Stochastic Optimization for Residential Demand Response with Unit Commitment and Time of Use

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***Abstract*—As compensation to power generation dispatch, demand response (DR) enables demand controllability by changing the consumers' electricity usage patterns, which can be used to reduce electricity cost, integrate renewable energy, and provide ancillary services. To reveal the benefits from residential DR, this study develops two approaches: 1) optimal load aggregation under augmented time-of-use (TOU) pricing; and 2) active DR participation in unit commitment (UC) under rewards. We have shown that plain TOU pricing is not a promising DR policy if residential customers are equipped with home energy management systems (EMS). We, therefore, propose an augmented TOU by radial basis functions (RBF). With a 60% participation level, the proposed optimal load aggregation model under the augmented TOU can reduce the power generation cost by 24% and decrease the standard deviation of the load profile by 42%. However, these results can be affected by the customer's participation level, which is also quantitatively studied. Specifically, when the participation level exceeds 80% this method becomes less efficient. The second proposed approach, a two-stage stochastic UC model with DR flexibility, reduces the power generation cost by 20% and decreases the standard deviation of the load profile by 77%. In addition, the inconvenience of DR participation is quantitatively evaluated, and a Pareto surface is developed, which can be used as a baseline for residential customers to set up the home EMS for DR implementation. Both the proposed mechanisms can be used to improve energy efficiency by uncovering the residential DR potential.**

***Index Terms*—Residential demand response, Residential microgrid, Time-of-use, Unit commitment, Energy management.**

NOMENCLATURE

Sets

$\mathcal{AP}$	Appliances
$\mathcal{BAP}$	Background Appliances
$\mathcal{CAP}$	Controllable Appliances
$\mathcal{T}$	Time horizon
Ω	Set of scenarios

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Symbols and Variables

λ_t^H	Penalty coefficient for a home H at time t
μ_j	Radial basis function centers
ω	Index of a scenario
$\overline{P_t^j}$	Maximum power the unit j can generate
$\overline{Q_H}$	Rate power of the power panel
π^{flat}	flat-rate
π_t	Electricity Price
$\pi_t^{\{off,mid,on\}}$	Price in off-peak, mid-peak and on-peak demand period
σ	Bandwidth of radial basis function
$\underline{P_t^j}$	Minimum power the unit j can generate
$\underline{t_{off}}$	Minimum down time
$\underline{t_{on}}$	Minimum up time
$\widehat{E^{ap}}$	Predicted energy consumption
$\widehat{l_t^{ap,\omega}}$	Predicted load in the scenario ω
$\widehat{l_t^{ap}}$	Predicted load
ξ_ω	Probability of the scenario ω
ap	Appliance
$c_j(\cdot)$	Operation cost of unit j
$c_j^m(\cdot)$	Marginal cost of reserve power j
C_t^A	Actual generation cost
C_t^M	Electricity market-based generation cost
$c_{j,t}^U$	Cost of starting up unit j at time t
d^{rated}	Rated driving distance
$f(\cdot)$	Augment function
L_t	Aggregated load at t
L_t^{AG}	Aggregated load at time t of a aggregator AG
$l_t^{ap,\omega}$	Load of ap at t in the scenario ω
l_t^{ap}	Load of ap at t
p_t^j	Amount of power generation
$p_t^{j,\omega}$	Amount of power generation of scenario ω
q_{rated}^{ap}	Rated power of ap
$r_{t,D}^{j,\omega}$	Generation down-reserve of the scenario ω
$r_{t,U}^{j,\omega}$	Generation up-reserve of the scenario ω
R_j^D	Ramping down limit
R_j^U	Ramping up limit
t_0^{ap}	Start time of of operating appliance in load forecast model
t_1^{ap}	Completing time of of operating appliance in load forecast model

t_2^{ap}	Must completing time of operating appliance
y_j^t	On/off status of unit j at time t

Acronyms

DR	Demand Response
EMS	Energy Management System
EV	Electric Vehicle
RBF	Radial Basis Function
SOC	State of Charge
TOU	Time of Use
UC	Unit Commitment

I. Introduction

THE balance of power generation and demand is crucial and challenging for power system operation. Increasing penetration of distributed energy resources, intermittent renewable energy and electric vehicles (EV) makes system operation more challenging. As an essential compensation to power generation control, DR enables demand controllability by changing the electricity usage patterns of consumers [2–9], which includes 1) shifting demand from on-peak to off-peak periods; 2) consuming power based on renewable energy availability; 3) responding to price signals; and 4) responding to control signals.

Accordingly, DR can 1) save significant capital cost for utilities by reducing peak demand; 2) reduce greenhouse gas emission by integrating renewable energy [3], [4]; 3) cost-effectively balance power generation and demand in electricity markets [5], [6]; and 4) provide economic ancillary services for power systems [7–9].

Residential customers consume about one-third of the electricity, and the residential sector has the most uncovered DR potential compared with commercial and industrial sectors [10], [11]. Furthermore, the adoption of EVs and vehicle-to-grid applications are bringing more DR potential to the residential sector. It is greatly beneficial to unlock the residential DR potential and transform residential homes/buildings into active DR participants. Residential DR has therefore received considerable attention from academia and industries [12].

Among others, optimization plays an important role in DR implementation and various deterministic optimization models [13] and stochastic optimization models [3], [5], [14] have been developed to aggregate controllable loads. Since residential electricity consumption is random in nature, using stochastic and robust optimization models has become a new trend in DR studies. It appears that robust optimization tends to provide more desirable results while stochastic programming requires less computational power [15]. Residential DR should also consider customers' comfort level in addition to energy cost [16–18]. Furthermore, since household loads are small but numerous, load aggregators can be introduced [19–21].

In addition to these DR technologies, to encourage DR participation, various policies have been developed and can be categorized into two groups: price and incentive-based [22]. More specifically, direct load control, ancillary services and market programs are considered as the incentive-based policies. On the other hand, price-based policies includes real-time pricing, critical peak pricing and TOU [23–27]. TOU is used worldwide in the residential sector since its structure is clear and easy to track [28–31]. For example, in Ontario, Canada, TOU is applied to 60% of buildings with the smart meters in place [32].

However, peak demand rebounding in the lowest price period has been reported under TOU since the home EMS tends to shift the load to the earliest time with the lowest price [33], [34]. To deal with this issue, augmented TOUs can be used, e.g., multiple TOUs [35]. However, this may raise fairness issues since customers are charged with different electricity prices. More appropriate augmenting methods should be developed.

A deeper reason behind the peak demand rebounding is that the electricity pricing and load aggregation are coupled. More specifically, the electricity price directly depends on the magnitude of the load; hence, the plain predetermined price structures may not work as expected. To incorporate this relationship, attempts have been made to employ game theory [36], [37], mechanism design [38] and bi-level optimization [39–41]. However, these methods require intense computation, which may not be available in embeded home EMSs.

Alternatively, demand flexibility can be incorporated into UC models, which are solved by a utility or an independent system operator. UC models can economically schedule various power generation units such as coal, gas and diesel to meet a predicted load profile. The traditional UC model can be modified to incorporate incentive-based DR [42]. For instance, modified UC models under DR were presented for renewable energy integration [43] and minimize the operational cost in the presence of controllable loads, fuel cells, and solar energy [44].

In this study, to reveal the residential DR benefits, we proposed two approaches: 1) optimal load aggregation under augmented TOU pricing; and 2) active DR participation in UC under rewards. In the first approach, the load aggregation problem is formulated as a stochastic optimization model and then reformulated as a deterministic linear programming (LP) model. The LP model can be efficiently solved by a home EMS. In the second approach, a two-stage stochastic UC model with demand flexibility is developed, which can be solved efficiently by a utility. A reward mechanism is then developed to encourage DR participation.

This study is extended from our earlier work in [1]. The difference and new contributions are: 1) Augmented TOU is developed. 2) UC model with demand flexibility is developed. 3) The time interval/resolution is enhanced from 1 hour to 5 minutes, which greatly improves the accuracy of the proposed models. 4) The inconvenience of DR participation is quantitatively evaluated, and a Pareto surface is developed.

The contributions of this work are summarized as follows:

1) A simple and effective augmented TOU pricing structure is proposed. An optimal load aggregation model is further developed to incorporate the proposed augmented TOU for DR applications.
2) A two-stage stochastic UC model with demand flexibility is developed, based on which a reward mechanism is developed to encourage DR participation. This method is simple, robust, and practical.

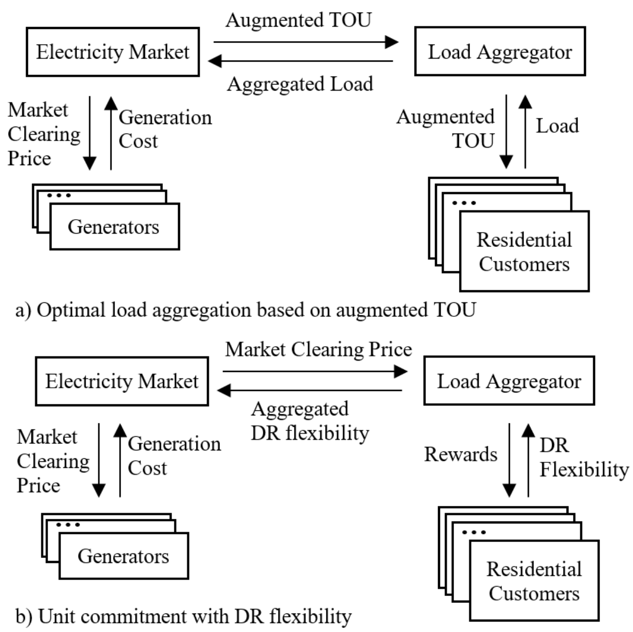

Fig. 1. System architecture of demand response in a residential microgrid

3) The inconvenience of DR participation is quantitatively evaluated and a Pareto surface is developed, which can be used as a baseline for residential customers to set up the home EMS for DR implementation.
4) Both the proposed mechanisms can be used to improve energy efficiency by uncovering the residential DR potential.

The rest of the paper is structured as follows. Section II presents the problem formulation. The simulation results are presented in Section III followed by a discussion in Section IV. Section V concludes this study.

II. Problem Formulation

Fig. 1 shows the system architecture of the two proposed DR approaches in a residential microgrid. The microgrid may have multiple load aggregators and each aggregator contracts with a number of homes to provide DR services. Each home has a set of controllable loads such as dishwasher, clothes dryer and EV. The load aggregators can forecast and aggregate demand flexibility of the residential loads and participate for DR applications under TOU or rewards.

This section presents the residential load forecast model, the stochastic optimal load aggregation model, the deterministic UC model, and the stochastic UC model with DR flexibility.

A. Stochastic Residential Load Models

In this study, we use a set of stochastic residential load models developed in our earlier study [33], [34]. These models include 19 appliances in which dishwasher, clothes dryer and EV are considered as controllable loads.

$$l_t^{ap} = q_{rated}^{ap}, \quad \forall ap \in \mathcal{AP}, t \in [t_0^{ap}, t_1^{ap}] \tag{1}$$

$$l_t^{ap} = 0, \quad \forall ap \in \mathcal{AP}, t \in \mathcal{T} \setminus [t_0^{ap}, t_1^{ap}] \tag{2}$$

where l_t^{ap} is the power consumption of appliance ap at time t. We assume that the appliances are operated at the rated power q_{rated}^{ap} and the operating period is $[t_0^{ap}, t_1^{ap}]$ shown in Eq. (1). The standby power of the appliances is assumed to be 0 shown in Eq. (2). $\mathcal{AP}$ is the set of appliances in a home, which is further classified as a set of background appliances $\mathcal{BAP}$ and a set of controllable appliances $\mathcal{CAP}$. The background appliances (e.g., light) cannot be rescheduled in a DR application. The controllable appliance can be rescheduled, e.g., EV. $\mathcal{T}$ is the time horizon of load forecasting and aggregation.

The load profile will be determined by the parameters of q_{rated}^{ap}, t_0^{ap} and t_1^{ap}. These parameters are stochastic in nature. For instance, the operation of most of the appliances is based on human activity. The rated power of appliances is different from home to home. The statistical information on how people use appliances are from the UK Time Use Survey [45]. Except for EVs, the parameters of the other appliances (e.g., light, refrigerator, oven, etc.) are obtained from [46], which was validated by a comprehensive comparison with actual electricity measurements in the UK.

Now, we discuss the method to determine the parameters for the EV charging (load) model. The rated power is based on the charger, which is usually a level 1 or level 2 charger in the residential sector. In this study, we only consider charging the EV at home since we focus on residential DR. The charging period is based on the battery capacity and its state of charge (SOC) when an EV arrives at home. Since the SOC approximately linearly depends on EV driving distance, the SOC can be calculated from the daily driving distance as follows [47], [48].

$$soc = \frac{d^{rated} - d}{d^{rated}} \tag{3}$$

where d^{rated} is the rated driving distance, i.e., the driving distance of a fully charged EV. d^{rated} can be found in the datasheet of EVs. d is the daily driving distance. The average and standard deviation of d can be found in [49].

The initial charging time t_0^{ap} is the same as EV home arriving time assuming that people plug-in the EV and start the charging on arrival. This time can be assumed as a normal distribution [47].

The aggregated load forecasting is defined as follows.

$$L_t^{AG} = \sum_{H \in AG} \left(\sum_{ap \in \mathcal{BAP}} l_t^{ap} + \sum_{ap \in \mathcal{CAP}} l_t^{ap} \right) \tag{4}$$

where L_t^{AG} is the aggregated load prediction at time t of a load aggregator AG.

B. Stochastic Optimal Aggregation Model

Although the residential power consumption is random in nature, the aggregation of a number of household loads can be statistically stable. Therefore, we develop an optimization model based on expected values.

$$\underset{l_t^{ap}}{\text{minimize}} \quad \mathbb{E}\left(\sum_{H \in AG} \sum_{t \in \mathcal{T}} \sum_{ap \in \mathcal{CAP}} l_t^{ap} \right) f(\pi_t) \tag{5}$$

subject to:

$$0 \leq l_t^{ap} \leq q_{rated}^{ap}, \quad \forall ap \in \mathcal{CAP}, t \in [t_0^{ap}, t_2^{ap}] \tag{6}$$

$$l_t^{ap} = 0, \quad \forall ap \in \mathcal{CAP}, t \in \mathcal{T} \setminus [t_0^{ap}, t_2^{ap}] \tag{7}$$

$$\sum_{t \in \mathcal{T}} l_t^{ap} = \widehat{E^{ap}}, \quad \forall ap \in \mathcal{CAP} \tag{8}$$

$$\sum_{ap \in \mathcal{AP}} l_t^{ap} \leq \overline{Q_H}, \quad \forall t \in \mathcal{T} \tag{9}$$

where the objective is to minimize the total electricity cost. Since the set of background appliances $\mathcal{BAP}$ are not considered as schedulable, they are not included in the objective function.

π_t is the electricity price. In this study, we use TOU as the price structure, which is discuss in the next section. $f(\cdot)$ is an augmenting function to augment the TOU since an un-augmented TOU can cause peak demand rebound. The RBF is used to augment the TOU pricing.

$$RBF = e^{\frac{-\|t-\mu_j\|^2}{2\sigma^2}} \tag{10}$$

$$f(\pi_t) = \pi_t - (RBF - \mu_{RBF}) \tag{11}$$

where σ is the bandwidth. $j = 1, \ldots, k$ and μ_j is the a RBF center. The value of an RBF depends on the distance between the input t and μ_j, given a value σ. μ_{RBF} is the average value of the RBF. By taking away the average value, the impact of RBF on TOU is minimized while the variation is still added to the TOU. Eq. (10) and (11) are discussed in detail in section III.

Eq. (6) and (7) are the appliance operation constraints. The difference from the forecasting model shown in Eq. (1) and (2) is the completing time t_2^{ap}. In the forecasting model, the completing time t_1^{ap} depends on t_0^{ap} and the operation period. In the optimization model, t_2^{ap} is the must completing time, which is more flexible. For instance, t_2^{ap} for EVs can be the home leaving time in the morning. In other words, when people arrive home and plug-in the EV, the optimization model will determine when to charge the EV based on electricity price π_t. In addition, the power consumption of the controllable loads are considered as interruptible.

Eq. (8) shows that the rescheduled load should consume the same amount of energy as predicted $\widehat{E^{ap}}$. We focus on the DR effect for peak demand reduction and load flattening rather than energy reduction. Eq. (9) shows that the rated power of the power panel cannot be exceeded, which limits the total demand of a single household.

In the optimization model, the decision variables are $l_t^{ap}, \forall ap \in \mathcal{CAP}$. The objective function is the summation of decision variables times predetermined TOU; therefore, the objective function is linear. In addition, all the constraints are affine. Therefore, the model is a stochastic LP model. By minimizing the expected electricity cost, the stochastic optimization model is transformed into a deterministic LP model.

C. Deterministic Unit Commitment Model

We use a standard deterministic UC model [50] to develop the TOU structures. The deterministic UC model is also used to calculate the generation cost under the plain TOU and augmented TOU. The demand flexibility is not incorporated into this model.

$$\underset{p_t^j, y_t^j}{\text{minimize}} \quad \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \left(c_j(p_t^j) + c_j^U y_t^j \right) \tag{12}$$

subject to

$$\sum_{j \in \mathcal{J}} p_t^j = L_t^{AG}, \forall t \in \mathcal{T} \tag{13}$$

$$y_t^j \in \{0, 1\}, \quad \forall t \in \mathcal{T}, j \in \mathcal{J} \tag{14}$$

$$\underline{P_t^j} y_t^j \leq p_t^j \leq \overline{P_t^j} y_t^j, \quad \forall t \in \mathcal{T}, j \in \mathcal{J} \tag{15}$$

$$-R_j^D \leq p_t^j - p_{t-1}^j \leq R_j^U, \quad \forall t \in \mathcal{T}, j \in \mathcal{J} \tag{16}$$

$$y_t^j - y_{t-1}^j \leq y_k^j \quad \forall j \in \mathcal{J}, t \in \{2 \ldots \mathcal{T} - 1\}, \quad k \in \left\{ \min\left(t + \underline{t_{on}} - 1, \mathcal{T}\right) \right\} \tag{17}$$

$$y_{t-1}^j - y_t^j \leq 1 - y_k^j \quad \forall j \in \mathcal{J}, t \in \{2 \ldots \mathcal{T} - 1\}, \quad k \in \left\{ \min\left(t + \underline{t_{off}} - 1, \mathcal{T}\right) \right\} \tag{18}$$

$$Eq. \; 6 - 9$$

The objective is to minimize the operational cost of power units. $c_j(p_t^j)$ is the operation cost of unit j as a function of the amount of power generation p_t^j. $c_{j,t}^U$ is the cost of starting up unit j.

Eq. (13) is the balance constraint of power generation and demand, where L_t^{AG} is the aggregated demand shown in Eq. (4). In Eq. (14), y_j^t is the on/off status of unit j at time t, which is a binary constraint. In Eq. (15), $\overline{P_t^j}$ and $\underline{P_t^j}$ are the maximum and minimum amount of power that the unit j can generate, respectively. Eq. (16) shows the unit's ramping up and down constraint, where R_j^U and R_j^D are the ramping up and down limit, respectively.

Eq. (17) represents that the power generation unit needs to stay on for a minimum amount of time $\underline{t_{on}}$ after it turns on due to mechanical design limits or economic reasons. Similarly, as shown in Eq. (18), a unit needs to stay off for a minimum amount of time $\underline{t_{off}}$ after it turns off before it can be turned back on.

D. Stochastic Unit Commitment Model

A two-stage stochastic UC model is also developed. In the first stage, the generation units are dispatched to meet the expected demand. The uncertainty is realized in the second stage by various scenarios: $\omega \in \Omega$, where ω is the index of a scenario, and Ω is the set of scenarios. Each scenario occurs with a probability of ξ_ω, and $\sum_{\omega \in \Omega} \xi_\omega = 1$. Also, the generation will match the demand in each scenario by varying generation up-reserve ($r_{t,U}^{j,\omega}$) and down-reserve ($r_{t,D}^{j,\omega}$). We also incorporate DR flexibility into this stochastic UC model so that the householders can use DR flexibility as a virtual power plant to participate in power economic dispatch.

$$\begin{aligned} \text{minimize} \quad & \sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}} \left(c_j(p_t^j) + c_j^U y_t^j\right) \\ & + \sum_{\omega\in\Omega}\sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}} \xi_\omega c_j^m \left(r_{t,U}^{j,\omega} - r_{t,D}^{j,\omega}\right) \\ & + \sum_{\omega\in\Omega} \xi_\omega \sum_{H\in AG} \left\| \lambda_t^H \sum_{ap\in\mathcal{CAP}} (l_t^{ap,\omega} - \widehat{l_t^{ap,\omega}}) \right\| \end{aligned} \tag{19}$$

subject to

$$\sum_{j\in\mathcal{J}} p_t^j = \mathbb{E}\left[L_t^{AG}\right], \forall t \in \mathcal{T} \tag{20}$$

$$p_t^{j,\omega} = p_t^j + r_{t,U}^{j,\omega} - r_{t,D}^{j,\omega}, \forall t \in \mathcal{T}, \forall \omega \in \Omega \tag{21}$$

$$\sum_{j\in\mathcal{J}} p_t^{j,\omega} = L_t^{AG,\omega}, \forall t \in \mathcal{T}, \forall \omega \in \Omega \tag{22}$$

$$\underline{P_t^j} y_t^j \le p_t^{j,\omega} \le \overline{P_t^j} y_t^j, \quad \forall t \in \mathcal{T}, \forall \omega \in \Omega, j \in \mathcal{J} \tag{23}$$

$$-R_j^D \le p_t^{j,\omega} - p_{t-1}^{j,\omega} \le R_j^U, \quad \forall t \in \mathcal{T}, \forall \omega \in \Omega, j \in \mathcal{J} \tag{24}$$

$$Eq.\ 6-9, 14-18$$

The objective is to minimize the operational cost of power units and the inconvenience of residential customers in the UC for DR purposes. The first term is the expected cost in the first stage, and the second term is the generation cost in the second stage. $c_j^m(\cdot)$ is the marginal generation cost function. The third term is the ℓ_1 norm of the difference between predicted load and rescheduled load from participating in the UC. λ_t^H is the penalty coefficient for a home H at time t, representing the unwillingness or inconvenience to participate in the UC for DR applications. This value can be different from home to home and from time to time.

Eq. (20) is the power-demand balance constraint in the stage 1. Eq. (21) is the realized power generation unit j in all the scenarios. Eq. (22) is the power-demand balance constraint in all the scenarios. Eq. (23) and Eq. (24) are the power unit operation constraints in all the scenarios.

The decision variables include $p_t^j, y_t^j, r_{t,U}^{j,\omega}, r_{t,D}^{j,\omega}$ and $l_t^{ap,\omega}, \forall ap \in \mathcal{CAP}$. The stochastic variables are household load l_t^{ap}. For instance, one home may use a dishwasher and anther home may not use a dishwasher in the simulation day. One homeowner may need to drive their EV at 8 am ($t_2^{ap} = 8$) and another homeowner may need it at 8:30 am. To realize the stochastic variables, sampling is applied for the 100 homes. More precisely, each home is one scenario with 1% probability. The Monte Carlo method is used to conduct the simulation.

III. Simulation Results and Analysis

We considered one load aggregator and 100 homes in the residential microgrid. Dishwashers, Dryers and EVs were considered as controllable loads, and 20% of homes were assumed to have EVs. The Nissan Altra-EV with Lithium-Ion Battery was considered in this study, and the capacity was 33 kW [47], [48]. We also assumed the DR participant had a home EMS to schedule the controllable appliances. The time horizon was 24 hours, and the time resolution was 5 minutes. The CVX [51], [52] and Gurobi solver [53] were used to solve the proposed optimization models. Case studies and simulation were conducted in three scenarios:

1) Residential loads were predicted and aggregated without DR application. This is our reference scenario.
2) Optimal load aggregation under TOU and augmented TOU.
3) DR applications in UC.

TABLE I
Parameters of the Controllable Loads [54], [55]

	q_{rated}^{ap}	t_0^{ap}	$t_1^{ap} - t_0^{ap}$	t_2^{ap}
EV	1.7 kW	$\mu = 17$ $\sigma : 2.8$ h	$\mu = 4.39$ h $\sigma = 0.61$ h	$\mu = 7$ $\sigma = 1$ h
Dishwasher	$\mu = 1.13$ kW $\sigma = 0.12$ kW	Some usages $\mu = 10:25$ $\sigma = 3$ h Other usages $\mu = 18:15$ $\sigma = 1.6$ h	$\mu = 1.41$ h $\sigma = 0.72$ h	$t \in \mathcal{T}$
Dryer	$\mu = 2.52$ kW $\sigma = 0.26$ kW	Some usages $\mu = 9:25$ $\sigma = 1.5$ h Other usages $\mu = 16:00$ $\sigma = 3.1$ h	$\mu = 1.41$ h $\sigma = 0.35$ h	$t \in \mathcal{T}$

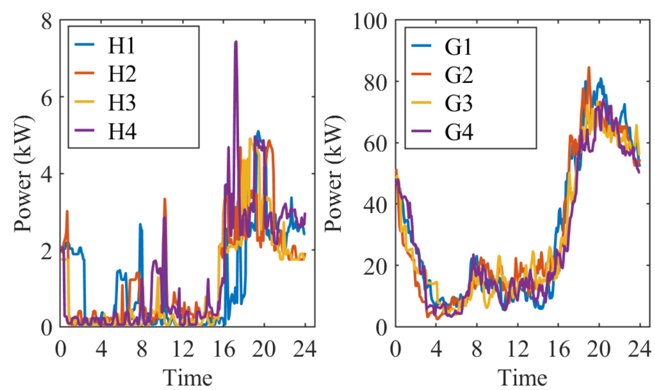

Fig. 2. Forecasted load profiles. Left: 4 individual homes (H); Right: aggregated load profile of 4 groups (G) of 25 homes

A. Scenario #1: Residential load forecast

We first simulated an aggregated load profile where there were no DR applications. The key parameters included q_{rated}^{ap}, t_0^{ap} and t_1^{ap}. These parameters for controllable loads were summarized in Table I, which were derived from our earlier research [54], [55].

Fig. 2 shows forecasted load profiles for individual homes, and an aggregated load profile of 25 homes. As can be seen from the left plot, the load profile is very random from home to home. However, the aggregated load profile can have high correlation with 25 home profiles shown on the right. Therefore, although the homes are heterogeneous, the aggregated load profile of a large number of homes can be statistically stable due to similar daily routines.

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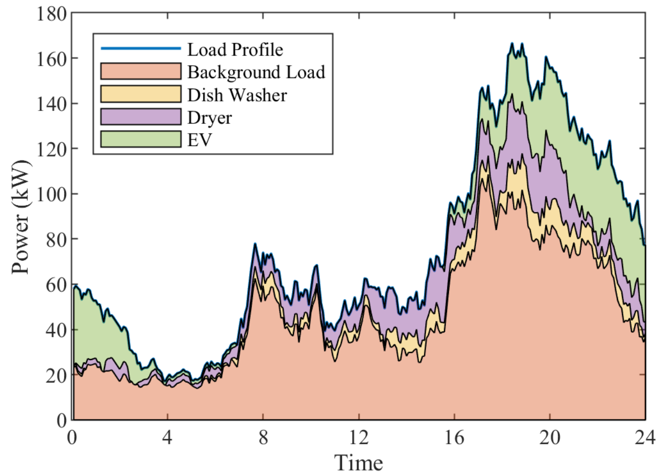

Fig. 3. Aggregated load profile of 100 homes

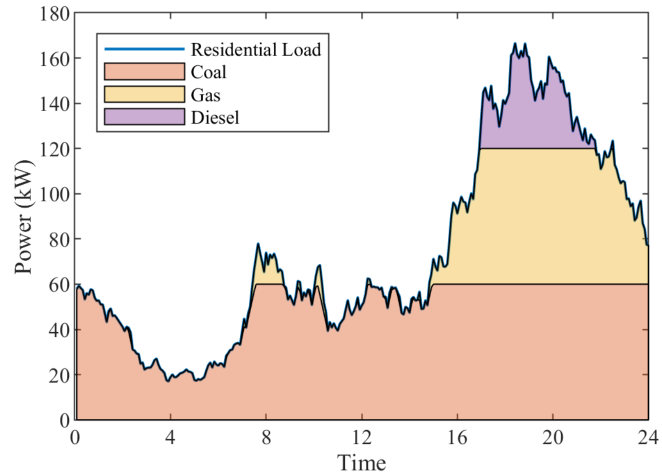

Fig. 4. Power generation and load profile in Scenario 1

TABLE II
PARAMETERS IN THE UNIT COMMITMENT MODEL

	Coal	Gas	Diesel
a_j	0.01	0.1	0.2
b_j	4	10	20
$\overline{P_t^j}$	60 kW	60 kW	60 kW
$\underline{P_t^j}$	10 kW	0 kW	0 kW
R_j^U, R_j^D	1 kW/min	–	–

Fig. 3 shows the aggregated load profile of 100 homes and the areas show load from different type of appliances. The background loads are non reschedulable loads such as lighting, TV, and Oven. To simulate this aggregated load profile, we ran the load forecast model with 1000 homes. The load profile of these 1000 homes are divided into 10 groups and each group has 100 homes. We then take the average load profile as the expected load aggregation of 100 homes as shown in Fig. 3.

We now discuss the method to use the deterministic UC model to calculate the generation cost. We also developed a flat-rate and a TOU structure based on the generation cost. The load profile shown in Fig. 3 was used as the demand in the deterministic UC model. For demonstration purposes, only three types of generation units were considered, including coal, gas, and diesel units. Also, since the simulated grid is much smaller than a real-world grid, the generation units' capacities were scaled down, which does not imply any real-world applications. We did not constrain the minimum on or off period for these units. The starting up cost was also assumed to be 0. The quadratic function was used for power generation cost shown in Eq. (25), and its first order derivative function at 80% of the capacity was used as marginal generation cost of reserve power shown in Eq. (26).

$$c_j(p_t^j) = a_j(p_t^j)^2 + b_j p_t^j \tag{25}$$

$$c_j^m\left(r_{t,U}^{j,\omega} - r_{t,D}^{j,\omega}\right) = 1.6\, a_j \overline{P_t^j}\left(r_{t,U}^{j,\omega} - r_{t,D}^{j,\omega}\right) \tag{26}$$

The key parameters of the UC model are summarized in Table II. Note that all these parameters can be readily tuned.

The simulation results from the UC are shown in Fig. 4. As can be seen, the units are dispatched in the merit order, i.e., the units with the lowest cost are dispatched first followed by more expensive ones. The are two types of generation costs: actual generation cost defined in Eq. (27) and market-based generation cost defined in Eq. (28).

$$C_t^A = \sum_{j\in\mathcal{J}}\left(c_j(p_t^j) + c_{j,t}^U y_t^j\right) \tag{27}$$

$$C_t^M = \max_{j\in\mathcal{J}}\left(c_j(p_t^j) + c_{j,t}^U y_t^j\right) \tag{28}$$

where C_t^A is the actual generation cost and C_t^M is the generation cost in an electricity market.

If all the units are owned by a utility or the microgrid operator, the actual generation cost should be considered. On the other hand, in a market context, the generation cost is determined by the generation cost of most expensive units at time t. The electricity market is cleared when the power generation units are dispatched to meet the demand. All the dispatched generation units are paid the same as the generation unit with the highest generation cost. For instance, at 20:00, all the units are operating and they are paid by the cost of Diesel unit since the Diesel unit has the highest generation cost.

Since dynamic pricing such as TOU is a market incentive measure, we use the market generation cost to calculate the TOU. For a comparison, we also calculate a flat-rate. To calculate the equivalent TOU and flat-rate based on market generation cost, we assume a budget balanced market, i.e., the power generation units do not yield profit. This does not lose generality since the price can be easily modified to incorporate profits.

Based on the TOU in Ontario Canada [56], we define the TOU with three tiers as follows.

$$\pi_t = \begin{cases} \pi_t^{off} & t \in \mathcal{T}_{off} \\ \pi_t^{mid} & t \in \mathcal{T}_{mid} \\ \pi_t^{on} & t \in \mathcal{T}_{on} \end{cases} \tag{29}$$

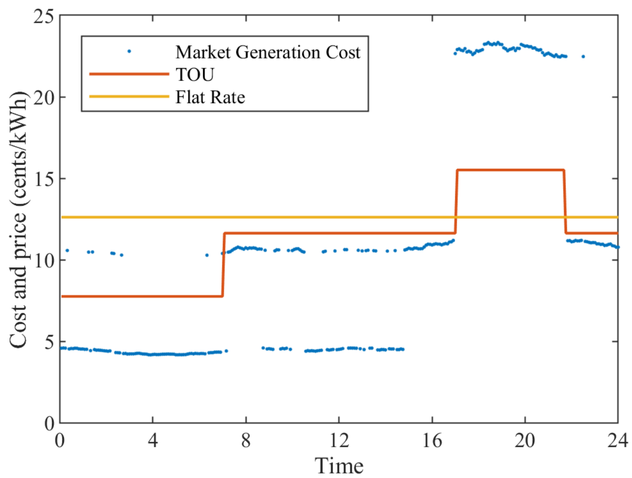

Fig. 5. The market-based generation cost, time-of-use price and flat-rate

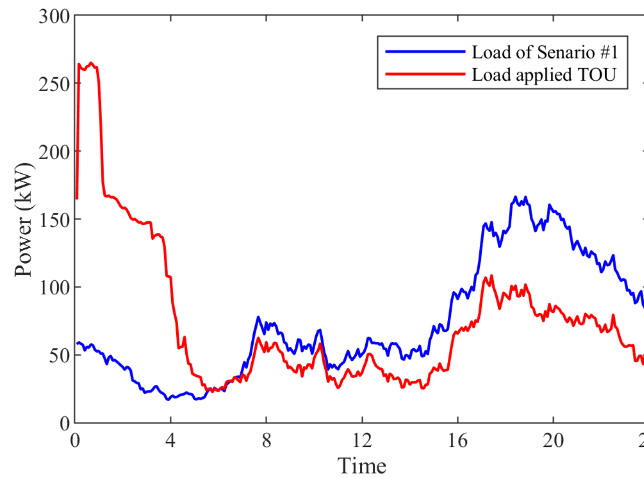

Fig. 6. Load profile before and after application of optimal load aggregation with TOU

where π_t is the TOU. $\pi_t^{\{off,mid,on\}}$ are the price in off-peak, mid-peak and on-peak demand period respectively. Similarly, $\mathcal{T}_{\{off,mid,on\}}$ are the corresponding time periods.

We assume $\pi_t^{mid} = 1.5\pi_t^{off}$ and $\pi_t^{peak} = 2\pi_t^{off}$. Then, the π_t^{off} is calculated from the following equation.

$$\sum_{t\in\mathcal{T}_{off}} \pi_t^{off} L_t + \sum_{t\in\mathcal{T}_{mid}} 1.5\pi_t^{off} L_t + \sum_{t\in\mathcal{T}_{on}} 2\pi_t^{off} L_t = \sum_{t\in\mathcal{T}} C_t^M \tag{30}$$

where L_t is the aggregated load at t. In this equation, the only unknown is π_t^{off}.

The flat-rate π^{flat} is calculated from the following equation.

$$\sum_{t\in\mathcal{T}} \pi^{flat} L_t = \sum_{t\in\mathcal{T}} C_t^M \tag{31}$$

Fig. 5 shows the market generation cost, TOU and flat-rate. The electricity market is cleared when the power generation units are dispatched to meet the demand. All the dispatched generation units are paid the same as the generation unit with the highest generation cost regardless their actual generation cost. The dots show the market-based generation cost, from which the off-peak, mid-peak and on-peak periods can be identified. The pricing of each tier of the TOU is calculated by Eq. (30). The flat-rate is calculated from Eq. (31).

The electrical energy consumption in this reference scenario was 1.77 MWh. The peak demand was 167 kW and the standard deviation of the load profile was 43 kW. The actual generation cost was \$118 and the market-based generation cost was \$224. The electricity price in the off-peak demand period was calculated as $\pi_t^{off} = 7.76$ ¢/kWh and the flat-rate was calculated as $\pi^{flat} = 12.61$ ¢/kWh.

B. Scenario #2: Optimal load aggregation under TOU

In this section, we applied the stochastic optimal aggregation model discussed in Section II.B. Both plain TOU and augmented TOU were used. We also evaluated the impact of DR participation levels on the DR implementation. We did not incorporate the flexible loads in the UC models. However, we used the deterministic UC model for generation dispatch to meet the aggregated load. The loads were aggregated under TOU with various DR participation levels. The aggregated load was used as the demand in the deterministic UC model. Eq. (28) was used to calculate the generation cost.

It is well understood that the application of plain TOU causes peak demand to rebound at the start of π_t^{off} as shown in Fig. 6. Within each tier of TOU, the electricity price is the same; therefore, the EMS will schedule the load to the earliest time of the tier with the lowest price.

To overcome this problem, an augmented TOU strategy is implemented in Eq. (10). The strategy provides some price variation within each tier so that the home EMSs will not schedule the load at the same time simultaneously. For example, Fig. 7 shows 5 zero mean negative RBF curves, $-(RBF - \mu_{RBF})$, with $\sigma = 1$ and different μ in the off-peak period of the TOU. If these functions are added to the off-peak period of the TOU and assigned to 5 homes, the augmented TOU will distribute the preference of using controllable appliances in different homes uniformly inside the tier. Fig. 8 shows 100 sets of TOU pricing signals augmented by the RBFs, and the graph in the right bottom corner shows a zoomed-in view of the off-peak demand period, in which 100 RBFs uniformly distributed their centers in the off-peak periods. These pricing signals will be randomly assigned to 100 homes, and each home will have a similar but unique TOU. σ was set as 1, and each home has a different μ.

These RBFs can be randomly assigned to different householders. The magnitude of these RBFs is tiny and has little impact on the electricity payment of the householders. However, they can effectively overcome the peak-demand rebound. Fig. 9 shows the load profile before and after the application of optimal load aggregation with augmented TOU with a 50% participation level. As can be seen, the augmented TOU can flatten the controllable load in the lowest price period.

However, the performance can be affected by DR participation levels. We evaluated the participation level from 0% to 100% in an interval of 10%, and the results are shown in

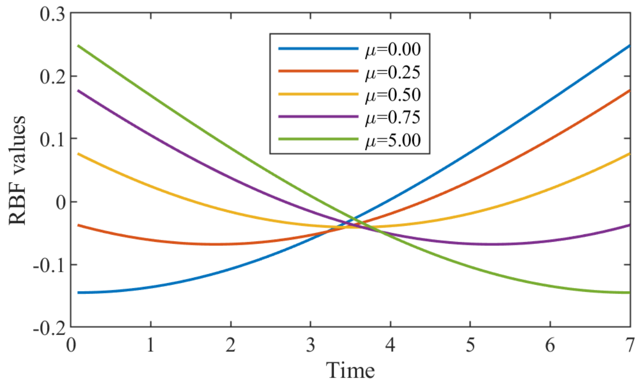

Fig. 7. Five negative radial base functions (RBF) ($\sigma = 1$) in the off-peak period of time-of-use (TOU)

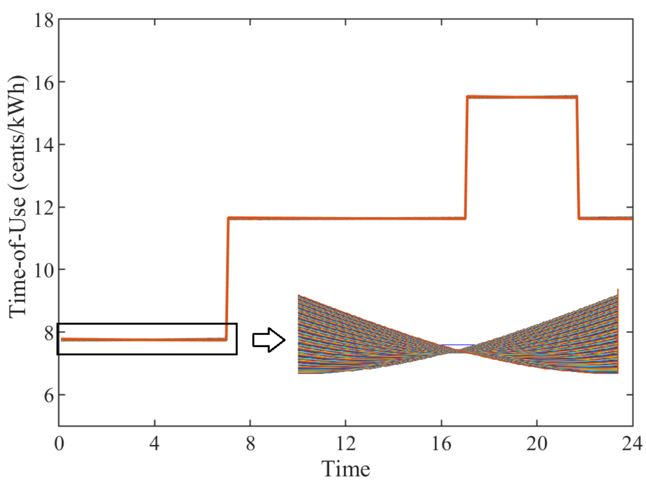

Fig. 8. One hundred sets of time-of-use (TOU) pricing signals augmented by the radial base functions (RBF)

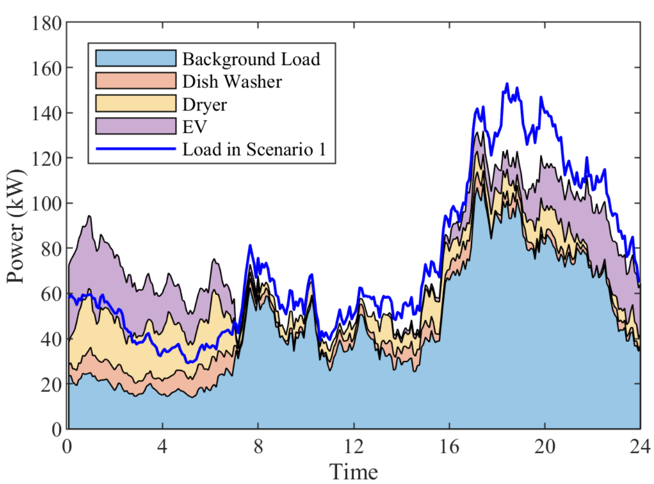

Fig. 9. Load profile before and after application of optimal load aggregation under augmented TOU with 50% of participation level

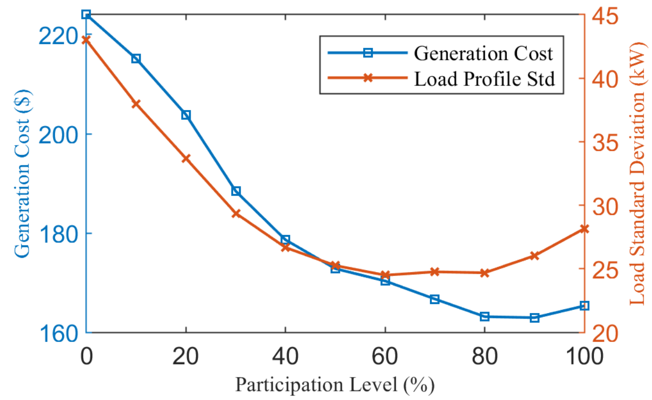

Fig. 10. The market-based generation cost ($) and load profile standard deviation (kW) based on different participation levels

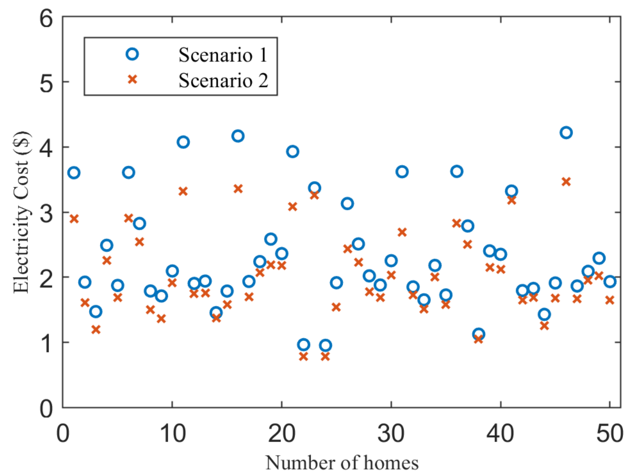

Fig. 11. Electricity cost of individual homes who participate in DR before and after the DR participation (50% participation level)

Fig. 10. The deterministic UC model was used for generation dispatch to meet the aggregated load. Eq. (28) was used to calculate the generation cost. The participation level of 10% means that there are ten homes responding to the augmented TOU using home EMSs. The participation level of 0% is the same as Scenario 1. As expected, the generation cost and standard deviation of the load profile started to reduce when people participate in the DR. The lowest generation cost ($163) occurred when the participation level was 90%, and the lowest standard deviation (24.5 kW) of the load profile was achieved at the participation level of 60%.

For the 50% participation level case, we also evaluated the individual homes' electricity cost (bills) before and after the DR participation under TOU shown in Fig. 11. All the homes had reduced electricity cost. The average saving of the homes was 13%. The #31 home has the largest saving with 26%. Note that the #11 home has an EV. The #38 home has the least saving with 6%.

C. Scenario #3: Stochastic Unit Commitment with DR

From the simulation results in Scenario 2, we have seen that the un-augmented TOU will cause peak demand rebound

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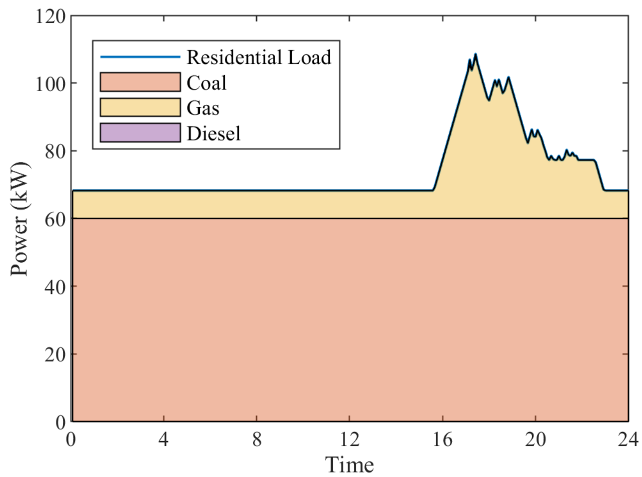

Fig. 12. Power generation in Scenario 3

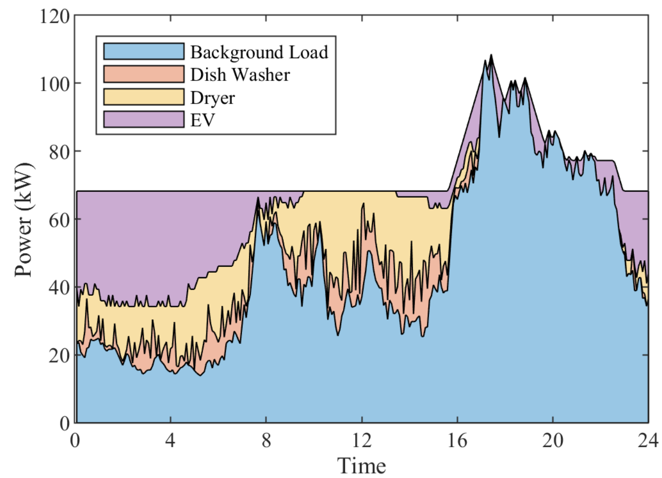

Fig. 13. Load profile of background and controllable loads

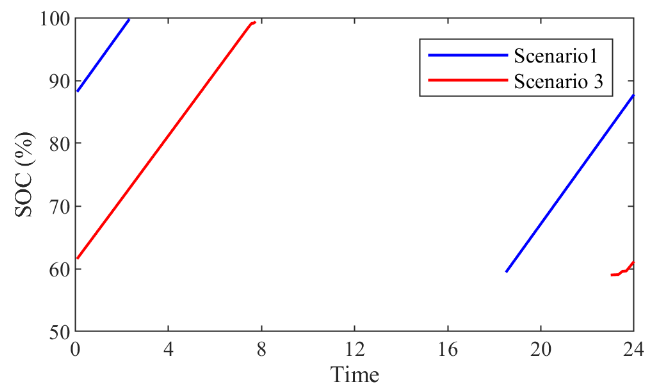

Fig. 14. SOC of the same EV in Scenario 1 and Scenario 3

and, therefore, not applicable if the homes are equipped with home EMSs to shift the loads automatically. With augmented TOU, the results are satisfactory when the participation level is less than 80%. However, the augmented TOU became less effective when the participation level is greater than 80%.

In this section, we will evaluate the proposed stochastic UC model with the incorporation of demand flexibility. We first assume $\lambda_t^H = 0, \forall t \in \mathcal{T}, H \in AG$. In words, all the homes have zero unwillingness or zero inconvenience to shift their controllable loads for DR purposes. This is a reasonable assumption since the home EMSs will automatically shift the load and the load will complete based on users' settings. For instance, if the householder set up 7am to drive the EV, then the EV will be fully charged by 7am. We will also present the effect of unwillingness on the model later in this section.

Fig. 12 shows the power generation from various units. By incorporating demand flexibility in the UC model, the market-based generation cost was reduced by 20% from \$224 to \$179. The standard deviation of the load profile was reduced by 77% to 10.41 kW, which helps with power system control. Fig. 13 shows the load profiles of background and controllable loads in this scenario. The controllable loads were coordinated to fill the load valleys. Note that most of the EVs were not able to charge in the period from 7 to 17 o'clock because of driving. In addition, the driving times were stochastic and followed a normal distribution. The SOC of a sample EV is shown in Fig. 14.

The total savings compared with the reference scenario of the generation cost was $224 - 179 = \$45$, which represents a 20% reduction. Also, the flattened load profile can greatly increase energy efficiency. If a budget balanced market is considered, these savings can be used as rewards r to the householders to encourage them to participate in DR. The rewards can be calculated as follows.

$$r = \frac{saving}{\sum_{H\in AG}\sum_{t\in\mathcal{T}}\sum_{ap\in\mathcal{CAP}}|l_t^{ap} - \widehat{l_t^{ap}}|} \tag{32}$$

where $\widehat{l_t^{ap}}$ is predicted load profile and l_t^{ap} is rescheduled load in UC. In this particular case, the $r = 4.38$¢/kWh, which was about $1/3$ of the flat rate.

Fig. 15 shows the electricity cost for individual homes in both Scenario 1 (with flat-rate) and Scenario 3. The average saving for the homes was 20%. The #56 home had the largest saving with 37%. Note that the #56 home had an EV. The #60 home had the least saving with 5%.

Since householders may have different preferences, some people may weigh convenience higher than others. This factor can be reflected by λ_t^H in the UC model. In this case, we can obtain Pareto optimal solutions by solving the UC model. By changing the setting of λ_t^H, householders can determine a trade-off between monetary benefit and convenience. Fig. 16 shows the Pareto surface by varying λ_t^H from 1 to 10. We also assumed a constant λ_t^H. The results can provide householders a baseline to select a good λ_t^H.

IV. Discussion

In this study, we have developed a stochastic optimal load aggregation model under TOU and a two-stage stochastic UC model with DR flexibility. We also develop an augmented TOU pricing structure. It should be noted that this study does not consider the impact of market power on the DR application. In other words, all the DR participants are price takers. However, if the DR participants are not honest or unwilling to participate in the DR applications, the results

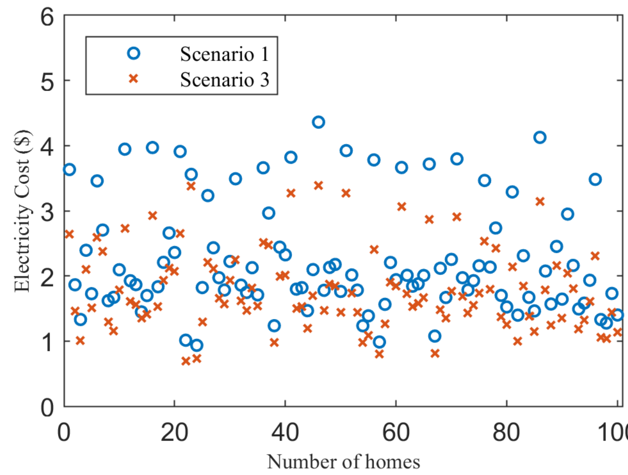

Fig. 15. Electricity cost for individual homes in Scenario 1 (with flat-rate) and Scenario 3

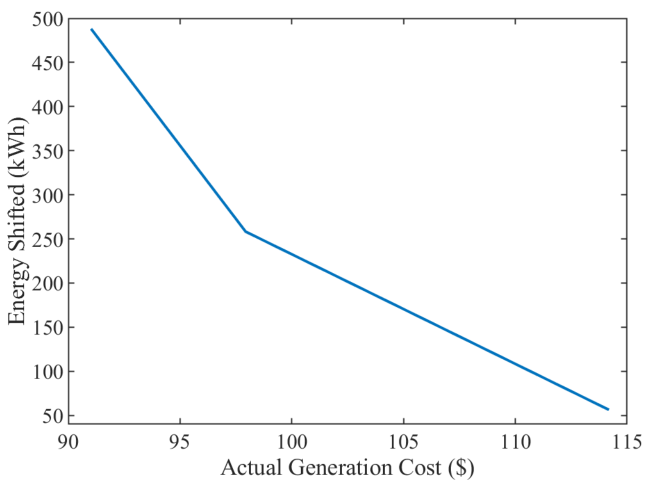

Fig. 16. Pareto surface by varying the penalty coefficient λ_t^H in the stochastic UC model

may be undesired. Approaches such as game theory can be applied to study this effect. This study also ignores the power flow in the distribution network. In power system integration, frequent reschedule of power usages may cause line congestion or transformer overload in some areas, e.g., the appliance usages are simultaneously rescheduled to one time under one transformer. Coordination may be required in such a situation.

To evaluated the proposed models, simulations were conducted in three scenarios. In the first scenario, we presented the load profile from the residential load forecasting model as well as the corresponding power generation cost by using the deterministic UC model. We also designed the augmented TOU pricing structure to encourage customers to participate in the DR application.

In the second scenario, we demonstrated that the plain (unaugmented) TOU structure could cause significant peak demand rebound. This shows that plain TOU is not a promising solution if residential customers are able to respond to TOU, e.g., using home EMSs. We, therefore, proposed an augmented TOU with negative RBF functions with various RBF centers. These centers can uniformly distribute the controllable load in the lowest price periods, which provides some price variation within each tier so that the home EMSs will not schedule the load at the same time simultaneously. The augmented TOU strategy is also fair for all DR participants. The RBFs are randomly assigned to different householders. In addition, the magnitude of these RBFs is tiny and has little impact on the electricity payment of the DR participants.

We also showed the impact of DR participation levels on the DR application. Simulation results show that the DR participation level between 50% and 80% provides low power generation cost and load profiles with low standard deviation. TOU is predetermined from the generation cost without consideration of DR, and it is not a good reflection of the generation cost. The generation cost is coupled with loads that can be affected by electricity prices. In other words, with DR, the load will increase in the lowest price period and hence increase the generation cost. Therefore, the augmented TOU became less effective when the participation level is greater than 80%.

In real-world plain TOU applications (e.g., in Ontario, Canada), this peak demand rebound has not been reported. We believe this is because most homes do not have EMSs. Since people respond to TOU manually, the demand rebound problem is avoided. However, utilities should be aware that if the customers install the home EMS, the augmented TOU should be used or some other mechanisms should be designed.

In the third scenario, we applied the two-stage stochastic UC model with demand flexibility in the residential microgrid. The simulation results were very promising, with the lowest standard deviation of load profiles and very low generation cost, among others. Based on the saved generation cost, we designed rewards to encourage residential customers to participate in the UC with DR. We further presented the impact of the householder's inconvenience or unwillingness on the DR application. A Pareto surface has been developed, which can be used by householders to set up the home EMS in DR participations. It can also be used by utilities or load aggregators to predict customer's behavior in DR and design contracts.

The energy usage in the three scenarios was 1.77 MWh. Table III shows the peak demand, the standard deviation of load profile, and market-based generation cost across the three scenarios. In Scenario #2, the participation level (PL) of 60% (PL=60%) is shown. All the observations in Scenarios #2 and #3 are better than Scenario #1. Although Scenario #2 has the lowest generation cost, Scenario #3 has the lowest peak and standard deviation, which are much lower than those in the Scenarios #2. In addition, the generation cost in Scenario #3 is only \$9 higher than Scenario #2. Therefore, both proposed mechanisms can be used to effectively unlock residential DR benefits. More precisely, the first approach is suitable in the current real-world situation where EMSs are not widely installed. The second approach provides the best results if EMSs are in place.

TABLE III
PEAK DEMAND, STANDARD DEVIATION OF LOAD PROFILE AND MARKET-BASED GENERATION COST IN THE SCENARIOS

	#1	#2 (PL=60%)	#3
Peak demand (kW)	167	129 (23%)	109 (35%)
Standard deviation (kW)	43	25 (42%)	10 (77%)
Generation cost ($)	224	170 (24%)	179 (20%)

* The values in the parenthesis are the decrease percentage compared with the scenario #1. PL: participation level

V. Conclusion

DR is one of the most economical methods to reduce peak demand, integrate intermittent renewable energy sources, and improve energy efficiency. The residential sector has the most unlocked DR potential and this needs to be incorporated into power system operation. This study proposes two mechanisms to unlock residential DR potential. These two approaches do not consider market power, i.e., the DR participants are assumed to be price takers. The first mechanism is to use augmented TOU to encourage residential customers to participate in DR. A stochastic optimal load aggregation model is designed to accomplish this goal. Simulation results show that it is a promising solution in the current real-world situation, in which residential customers can only partially control their appliances. For example, when 60% of homes participate in DR, the standard deviation and generation cost can be reduced by 42% and 24%, respectively. However, the mechanism becomes less efficient if the participation level exceeds 80%.

As the second mechanism, we propose a two-stage stochastic UC model to incorporate the DR flexibility. Simulation results show that this model can dramatically decrease the peak demand, standard deviation, and generation cost. The saved generation cost can be used as rewards to encourage residential customers for DR participation. We further present the impact of the householder's inconvenience or unwillingness on the DR applications. A Pareto surface has been developed, which can be used by householders to set up their home EMS for DR participation. It can also be used by utilities or load aggregators to predict customer's behavior in DR and design contracts.

Both the proposed mechanisms can be used to unlock residential DR potential to reduce power generation costs, decrease customers' electricity bills, and improve energy efficiency.

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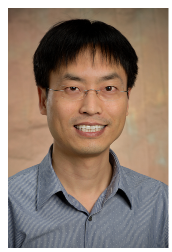

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