IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

Linear Programming for Multi-Agent Demand Response

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This work is supported in part by the National Science Foundation Grant ECCS-1128871.

ABSTRACT This research describes a real-time optimization model for multi-agent demand response (DR) from a Load Serving Entity (LSE) perspective. We consider three major categories of customers and five types of energy resources simultaneously to achieve efficient DR decision making in highly stochastic future energy markets. 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. Because preferences of these two agents are different, they are inseparable and difficult to solve. We solve a deterministic finite horizon linear program as an approximation of the suggested stochastic model and provide computational experiments.

INDEX TERMS Demand-side management, dynamic pricing customers, linear programming, multi-agent demand response, smart grid.

I. 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 and their rapidly falling costs, most recent clean energy initiatives aim to achieve a much higher share of renewable energy in strategic plans. For instance, the Clean Energy Act of California aims to achieve 50% penetration of renewable energy by 2030 [16]. However, renewable energy introduces high stochasticity in the future energy market. We expect the potentially 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 demand response (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 Load Serving Entity (LSE) to handle massive market and customer information and optimize decision making. They have strived for a realistic operating scenario in which DR LSE 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 LSE. 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 below.

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 (DLCC)

In direct load control programs, the LSE or aggregator has remote control over certain appliances of the customers based on a customer 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 DLCC, 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 a forecasted trajectory of the price. Based upon this information, the device might delay some level of operation of appliances such as an air conditioner or dishwasher.

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 the 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.

II. 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, 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 line 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].

Researchers in the DR field have conducted many research projects [34]–[44]. We will review a few that pertain to our work. Li *et al.* [45] propose a DR 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 will ultimately saturate. Conejo *et al.* [46] build a real-time DR model to adjust the hourly load level of a given consumer by considering hourly electricity price. They use a simple linear programming 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 DR 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 Commission 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, earned income from selling energy on the market, 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 DLCC 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 DLCC, real-time dynamic pricing, and FPC.

III. 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 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.

IV. STOCHASTIC PROCESS

Figure 1 presents the sequential two-agent stochastic process that we use in this research. The first step is to set the initial parameter values. We use battery specifications of [62] as a baseline for this paper. Some other parameter values are as follows. Battery inventory at the beginning and the end of the period is 20% of its capacity. The recapture rate is 75%, 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 [62]–[64]. They used support vector regression to make predictions in a deregulated market. In addition, we take advantage of a Martingale Model Forecast Evolution (MMFE) to model the uncertainty of these forecasting models. We discuss these forecasts in more detail in Section VI.

Then, to solve the LSE problem, we need to know how much electricity we should transfer to or from the DPC. So, we call the DPC model and solve it, and next send back the information to the LSE model. After solving the LSE model, we will have all decision variable values. The LSE will determine how to supply the power to the DLCC and would be reactive based upon the DPC and FPC. In addition, we update the battery storage for the next period. Mathematical descriptions of the LSE and DPC models are in Section VII.

The fifth step is sampling. Like [61], 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 recourse functions to adjust decision variable values.

Therefore, we have enough information to calculate the LSE objective function in the sixth step. We of course use the adjusted decision variable values after the recourse functions. We repeat this algorithm from $t = 1, \ldots, T$, which is 96 15-minute periods, or 24 hours in simulation time.

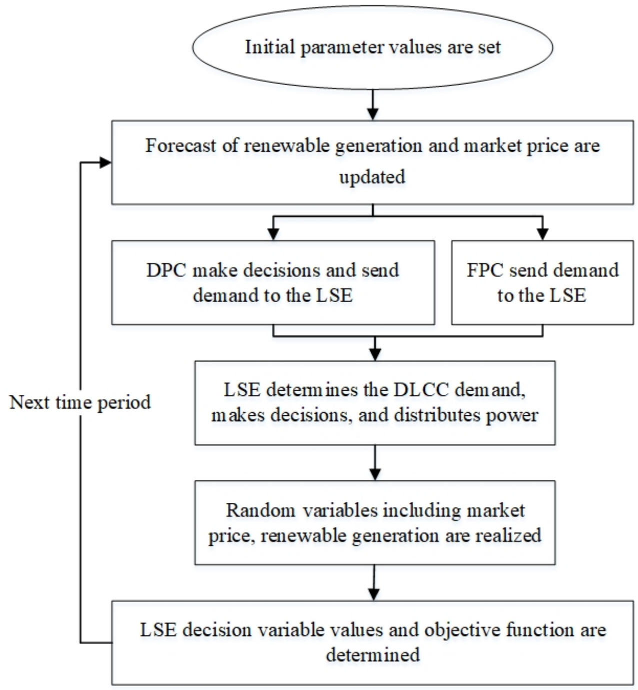

FIGURE 1. **Sequential two-agent stochastic process.**

V. 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 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 refer to this as *pre-purchased electricity*. 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 MW, 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 [65].

Installed solar capacity in Texas exceeded 1,000 MW in October 2017, according to ERCOT [65]. We assume that both the LSE and DPCs have solar energy resources. The LSE can access a solar park, and the DPCs can have rooftop solar panels.

Given [61], 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 [61]. The other assumption is that the LSE has ten battery slots, and DPCs cumulatively have 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 in excess.

VI. FORECASTING METHODS

As mentioned in Section IV, we use methods described in [62]–[64] for forecasting market price, wind generation, and solar photovoltaic (PV) generation. For wind generation, we 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. Figure 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. Figure 2 shows the forecasted solar generation for an assumed LSE in a one-day problem.

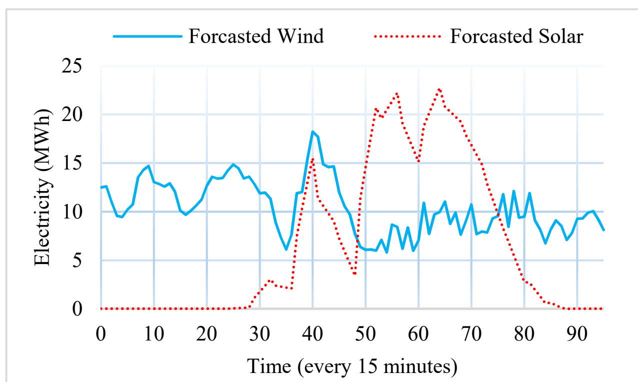

FIGURE 2. **Forecasted renewable energy.**

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

VII. PROBLEM FORMULATION

In this section, we present two infinite horizon stochastic programming models for LSE and DPCs. We use three terms to explain these models 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 stochastic optimization program for the real-time market. Table 1 lists the notation of the model parameters that we use throughout the article. Tildas denote uncertain stochastic parameters.

TABLE 1. Model parameters.

r	Renewable energy generation
g	The main energy grid
b	Battery storage
d_1	Load demand from DLCC
d_2	Load demand from DPCs
d_3	Load demand from FPC
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 DLCC
$\tilde{c}_t$	Random variable for the real-time market price in time period t
$\tilde{r}_t$	Random variable for the LSE 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 renewable generation in time period t
$\tilde{d}_{t1}$	Random variable for the load demand from the DLCC in time period t
$\tilde{d}_{t3}$	Random variable for the load demand from the FPC 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 DLCC in a period
u_{td}	Upper limit on energy supplied to the DLCC 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,…, t+T

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

TABLE 2. 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 DLCC, for each time period $\bar{t}$ =t,…, t+T
$d_{\bar{t}t1}$	Recaptured demand from time period $\bar{t}$ to time period t for the DLCC, for each time period $\bar{t}$ =t-T,…, t
d_{tt1}	Satisfied demand for the DLCC at time t

Figure 3 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.

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

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

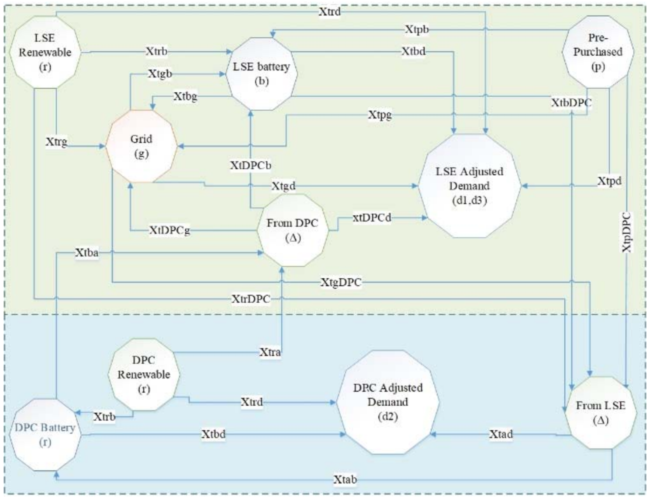

FIGURE 3. Demand-supply flow chart

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].

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

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, which is the same as that in [59].

$$I_{t+1}^{a} = I_{t}^{a} - \frac{x_{tbg}^{a} + x_{tbd}^{a} + x_{tbDPC}^{a}}{e_{d}^{a}} + e_{c}^{a}\left(x_{trb}\, x_{trb}^{a} + x_{tgb}^{a} + x_{tpb}^{a} + x_{tDOCb}^{a}\right) \ \forall t = 0, \dots \tag{3}$$

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

$$\tilde{r}_{t}^{a} = x_{trg}^{a} + x_{trb}^{a} + x_{trd}^{a} + x_{trDPC}^{a} \ \ \forall t = 0, \dots \tag{4}$$

$$p_{t}^{a} = x_{tpb}^{a} + x_{tpg}^{a} + x_{tpd}^{a} + x_{tpDPC}^{a} \ \ \forall t = 0, \dots \tag{5}$$

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 DLCC, and the FPC. The right side shows the electricity transmitted to demand from renewable generation, the grid, battery storage, pre-purchased electricity, and the DPC surplus.

$$\sum_{\bar{t}=t-T}^{t} d_{\bar{t}t1} + \tilde{d}_{t3} = x_{trd}^{a} + x_{tgd}^{a} + x_{tbd}^{a} + x_{tpd}^{a} + x_{tDPCd}^{a} \ \ \forall t = 0, \dots \tag{6}$$

The fifth set of constraints shows the transferred electricity from the LSE to the DPC, Δ_{t}^{+}, and the transferred surplus electricity from the DPC to the LSE, Δ_{t}^{-}.

$$\Delta_{t} = \Delta_{t}^{+} - \Delta_{t}^{-} \ \ \forall t = 0, \dots \tag{7}$$

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

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

$$\Delta_{t}^{+}(\tilde{c}, \tilde{d}_{2}, \tilde{r}) = x_{tpDPC}^{a} + x_{tbDPC}^{a} + x_{tgDPC}^{a} + x_{trDPC}^{a} \quad \forall t = 0, \dots \tag{10}$$

$$\Delta_{t}^{-}(\tilde{c}, \tilde{d}_{2}, \tilde{r}) = x_{tDPCg}^{a} + x_{tDPCb}^{a} + x_{tDPCd}^{a} \ \ \forall t = 0, \dots \tag{11}$$

Recaptured *demand balance* is the sixth set of constraints (12). It ensures that a fraction (a_{t}^{a}) of the amount of demand that is unsatisfied now must satisfy in future periods. We refer to this fraction as the *recapture rate*. We assume that the recapture rate is 75% in the computational experiments.

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

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_{to}^{a}. Constraint set (14) ensures that the charge of the battery in a period is limited to u_{tc}^{a}.

$$x_{tbg}^{a} + x_{tbd}^{a} + x_{tbDPC}^{a} \le u_{to}^{a} \quad \forall t = 0, \dots \tag{13}$$

$$x_{trb}^{a} + x_{tgb}^{a} + x_{tDPCb}^{a} + x_{tpb}^{a} \le u_{tc}^{a} \quad \forall t = 0, \dots \tag{14}$$

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

$$l_{b}^{a} \le I_{t}^{a} \le u_{b}^{a} \quad \forall t = 0, \dots \tag{15}$$

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

$$I_{T}^{a} = I_{0}^{a} \tag{16}$$

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

$$x_{t}^{a}, \Delta_{t}^{+}, \Delta_{t}^{-} \ge 0 \quad \forall t = 0, \dots \tag{17}$$

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

The second multi-stage model, shown in Table 3, is the DPC stochastic optimization program for the real-time market. For simplicity, we choose the parameters and decision variables of this model similar to the LSE 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 spilling load at time *t*.

TABLE 3. The stochastic optimization model to estimate load demand for the DPC.

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

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

If this two-agent model were separable, we could solve each agent separately and then combine the results. However, we see evidence that the problem is inseparable, implying that the LSE decisions regarding the DLCC depend upon the DPC decisions. Figure 4 shows an example how this two-agent problem is inseparable. Specifically, we solve deterministic problems for three cases: (1) all customers are DLC, (2) all are DPC, and (3) 50% are DLC and 50% are DPC. We can clearly see that the adjusted demand for the case of having a mix of 50-50% does not provide an average of the two other cases. Examples are time intervals 44, 45, 55, 56, 66, 68–70.

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.

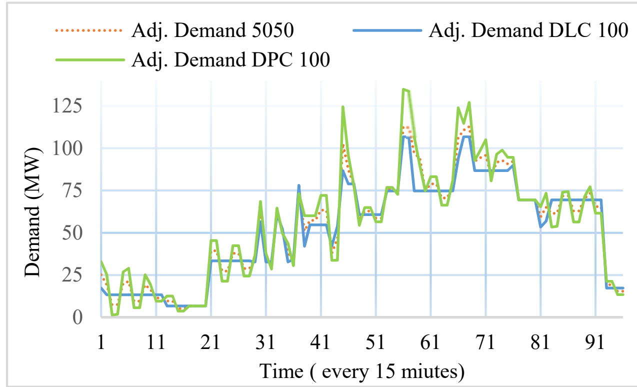

FIGURE 4. Illustration of inseparable adjusted demand

VIII. COMPUTATIONAL EXPERIMENTS

In this section, we present results for solving the suggested model for one day (96 intervals; every 15 min) using MATLAB. Figure 5 shows demand and the DR adjusted demand profile for an assumed LSE in the Dallas/Fort Worth area in summer for every 15 minutes. We define DR adjusted demand as actual demand after solving the two-agent optimization problem. The difference between DR adjusted demand and demand is the spilled demand. The plot shows how this two-agent optimization problem affects the peaks and transfers some of the loads to the inexpensive periods. We assume that we divide the total demand evenly for each type of customer, 33% each.

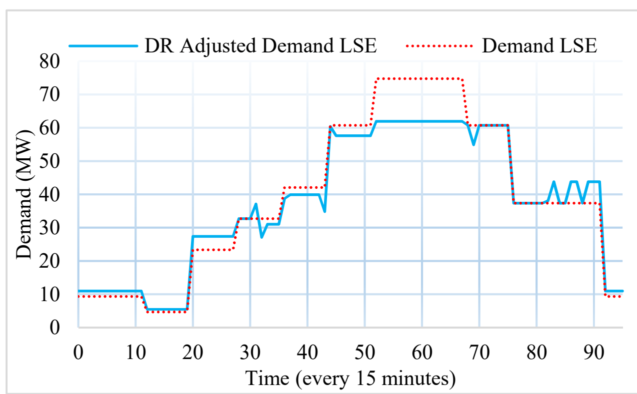

FIGURE 5. Demand profile

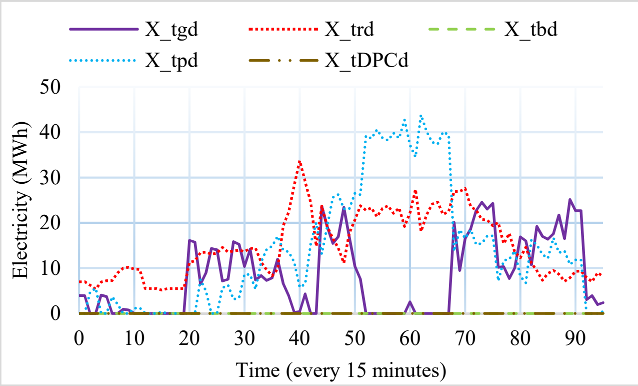

FIGURE 6. Demand pulled from different sources.

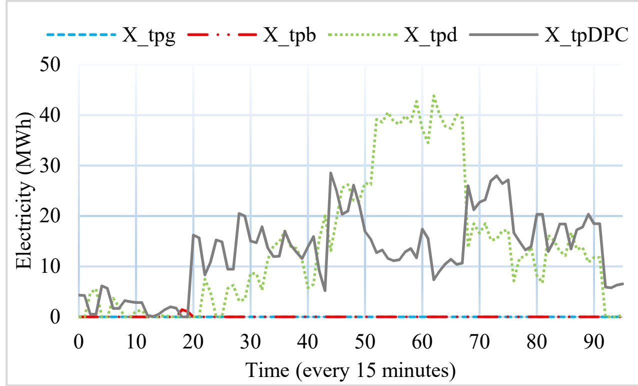

FIGURE 8. Load transferred from pre-purchased electricity.

Figure 6 shows the electricity that transfers to DLCC demand from the grid, renewable generation, battery storage, the pre-purchased electricity, and the DPC for a one-day deterministic problem. As we expect, pre-purchased and renewable 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. Battery inventory is the other source for the demand.

We use the retail electricity market price in summer 2012 in Texas [60], [61]. Figure 7 shows the market price and the battery level for the LSE for one day of a deterministic problem. At t=18, 4:30 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=64, 2:45 p.m., when the market price is at its peak. Finally the battery storage starts charging at t=92, 11:00 p.m., when the electricity price is low.

Four sources transfer load to the battery: the grid, renewable generation, pre-purchased, and extra electricity from the DPC. The LSE battery is resupplied by the grid when the market price is low, mostly at the end of the day and early in the morning. It uses wind energy in early morning as well. 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 DPC.

We see similar results for the DPC. 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 electricity is rooftop solar panels.

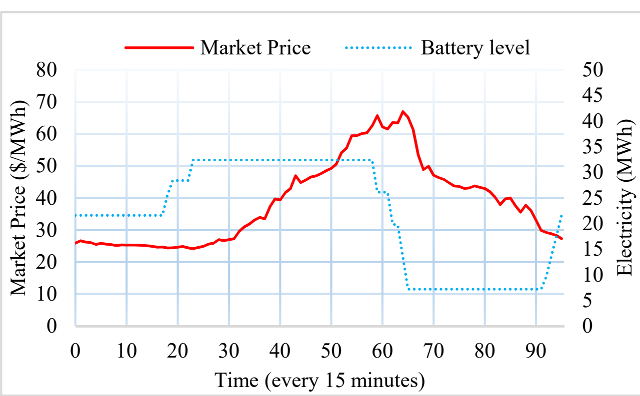

FIGURE 7. Electricity market price and battery level for the LSE.

The other source of energy for the LSE is pre-purchased electricity. Figure 8 shows the pre-purchased electricity that transfers to the grid, battery storage, demand, and the DPC. As we expect, most of it transfers to demand and the DPC. However, small portions of it transfers to the grid when the market price is high and to the battery for storage.

Renewably generated electricity transfers to demand, battery storage, the grid, or the DPC. Figure 9 shows that most of it satisfies demand. It also displays that the LSE sells back to the grid some of the renewable generation, especially in the middle of the day when we have more solar generation. Some of it transfers to the DPC, and a little of it charges the battery.

Figure 10 displays the electricity sold back to the grid from renewable generation, battery storage, the pre-purchased electricity, and the DPC in order to minimize the operational cost of the LSE. It demonstrates that the transferred electricity to the grid is highest when the market price is high. As Figure 11 shows, the other side might also happen. We might transfer electricity from the grid to DLCC demand, battery storage, or the DPC 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 DLCC demand at the end of the day, because load transfers from previous hours. In fact, DR adjusted demand is relatively high at the end of the day.

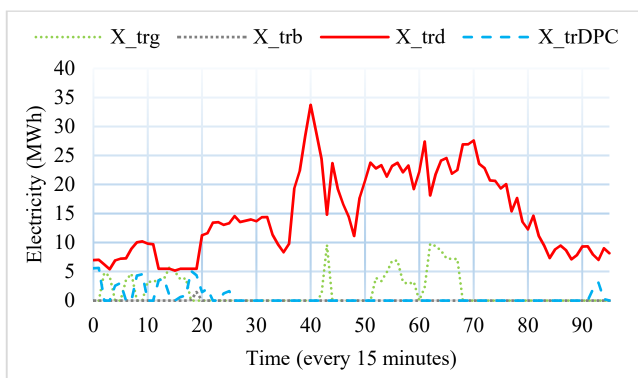

FIGURE 9. Transferred electricity from renewable.

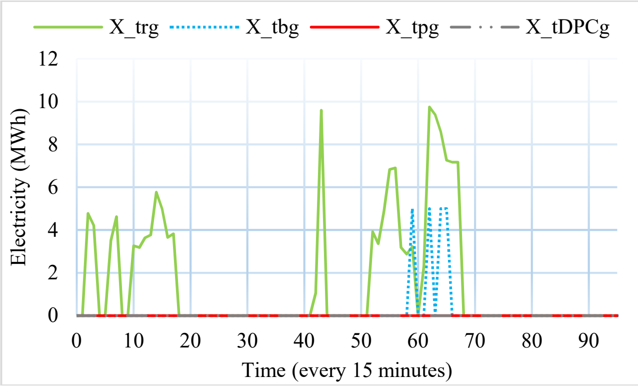

FIGURE 10. Electricity transferred to the grid.

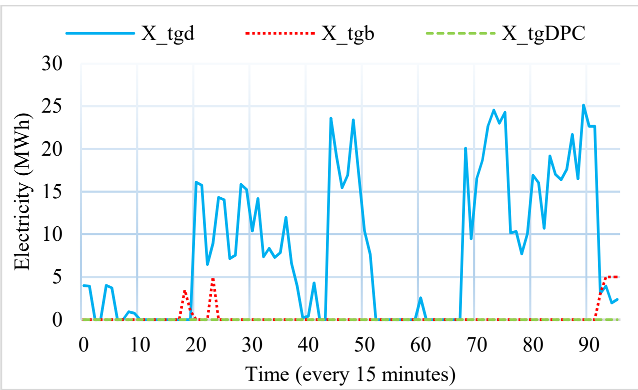

FIGURE 11. Electricity transferred from the grid.

IX. CONCLUSION AND FUTURE WORK

In this research, we propose a comprehensive optimization model for demand response in the future electricity market. We formulate a two-agent stochastic linear programming model for both the LSE and DPC. The objectives of the models are 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 a two-agent infinite horizon stochastic optimization system to allow for the LSE and DPC decisons to hedge for uncertainty.

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