boldsymbol{\xi})$$

We have found a counter example that $WS' \nleq EEV$. Specifically, if both agents have perfect information, we cannot necessarily guarantee a better policy for the second agent. Table 4 shows a counter example. For Summer and Fall weekends, stochastic gap is negative which is not reasonable.

Table 4. Counter example for stochastic bounds

	WS	***EEV***	**Stochastic Gap**
Spring WD	-40,024.2	-38,060.0	1,964.2
Spring WE	-37,722.9	-35,613.8	2,109.1
Summer WD	-34,899.9	-33,121.7	1,778.2
Summer WE	-23,690.4	-24,183.4	**-493.0**
Fall WD	-51,095.3	-49,636.0	1,459.2
Fall WE	-18,444.4	-18,859.7	**-415.3**
Winter WD	-27,837.2	-25,674.8	2,162.4
Winter WE	-18,184.3	-17,511.3	673.0

WD: weekday; WE: weekend

However, if we assume that LSE knows the DPC's consumption, as opposed to the exact set of actions, then the bounds could be constructed as a function of that consumption. Now, we are in a position to compute the expected value of the optimal solution, known as the *wait-and-see* solution (*WS*, see [1] and [23]) where

$$WS(\tilde{x}_1) = E_{\xi}[\min z_2(\tilde{x}_1, x_2, \boldsymbol{\xi})] \tag{23}$$

Eq. (23) indicates that DPCs behave the same way, and the LSE has perfect information. In addition, we define the recourse problem (RP) as follows

$$RP(\tilde{x}_1) = \min_{x_2} E_{\xi} z_2(\tilde{x}_1, x_2, \boldsymbol{\xi}) \tag{24}$$

As stated, in this paper, we find the upper and lower bounds for the optimal policy as described in [1] for the aforementioned problem. We call the difference between these two solutions, *stochastic bounds*. Proof of these bounds for the second agent of a two-agent problem is next.

Proposition: For a given $\tilde{x}_1$

$$WS(\tilde{x}_1) \leq RP(\tilde{x}_1) \leq EEV(\tilde{x}_1) \tag{25}$$

Proof:

For every realization, ξ, we have the relation

$$z_2(\tilde{x}_1, \bar{x}_2(\xi), \xi) \leq z_2(\tilde{x}_1, {x_2}^*, \xi)$$

where ${x_2}^*$ denotes an optimal solution to the recourse problem. Taking the expectation of both sides yields the first inequality. ${x_2}^*$, being an optimal solution to the recourse problem while $\bar{x}_2(\bar{\xi})$ is just one solution to it, yields the second inequality. ■

6. COMPUTATIONAL EXPERIMENTS

As stated, solving the described stochastic program is computationally intractable. In this section, we explain simulating the stochastic process and outputs of a demand response problem, the case study of this research. The following algorithm shows the process of solving the LSE's and DPCs' models.

1. Set initial parameter values
2. Forecast wind, solar, and market price using a support vector regression model for $t = 1, \ldots, T$
3. Solve the DPCs' problem to obtain their decision variable values and send load demand to the LSE's problem
4. Solve the LSE's minimization problem
5. Sample realizations of the forecasted wind, solar, and market price.
6. Update x_{trg}, x_{trb}, x_{tgd}, and x_{tbd} using recourse functions
7. Calculate LSE's objective function
8. If $t = T$ end, otherwise $t = t+1$ and go to step 2.

The first step is to set the initial parameter values. We use battery specifications of [24] as a baseline for this paper. Some other parameter values are as follows. Battery inventory at beginning and the end of the period is 20% of its capacity. The recapture rate is 70%, and recaptured demand needs to be satisfied within 16 periods, 4 hours. Moreover, we assume the same portion of demand for all three types of customers.

The second step is to forecast wind generation, solar photovoltaic generation, and market price. We use methods described in [24]–[26]. They used support vector regression to make predictions in a deregulated market. In addition, they take advantage of a Martingale Model Forecast Evolution (MMFE) to model the uncertainty of these forecasting models.

Then, to solve the LSE's problem, we need to know how much electricity we should transfer to or from the DPCs. So, we call the DPCs model and solve it, and next send back the information to the LSE's model. After solving the LSE's model, we will have all decision variable values. In addition, we update the battery storage for the next time period.

The fifth step is sampling. Like [22], we sample for wind, solar, and market price using SVR and MMFE to determine the realizations. When the uncertainty is revealed, we take advantage of following recourse functions to adjust decision variable values.

if $\tilde{w}_t + \tilde{s}_t > E[\tilde{W}_t] + E[\tilde{S}_t]$ (26)
    if $x_{trg} > 0$
        $x_{trg} = (\tilde{w}_t + \tilde{s}_t) - (E[\tilde{W}_t] + E[\tilde{S}_t]) + x_{trg}$
    else
        $x_{trb} = (\tilde{w}_t + \tilde{s}_t) - (E[\tilde{W}_t] + E[\tilde{S}_t]) + x_{trb}$

if $\tilde{w}_t + \tilde{s}_t \leq E[\tilde{W}_t] + E[\tilde{S}_t]$
    if $x_{tgd} > 0$
        $x_{tgd} = (E[\tilde{W}_t] + E[\tilde{S}_t]) - (\tilde{w}_t + \tilde{s}_t) + x_{tgd}$
    else
        $x_{tbd} = (E[\tilde{W}_t] + E[\tilde{S}_t]) - (\tilde{w}_t + \tilde{s}_t) + x_{tbd}$

Therefore, we have enough information to calculate the LSE's objective function at time *t* in the seventh step. We of course use the adjusted decision variable values after the recourse functions. We repeat this algorithm from *t*=1, …, *T*, which is 96 15-minute periods, or 24 hours simulation time. Figure 3 shows the aggregated LSE and DPC customer demands and the adjusted demand profile in the Dallas/Fort Worth area for one day in 2015.

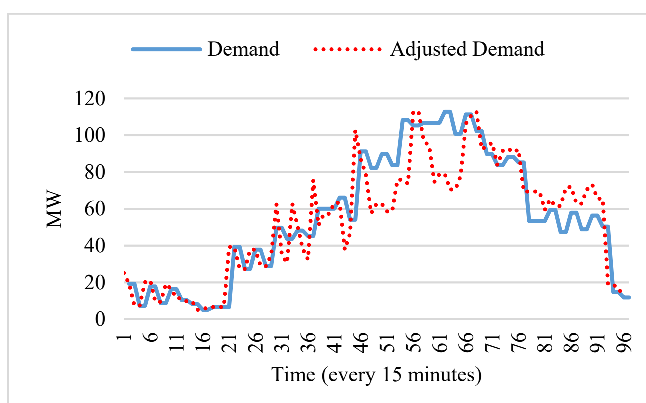

Fig. 3. One-day demand and adjusted demand

In order to evaluate our proposed stochastic programming algorithm and find bounds, we simulate the aforementioned problem and find stochastic bounds using 8 datasets in four seasons for both weekday (WD) and weekend (WE). For the *EEV* problem, we solve the LP repeatedly. We replace all the random variables with their expected values obtained from the forecasting at each time period t. Next, the aforementioned LSE model is simulated to find the decision values and objective of the stochastic programming problem. For instance, for two days, we solve it 96*2 times. By solving it at the beginning of the day, we learn how to allocate our resources. Then, 15 minutes later, we observe actual events, and our forecast is updated for the next 15 minutes' period. We solve it again for the new forecast from that second period all the way through the next 96 periods. Then, we repeat the process. For the *WS* solution, when we simulate the *EV*, we find scenarios for wind, solar, and market price. Then, we optimize the LSE's model from $t = 1, \ldots, 2T$ to determine the objective value using the perfect information of each scenario. Stochastic bounds using averaged objective values for *EEV* and *WS* are provided in Table 5.

Table 5. Stochastic bounds for different data sets.

	WS	***EEV***	**Stochastic Gap**
Spring WD	-37,585.4	-36,936.4	649.0
Spring WE	-35,680.7	-35,075.0	605.8
Summer WD	-35,603.4	-33,460.3	2,143.1
Summer WE	-25,722.7	-24,219.8	1,502.9
Fall WD	-51,213.8	-50,292.3	921.5
Fall WE	-19,087.5	-18,985.9	101.7
Winter WD	-26,194.9	-25,771.6	423.3
Winter WE	-17,736.8	-17,394.8	342.0

WD: weekday; WE: weekend

7. CONCLUSION AND FUTURE WORK

In this paper, we proved that there are bounds for a special class of two-agent stochastic linear programming models in which the first agent follows the same set of actions. It is applicable to many practical problems; we chose a two-agent demand response problem to show this practically. The objective is to minimize the LSE's long-term cost and discomfort penalty. In order to find bounds for the objective function, two stochastic measures, expected value problem and wait-and-see solution, are improved. The proposed algorithm is assessed on 8 different datasets, weekdays and weekends of four seasons. The results show that we are able to gather bounds using the suggested algorithm. In the next step, we suggest solving this problem as an infinite horizon stochastic optimization system to make it more realistic.

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Chapter 5

GENERAL CONCLUSIONS

In the first paper, we propose a comprehensive optimization model for demand response in the future electricity market. We formulate two linear programming stochastic models for both the LSE and DPCs. The objective of the models is to minimize long-term cost and discomfort penalty. Computational experiments of a one-day deterministic problem show the behavior of the system. It suggests that buying from the grid for the purpose of storage or satisfying demand when market price is low or when there is a shortage of supply. It also suggests selling back to the grid when market price is high in order to make a profit. In the second paper, we proved that there are bounds for a special class of two-agent stochastic linear programming models in which the first agent follows the same set of actions. It is applicable to many practical problems; we chose a two-agent demand response problem to show this practically. The objective is to minimize the LSE's long-term cost and discomfort penalty. In order to find bounds for the objective function, two stochastic measures, expected value problem and wait-and-see solution, are improved. The proposed algorithm is assessed on 8 different datasets, weekdays and weekends of four seasons. The results show that we are able to gather bounds using the suggested algorithm. As a future research, we suggest solving this problem as an infinite horizon stochastic optimization system. Upper and lower bounds found in the second paper can be used to evaluate the stochastic model.

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