Fair Demand Response With Electric Vehicles for the Cloud Based Energy Management Service

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***Abstract*—Fluctuated penetration of electric vehicle (EV) loads and production capacities from distributed energy resource (DER) bring large impacts to power systems. To smooth fluctuations, financial incentives have to be maximized for customers controlling their consumption patterns. A fair demand response with electric vehicles (F-DREVs) is proposed for the cloud-based energy management service. Customers with EV, DER, storage and multiple loads form communities and obtain optimal choices (electricity usage and trading) from F-DREV. F-DREV aims to maximize incentives by minimizing global cost for each community within the given time period, and smooth fluctuations. In order to attract customers to actively participate, we propose the fairness as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community," which is attainable by customizing trading prices. A binary linear programming model is formulated, and performances are evaluated in experiments.**

***Index Terms*—Fairness, demand response, fluctuation, electric vehicle, distributed energy resource, smart grid, cloud based, energy management, EMaaS, scheduling.**

NOMENCLATURE

Parameters

G	DER production capacity.
T^c	Assigned capacity for power distribution line.
P^b	Price for buying energy from power grid to community.
P^s	Price for selling produced renewable energy from community to power grid.
P^u	Highest trading price within community.
P^l	Lowest trading price within community.
P^{rb}	Customized buying price within community.
P^{rs}	Customized selling price within community.
P^e	Price for exporting energy from EV.
D	Summation of the requested fix loads.
R	Required operating time for deferrable load.
α	Starting time for deferrable loads and EV.
β	Ending time for deferrable loads and EV.
γ	Power consumption rate for EV.
ηc	Charging efficiency for storage and EV.
ηd	Discharging efficiency for storage and EV.
EV^{init}	Initial capacity of EV when arriving.
EV^{end}	Required capacity of EV when leaving.
T^u	Upper bound for smoothing the fluctuation.
T^l	Lower bound for smoothing the fluctuation.
w	Weight for different load types.

Subscripts

i	i_{th} customer.
j	j_{th} interruptible or non-interruptible load.
t	t_{th} time step.
z	z_{th} power distribution line.

Superscripts

r	Distributed energy resource (DER)
m	Power grid
c	Community
e	Electric vehicle (EV)
s	Storage
d	Load usage
fl	Fixed load
il	Interruptible load
nl	Non-interruptible load

Sets

$\mathbb{N}$	For customer from 1 to N.
$\mathbb{T}$	For time step from 1 to K.
$\mathbb{Z}$	For power distribution lines.
$\mathbb{L}$	For customers connected to the same power distribution line.
$\mathbb{IL}$	For interruptible loads.
$\mathbb{NL}$	For non-interruptible loads.

Choice Variables for DER

E^{rc}	Export produced energy from DER to community.
E^{rm}	Export produced energy from DER to power grid.
E^{re}	Export produced energy from DER to EV.
E^{rs}	Export produced energy from DER to storage.
E^{rd}	Export produced energy from DER for load usage.

Choice Variables for Storage

I^{ms}	Import energy from power grid to storage.
I^{cs}	Import energy from community to storage.
I^{rs}	Import energy from DER to storage.
I^{es}	Import energy from EV to storage.

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E^{sm} Export energy from storage to power grid.
E^{sc} Export energy from storage to community.
E^{se} Export energy from storage to EV.
E^{sd} Export energy from storage for load usage.
S State of charge for storage.

Choice Variables for EV

I^{me} Import energy from power grid to EV.
I^{ce} Import energy from community to EV.
I^{re} Import energy from DER to EV.
I^{se} Import energy from storage to EV.
E^{em} Export energy from EV to power grid.
E^{ec} Export energy from EV to community.
E^{es} Export energy from EV to storage.
E^{ed} Export energy from EV for load usage.
S^{e} State of charge for EV.

Choice Variables for Loads

I^{md} Use the energy from power grid.
I^{cd} Use the energy from community grid.
I^{rd} Use the energy from DER.
I^{sd} Use the energy from storage.
I^{ed} Use the energy from EV.

Binary Control Variables

$\{O^{il}, O^{nl}, O^{a}\}$.

I. Introduction

In RECENT years, electric vehicle (EV) and distributed energy resource (DER) have been dramatically increased and popularized, due to their effectiveness in reducing greenhouse emissions and making power grid environment-friendly. The expected fluctuated penetration of EV loads and production capacities from DER bring large impacts to the power system not only as additional positive and negative loads, but also on reserving capacity [1]. Impacts of these fluctuated loads become more significant without proper management when technology such as Vehicle-to-Grid (V2G) enables EVs to work as the grid resources by providing power back to the power grid [2]. In order to smooth the fluctuation of EVs and DERs to allow them operate grid-friendly, it is critical to provide financial incentives for customers controlling their consumption patterns and their EV charging schedules. Providing the financial incentives is the focus of this paper.

Literatures of demand response and EV charging scheduling have provided financial incentives as *"electricity usage choices"*, which allow customers to utilize DERs, controllable loads and storages to change demands in response to the fluctuated electricity prices over time. Residential electricity costs are minimized with the cooperation of various types of loads through the home energy management system in [3], and smart home controller in [4]. An optimization algorithm in the residential level is proposed in [5]. Chen *et al.* [6] and Mohsenian-Rad *et al.* [7] propose the demand response schemes to minimize the global cost through a formulated game. Reference [8] deals with load control in multiple residences. Scheduling managements are discussed in virtual power plant [9] for DERs with storage to maximize profits, and in EV aggregator [1] to absorb the EVs penetration while minimizing costs for aggregator. To accommodate EV charging while keeping the peak demand unchanged, [10] proposes an incentive based demand response strategy with critical and controllable loads. However, unlike the cloud based framework, difficulty exists in above literatures due to the requirement of duplicated, dedicated control entity and corresponding control mechanisms. Moreover, none of them consider the *"trading choices"* among customers, which can boost the incentives for customers.

Trading choices appear when customers become owners of grid resources, such as EV with V2G and DER. They are utilized in net metering mechanism as incentive by retail electricity providers (REP) [11], but only few buy-back programs are offered and are not available among customers. Our previous work [12] proposes a cloud based framework to provide customer-oriented Energy Management as a Service (EMaaS) for *"community"*, which are formed as virtual REPs by involved DERs providers. A new price appears when the community is formed, and is utilized for customers performing the *"virtual trading"* for their produced renewable energy within the community to benefit mutually. The trading is performed virtually due to the physical power distribution lines may not exist among customers, and can be realized efficiently via a mapping mechanism with the cloud based framework. The cloud based energy management is provided as a service via an extensive framework and is also a business model for distributed renewable integration. It significantly reduces infrastructure costs and increases efficiency, reliability and scalability. But still, how to utilize it for demand response and EV charging scheduling to adjust electricity usage for customers within community is an unexplored area.

Furthermore, to substantially attract individual customer, allowing customers form the community to trade mutually with the same new formed price might not be enough. Customers are intuitively expecting to gain more benefits if they can actively participate and contribute to others within the community. Incentives should be provided in a fair manner. Different from the discussed fairness in the few literatures, where [13] defines it as assigning the long-term average delay equally for each user and [14] addresses it as social fairness, we propose the *fairness* based on the participation level. The participation level has been utilized by cooperation [15] in business to distribute benefits accordingly. In other words, the fairness in this paper is defined as "customers with higher participation level can reduce their individual cost (as the distributed benefits in cooperation) more than those with lower participation level within the same community". To achieve this *fairness*, customizing trading prices for customers according to the participation level is an effective approach.

A fair demand response with electric vehicles (F-DREV) is proposed for the cloud based energy management service, based on our previous work [12]. Inheriting the characteristics of the cloud based energy management service, F-DREV can be adopted by existing REPs or utilities, and is flexible, scalable, reconfigurable and cost-efficient. The interoperability is shown by considering DER, EV with V2G, storage, and multiple loads (fixed, interruptible and non-interruptible) in this paper. The proposed fairness is maintained by customizing trading prices for each customer according to the customer's participation level and other involved customers. It is related to the production capacity of DER and the flexibilities of requested loads. Customer who invests the DER more can acquire higher participation level and more return of the original investment (i.e., reduced individual cost). With the formed community and customized trading prices, choices of electricity usage and trading are combined for customers. Due to the increasing complexity of massive combinations, finding the optimal choices for customers within the community is non-trivial. A binary linear programming model is formulated for F-DREV facilitating among customers within the community to determine the optimal choices for each customer in the given time periods. F-DREV achieves two goals for each community: 1) maximizing incentives as minimizing the global cost while maintaining the proposed fairness for each customer, and 2) smoothing the fluctuation within the community according to commitments, which are similar to existing contracts between REPs [11] and utilities. According to the determined optimal choices for entire community in the following time periods and the commitments, utilities (i.e., power companies) can schedule and control their conventional generators efficiently.

The contributions of this paper are summarized as follow. (i) To the best of our knowledge, this is the first work that proposes fairness as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community" for the demand response and EV charging scheduling. The participation level is quantified by a fairness index and utilized to customize the trading prices. Incentives are directed to customers for actively controlling their consumption patterns and investing DER. (ii) F-DREV realizes the demand response and EV charging scheduling in the cloud based energy management service [12]. Choices of electricity usage and trading are combined and determined optimally to achieve the minimized global cost as the maximized incentives for each community, which is formed by involved customers owning various combination of DER, EV, storage, and multiple load types. Fluctuation within each community can be smoothed accordingly to operate DERs and EVs within the community grid-friendly, and help utilities managing their generators scheduling more efficiently. (iii) A binary linear programming model is formulated, and detailed performances are evaluated with different experiments.

The remainder of this paper is organized as follows: the system model is introduced in Section II, and the formulated binary linear programming model is presented in Section III. Performance evaluation is discussed in Section IV, and conclusions are summarized in Section V.

II. System Model

F-DREV realizes the fair demand response and EV charging scheduling for the cloud based energy management service, and extends the system model from [12]. The following subsections firstly introduce the extended framework and the load types. Then fairness indexes are presented to quantify participation levels, and price indicators are discussed with the customized trading prices. Last, the procedure of operating F-DREV for each community is illustrated.

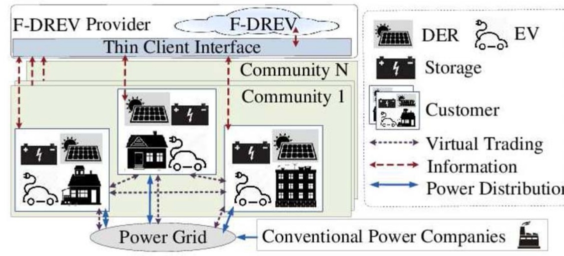

Fig. 1. Extended framework.

TABLE I
Customer Types

Customer type	DER	Storage	EV	V2G
1.	1	1	1	1
2.	1	1	1	0
3.	1	1	0	0

A. Extended Framework

The extended framework is illustrated in Fig. 1. It is constructed by the F-DREV provider, a power grid, conventional power companies and multiple communities. F-DREV is operated on the cloud infrastructure to serve multiple communities through the thin client interface, i.e., Web browsers or application programming interface (API). The power grid is supported by DERs within communities and conventional power companies with various conventional generators. Different service plans are provided by the F-DREV provider, and are similar to the various plans provided by existing REPs. Customers can choose to join a service plan by agreeing the benefits and rules in contract to F-DREV provider. Then they become customers of a certain community that is formed by other customers who also joined the same service plan. In other words, communities are formed by customers involved in the same service plan, and have different requirements and benefits (i.e., trading prices among customers). Each customer stands for various sizes of household, from single to multiple ones. In our framework, F-DREV is provided to customers owning various combinations of three components: DER, storage and EV. To simplify, three types of customer in Table I are considered in this paper, and customers own at most one of each component. The considered components are discussed blow.

1) DERs: Are focusing on small-scale non-dispatchable distributed renewable energy generators, such as the solar arrays equipped on rooftops. They are connected to the power grid following the interconnection agreements with local electric transmission and distribution utilities [16]. Each DER has a set of choice variables, $\{E^{rm}, E^{rc}, E^{re}, E^{rs}, E^{rd}\}$ with its production capacity G.

2) Storages: Are able to be powered by both DERs and conventional generators, and the (dis)charging efficiency are indicated as ηd^s and ηc^s respectively. It is assumed can be store and release energy quickly in this paper. The minimum and maximum storage capacities are denoted as S^{min} and S^{max}. Each storage system comes with two sets of choice variables: $\{I^{ms}, I^{cs}, I^{rs}, I^{es}\}$ and $\{E^{sm}, E^{sc}, E^{se}, E^{sd}\}$.

3) EVs: Are not limited to the charging scenario. They also have the ability of providing energy back to the power grid, which is known as V2G [17]. Each EV has a set of importing choice variables $\{I^{me}, I^{ce}, I^{se}, I^{re}\}$, and another set of exporting choice variables $\{E^{em}, E^{ec}, E^{es}, E^{ed}\}$ exists when it has the V2G ability. Depending on different driving behaviors and schedules, each EV connects to F-DREV at the arriving time α^e with the initial capacity EV^{init} in its battery, and disconnects at the leaving time β^e with the required capacity EV^{end}. The (dis)charging efficiencies are denoted as ηd^e and ηc^e with the rate γ^e. The minimum and maximum capacity are denoted as $S^{e,min}$ and $S^{e,max}$.

B. Load Types

Multiple fixed loads and deferrable loads are considered to be requested by each customer in this paper. Fixed loads cannot be shifted and are required to be able to turn on and off immediately (e.g., television and computers). The summation of every fixed load is denoted as D. Deferrable loads can be divided up into interruptible load (e.g., space cooling/heating) and non-interruptible load (e.g., washing machine and dryer). Interruptible load has higher flexibility since its operation can be delayed and is able to shut down or turn on after it is active. The operation of non-interruptible load can be delayed as well, but requires to remain active until the load is fulfilled. In this paper, deferrable load is formulated depending on its required operating time R, power consumption rate γ, and the allowed operating time frame form α to β. The values of the prior two (R, γ) are based on the standard of various appliances, and the latter two (α, β) can be assigned by customers directly.

A binary control variable O^{il} is used to indicate the operating status for each interruptible load at each time step. It is set to 1 when the interruptible load is activated, and its summation over the allowed operating time frame has to be equal to the required operating time, as shown in (1).

$$\sum_{t=\alpha^{il}_{i,j}}^{\beta^{il}_{i,j}} O^{il}_{i,j,t} = R^{il}_{i,j}, \;\; \forall i \in \mathbb{N}, \;\; \forall j \in \mathbb{IL}_i. \tag{1}$$

For each non-interruptible load, the operating statuses are indicated by a binary control variable O^{nl} at each time step. Similar to (1), the summation of the activated status over the allowed operating time frame is equal to the required operating time in (2). Moreover, to ensure the continuity of non-interruptible loads, another binary control variable O^a is brought in to denote the starting time of activating the load. Only one starting time exists between time α and $\beta - R + 1$ as shown in (3). Once the starting time is determined at time t, the O^{nl} between time step t and $t + R - 1$ need to be 1 to maintain the continuity. This relationship is presented in (4), and can be transformed to (5) to eliminate the non-linearity.

$$\sum_{t=\alpha^{nl}_{i,j}}^{\beta^{nl}_{i,j}} O^{nl}_{i,j,t} = R^{nl}_{i,j}, \qquad \forall i \in \mathbb{N}, \;\; \forall j \in \mathbb{NL}_i. \tag{2}$$

$$\sum_{t=\alpha^{nl}_{i,j}}^{\beta^{nl}_{i,j}-R^{nl}_{i,j}+1} O^{a}_{i,j,t} = 1, \qquad \forall i \in \mathbb{N}, \;\; \forall j \in \mathbb{NL}_i. \tag{3}$$

$$\sum_{t=\alpha^{nl}_{i,j}}^{\beta^{nl}_{i,j}-R^{nl}_{i,j}+1} O^{a}_{i,j,t} \times \sum_{t'=t}^{t+R^{nl}_{i,j}-1} O^{nl}_{i,j,t'} = R^{nl}_{i,j}, \;\; \forall i \in \mathbb{N}, \;\; \forall j \in \mathbb{NL}_i. \tag{4}$$

$$\begin{aligned} &O^{nl}_{i,j,t'} - O^{a}_{i,j,t} = 0, && t = \alpha^{nl}_{i,j}, \ldots, \beta^{nl}_{i,j} - R^{nl}_{i,j} + 1, \\ &t' = t, \ldots, t + R^{nl}_{i,j} - 1, && \forall i \in \mathbb{N}, \;\; \forall j \in \mathbb{NL}_i. \end{aligned} \tag{5}$$

C. Fairness Index

In this paper, fairness is defined as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community". The participation level has been used by cooperative [15] to distribute benefits to members accordingly. To achieve the proposed fairness, trading prices are customized for each customer according to a fairness index (F) that quantify the participation level over the given time periods. The customized trading prices P^{rs} and P^{rb} will be discussed in detail in Section II-D with other price indicators.

Fairness index is designed as the forecasted DER's production capacity (G) multiplying the flexibility ($Flex$) of total requested loads, as shown in (6). Customers with larger production capacity of DER have more chance to participate by initiating the trading to others within the community. The DER production capacity depends on the original investment and is affected by the different conditions of each DER (e.g., local weather, angles of DER). Likewise, customers with higher flexibility of their requested loads are able to participate more by adjusting the operating time. Thus, their fairness indexes would be higher.

$$F_i = \sum_{t \in \mathbb{T}} \{G_{i,t}\} \times Flex_i, \;\; \forall i \in \mathbb{N}. \tag{6}$$

$Flex$ is expressed in (7) as the summation of four terms, indicated for fixed load, interruptible loads, non-interruptible loads, and EV load sequentially. The denominator for each term is the total requested amount times a weight. For the deferrable loads, the total requested amount is calculated as the summation of each deferrable load's required operating time R multiplied by the power consumption rate γ. Three weights (w^{fl}, w^{il}, w^{nl}) are used to distinguish fixed, interruptible, and non-interruptible loads respectively. Due to the similar behavior of EV load to interruptible load, w^{il} is also used for EV loads. The numerator in each term of $Flex$ depends on the allowed operating time frame. It is set to 1 for fixed load, and is calculated as the allowed operating time frame $(\beta - \alpha + 1)$

minus the required operating time for deferrable loads and EV loads.

$$Flex_i = \sum_{t\in\mathbb{T}}\left(\frac{1}{w^{fl}D_{i,t}}\right) + \frac{\sum_{j\in\mathbb{IL}_i}\left(\beta^{il}_{i,j} - \alpha^{il}_{i,j} + 1 - R^{il}_{i,j}\right)}{w^{il}\sum_{j\in\mathbb{IL}_i}\left(\gamma^{il}_{i,j}R^{il}_{i,j}\right)} + \frac{\sum_{j\in\mathbb{NL}_i}\left(\beta^{nl}_{i,j} - \alpha^{nl}_{i,j} + 1 - R^{nl}_{i,j}\right)}{w^{nl}\sum_{j\in\mathbb{NL}_i}\left(\gamma^{nl}_{i,j}R^{nl}_{i,j}\right)} + \frac{\beta^e_i - \alpha^e_i + 1 - \left\lceil \frac{EV^{init}_i - EV^{end}_i}{\gamma^e_i} \right\rceil}{w^{il}\left(EV^{init}_i - EV^{end}_i\right)}. \quad (7)$$

D. Price Indicators

$\{P^b, P^s, P^u, P^l, P^{rs}, P^{rb}, P^e\}$ are seven price indicators used by F-DREV, where the cost of electricity and environment are included in the first six price indicators to promote the usage of renewable energy. P^b is the price of buying energy that is supported by conventional generators from the power grid. It is provided as a known input value for each time step via the prediction in real-time electricity pricing or the regulating retail prices that depend on service provider and utilities. It is similar to the provided selling prices by the existing REP. The price of selling produced renewable energy to the power grid is P^s. It can be viewed as a smaller value than P^b since it excludes the environment cost, such as CO_2 emission cost or tax savings provided by government [18]. The relationship between P^b and P^s is shown in (8), where λ depends on various environment penalties in each region.

P^u and P^l appear with value between P^b and P^s when the community is formed. Similar to the new appeared price in [12] and the price provided by existing REP, they are assigned by contracts that are agreed between customers and F-DREV provider. As mentioned in Section II-A, they could be different values for each community. The agreed P^u and P^l are utilized by F-DREV to customize the trading prices (P^{rs}, P^{rb}) for each customer based on the customer's individual fairness index as discussed in Section II-C and other involved customers. Both P^{rs} and P^{rb} are guaranteed to be the values between P^u and P^l as interpreted in (9) and (10). N is the total number of customers in the community, and $rank\{F_i\}$ is the ranking of individual fairness index within the community. Customer with the highest fairness index in the community will acquire the largest ranking, and able to obtain the largest P^{rs} and smallest P^{rb}. The proposed fairness can be shown instinctively since customers with higher participation level have advantage of reducing their individual cost more than others by initiating the trading to others with the customized price.

$$P^s_t = \lambda P^b_t, 0 < \lambda < 1, \qquad \forall t \in \mathbb{T}. \quad (8)$$

$$P^{rs}_{i,t} = P^l_t + \frac{rank\{F_i\}}{N}\left(P^u_t - P^l_t\right), \ \forall i \in \mathbb{N}, \ \forall t \in \mathbb{T}. \quad (9)$$

$$P^{rb}_{i,t} = P^u_t - \frac{rank\{F_i\}}{N}\left(P^u_t - P^l_t\right), \ \forall i \in \mathbb{N}, \ \forall t \in \mathbb{T}. \quad (10)$$

P^e is the price of exporting energy from EVs, and is interpreted as the cost of battery degradation in V2G technologies in this paper. It depends on the amount and rate of energy withdrawn and is a function of discharge depth discharge and cycling frequency [19]. For simplification, we assume it can be acquired as a known value in advance.

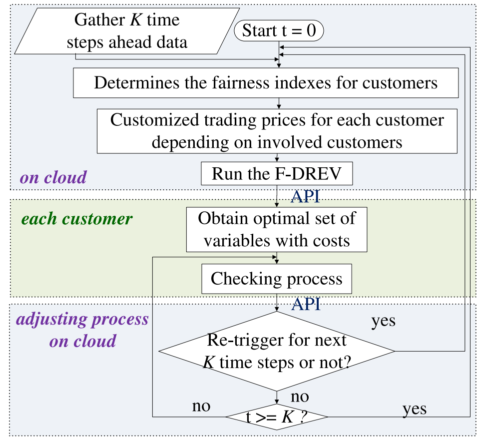

Fig. 2. Procedure of operating F-DREV for one community.

E. Procedure

The procedure of operating F-DREV for one community is shown in Fig. 2. Firstly, F-DREV provider actively operates on the cloud infrastructure to gather K time steps ahead data, which includes $\{G, T^c, P^b, P^s, P^u, P^l, P^e\}$ and all the parameters of components and loads. They are provided to F-DREV as know values via forecast technics (G, P^b, P^s), directly input from customers (P^e, parameters of components and loads) or the agreed contracts (P^u, P^l, T^c), where T^c is the assigned capacity for each power distribution line. T^c is provided by local utilities, and depends on the physical distribution network which supports both customers and non-customers of F-DREV.

After acquiring the above data, fairness indexes are determined via (6) for each customer. Depending on other involved customers within the community, the individual fairness indexes are utilized for customizing trading prices for each customer. Then, the proposed F-DREV will be run to find the optimal global cost for each community and inform the determined optimal set of variables to each customer through APIs. With the received optimal set of variables, each customer operates the requested loads, and (dis)charges storage and EV accordingly for the following given K time steps through advanced smart home appliances. A mapping mechanism is used to realize the virtual trading within community. Local utility will only receive the mapped amount of requested energy by each customer as ($A_{i,t}$) in (11), which is similar to the requests made from non-F-DREV customers.

$$A_{i,t} = I^{md}_{i,t} + I^{cd}_{i,t} + I^{ms}_{i,t} + I^{cs}_{i,t} + I^{me}_{i,t} + I^{ce}_{i,t} - E^{rm}_{i,t} - E^{rc}_{i,t} - \eta d^s E^{sc}_{i,t} - \eta d^s E^{sm}_{i,t} - \eta d^e E^{ec}_{i,t} - \eta d^e E^{em}_{i,t}, \quad \forall i \in \mathbb{N}, \ \forall t \in \mathbb{T}. \quad (11)$$

To deal with uncertainties (e.g., unpredicted changes in electricity usage or unscheduled operations) and forecast errors, two processes (checking process and adjusting process) are included after each customer obtaining the optimal sets of variables as shown in Fig. 2. The real-time data is checked by customers for each adjustment interval in the checking process, and is used by service provider to determine whether to trigger the F-DREV for the next K time steps or not in the adjusting process. These two processes are adopted from our previous work [12], where the complete information can be found.

III. Formulation

A binary linear programming model is formulated for F-DREV minimizing the global cost with the customized trading prices and smoothing the fluctuation for each community. Variables of the model are listed in nomenclature, which include three binary control variables and the choice variables for components (DER, storage, EV) and loads. The operation costs of components are assumed to be negligible in this paper.

The objective function in (12) is minimizing the global cost for each community over K time steps. It is interpreted as the summation of each customer's individual cost, which includes the cost of satisfying requested loads ($C^d_{i,t}$), trading within the community ($C^r_{i,t}$), utilizing the storage system ($C^s_{i,t}$) and EV ($C^e_{i,t}$). They are shown in (13)-(16) respectively.

$$\text{Minimize} \quad \sum_{t\in\mathbb{T}}\left(\sum_{i\in\mathbb{N}}\left(C^d_{i,t}+C^r_{i,t}+C^s_{i,t}+C^e_{i,t}\right)\right) \tag{12}$$

$$C^d_{i,t}=I^{md}_{i,t}P^b_t+I^{cd}_{i,t}P^{rb}_{i,t} \tag{13}$$

$$C^r_{i,t}=-E^{rm}_{i,t}P^s_t-E^{rc}_{i,t}P^{rs}_{i,t} \tag{14}$$

$$C^s_{i,t}=I^{ms}_{i,t}P^b_t+I^{cs}_{i,t}P^{rb}_{i,t}-\eta d^s E^{sm}_{i,t}P^s_t-\eta d^s E^{sc}_{i,t}P^{rs}_{i,t} \tag{15}$$

$$\begin{aligned}C^e_{i,t}=&\,I^{me}_{i,t}P^b_t+I^{ce}_{i,t}P^{rb}_{i,t}-\eta d^e E^{em}_{i,t}\left(P^s_t+P^e_t\right)\\&-\eta d^e E^{ec}_{i,t}\left(P^{rs}_{i,t}+P^e_t\right)\end{aligned} \tag{16}$$

The objective function subjects to several constraints, where (1)-(3) and (5) are included to assure the requirements of deferrable loads. For each customer at each time step, (17) guarantees the total requested amount of energy can be fulfilled. Constraint (18) shows the summation of requested energy, $A_{i,t}$ in (11), from customers connected to the same z_{th} power distribution line cannot exceed the assigned capacity for the corresponding power distribution line (T^c_z).

$$\begin{aligned}D_{i,t}+&\left(\sum_{j\in\mathbb{IL}_i}\gamma^{il}_{i,j}O^{il}_{i,j,t}\right)+\left(\sum_{j\in\mathbb{NL}_i}\gamma^{nl}_{i,j}O^{nl}_{i,j,t}\right)\\&=I^{md}_{i,t}+I^{cd}_{i,t}+I^{rd}_{i,t}+I^{sd}_{i,t}+I^{ed}_{i,t},\ \forall i,\ \forall t.\end{aligned} \tag{17}$$

$$\sum_{i\in\mathbb{L}_z}A_{i,t}\le T^c_{z,t}, \qquad \forall z,\ \forall t. \tag{18}$$

The exported energy from each DER is assured to be same as its production capacity in (19). Constraint (20) prevents customers from exporting more than the import amount of energy from the community to avoid customers with higher participation level potentially making profit by exporting the produced renewable energy to the community with higher P^{rs} and import the required amount from the community with lower P^{rb}. Constraint (21) tracks the available power within the community to prevent the requested amount within the community surpass the available amount.

$$G_{i,t}=E^{rm}_{i,t}+E^{rc}_{i,t}+E^{re}_{i,t}+E^{rs}_{i,t}+E^{rd}_{i,t},\ \forall i,\ \forall t. \tag{19}$$

$$E^{rc}_{i,t}-I^{cd}_{i,t}-I^{ce}_{i,t}-I^{cs}_{i,t}\le 0,\ \forall i,\ \forall t. \tag{20}$$

$$\sum_{i\in\mathbb{N}}\eta d^s E^{sc}_{i,t}-I^{cs}_{i,t}+E^{rc}_{i,t}+\eta d^e E^{ec}_{i,t}-I^{ce}_{i,t}-I^{cd}_{i,t}=0,\ \forall t. \tag{21}$$

Constraints (22)-(25) are related to the storage, where (22) shows the state variable (S) depends on the previous state variable and variables in the current time step. Equations (23) and (24) describe that the state variable can only operate in the range from S^{min} to S^{max} after exporting energy at each time step. Equation (25) shows the exported amount of energy cannot exceed the previous imported amount of energy from DREs and community. It indicates only the energy that is imported from the DERs can be sold with the trading price (P^{rs}) that excludes the environment cost.

$$\begin{aligned}S_{i,t+1}=&\,S_{i,t}+\eta c^s\times\left(I^{ms}_{i,t}+I^{cs}_{i,t}+I^{rs}_{i,t}+I^{es}_{i,t}\right)\\&-\left(E^{sm}_{i,t}+E^{sc}_{i,t}+E^{se}_{i,t}+E^{sd}_{i,t}\right),\ \forall i,\ \forall t.\end{aligned} \tag{22}$$

$$S_{i,t}-E^{sm}_{i,t}-E^{sc}_{i,t}-E^{se}_{i,t}-E^{sd}_{i,t}\ge S^{min}_i,\ \forall i,\ \forall t. \tag{23}$$

$$S^{min}_i\le S_{i,t}\le S^{max}_i,\ \forall i,\ \forall t. \tag{24}$$

$$\sum_{t'=1}^{t-1}\left(\eta^{sc}I^{rs}_{i,t'}+\eta^{sc}I^{cs}_{i,t'}-E^{sc}_{i,t'}\right)-E^{sc}_{i,t}\ge 0,\ \forall i,\ \forall t. \tag{25}$$

Constraints (26)-(34) are related to the EV. The initial capacity for each EV is assigned to its state variable (S^e) at the arriving time in (26), and (27) guarantees it can acquire larger or equal to the required capacity at the leaving time. Constraints (28)-(30) show the state variable of EV equals to 0 when it is not connecting to the F-DREV, and is always larger or equal to the minimum capacity after exporting energy. The state variable is constrained by (31) to operate in the range between $S^{e,min}$ and $S^{e,max}$. The relationship among (dis)charging rate, variables and efficiency are presented in (32) and (33). Similar to (25), (34) guarantees the exported amount of energy cannot exceed the previous imported power from DERs and community. If customers don't own the EV, all the variables for EV are equal to 0. Likewise, if the owned EV doesn't have the V2G ability, the variables related to the exporting are equal to 0.

$$S^e_{i,t}=EV^{init},\ t=\alpha_i,\ \forall i,\ \forall t. \tag{26}$$

$$S^e_{i,t}\ge EV^{end},\ t=\beta_i,\ \forall i,\ \forall t. \tag{27}$$

$$\begin{aligned}S^e_{i,t}=0,\ t=0,1,\ldots,\alpha_i-1,\text{ and }\beta_i+1,\beta_i+2,\ldots,K,\\ \forall i,\ \forall t.\end{aligned} \tag{28}$$

$$\sum_{t'=1}^{t-1}\left(\eta c^e I^{re}_{i,t'}+\eta c^e I^{ce}_{i,t'}-E^{ec}_{i,t'}\right)-E^{ec}_{i,t}\ge 0,\ \forall i,\ \forall t. \tag{29}$$

$$S^e_{i,t}-\left(E^{em}_{i,t}+E^{ec}_{i,t}+E^{es}_{i,t}+E^{ed}_{i,t}\right)\ge S^{e,min},\ \forall i,\ \forall t. \tag{30}$$

$$S^{e,min}\le S^e_{i,t}\le S^{e,max},\ \forall i,\ \forall t. \tag{31}$$

$$\eta c^e\times\left(I^{me}_{i,t}+I^{ce}_{i,t}+I^{se}_{i,t}+I^{re}_{i,t}\right)\le\gamma^e_i,\ \forall i,\ \forall t. \tag{32}$$

$$\eta d^e\times\left(E^{em}_{i,t}+E^{ec}_{i,t}+E^{es}_{i,t}+E^{ed}_{i,t}\right)\le\gamma^e_i,\ \forall i,\ \forall t. \tag{33}$$

$$\begin{aligned}S^e_{i,t+1}=&\,S^e_{i,t}+\eta c^e\left(I^{me}_{i,t}+I^{ce}_{i,t}+I^{se}_{i,t}+I^{re}_{i,t}\right)\\&-\left(E^{em}_{i,t}+E^{ec}_{i,t}+E^{es}_{i,t}+E^{ed}_{i,t}\right),\\ t=&\,\alpha_i,\alpha_i+1,\ldots,\beta_i-1,\ \forall i,\ \forall t.\end{aligned} \tag{34}$$

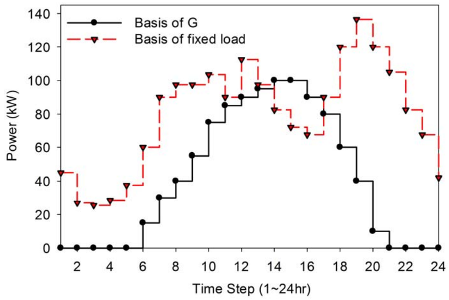

Fig. 3. Basis for the DER production capacity and fixed loads.

TABLE II
EXPERIMENT PARAMETERS SETTING

# of $j \in \mathbb{IL}, \mathbb{NL}$	$\mathcal{U}(1,5)$	w^{fl}, w^{nl}, w^{il}	$3, 2, 1$
R	$\mathcal{U}(1,3)$	S^{max}	10 kWh
γ^{nl}, γ^{il}	$\mathcal{U}(1,5)$	S^{min}	$15\% \times S^{max}$
α^{nl}, α^{il}	$\mathcal{U}(1, K-R)$	ηd^s, ηc^s	0.96
β^{nl}, β^{il}	$\mathcal{U}(\alpha+R, K)$	$S^{e,max}$	24 kWh
P^e	130 \$ per MWh	$S^{e,min}$	$20\% \times S^{e,max}$
α^e	$\mathcal{U}(8,16)$	ηd^e, ηc^e	0.95
EV^{init}	$\mathcal{U}(1,4)$	γ^{ev}	4 kWh
β^e	$\mathcal{U}(\alpha + \lceil(EV^{init} - EV^{end})\rceil, K)$		
EV^{end}	$\mathcal{U}(EV^{init}+4, EV^{init}+20)$		

Constraints (35)-(41) indicate the exported amounts between customers' components need to match the corresponding imported amount with the efficiency rate.

$$I_{i,t}^{rd} - E_{i,t}^{rd} = 0, \ \forall i, \ \forall t. \tag{35}$$
$$I_{i,t}^{re} - E_{i,t}^{re} = 0, \ \forall i, \ \forall t. \tag{36}$$
$$I_{i,t}^{rs} - E_{i,t}^{rs} = 0, \ \forall i, \ \forall t. \tag{37}$$
$$I_{i,t}^{es} - \eta d_i^e E_{i,t}^{es} = 0, \ \forall i, \ \forall t. \tag{38}$$
$$I_{i,t}^{ed} - \eta d_i^e E_{i,t}^{ed} = 0, \ \forall i, \ \forall t. \tag{39}$$
$$I_{i,t}^{se} - \eta d_i^s E_{i,t}^{se} = 0, \ \forall i, \ \forall t. \tag{40}$$
$$I_{i,t}^{sd} - \eta d_i^s E_{i,t}^{sd} = 0, \ \forall i, \ \forall t. \tag{41}$$

T^u and T^l are the upper and lower bound to smooth the fluctuation within the community. Through the coordination among every component from customers, the fluctuated penetration of EV loads and production capacities from DERs could be complemented to allow EVs and DERs within the community operate grid-friendly. It can be interpreted as the total imported energy from the power grid, and is bounded in (42). Less capacity needs to be reserved by the conventional generators when the difference between T^u and T^l is smaller.

$$T_t^l \leq \sum_{i \in \mathbb{N}} \Big\{ I_{i,t}^{md} + I_{i,t}^{ms} + I_{i,t}^{me} - E_{i,t}^{rm} - \eta d^s E_{i,t}^{sm} - \eta d^e E_{i,t}^{em} \Big\} \leq T_t^u, \ \forall t. \tag{42}$$

The formulated binary linear programming model is solved by IBM ILOG CPLEX Optimizer 12.6 [20] in this paper with all variables greater or equal to 0.

IV. PERFORMANCE EVALUATION

A. Experiment Environment

Experiments are conducted in the hourly day-ahead operation interval, where a time step is an hour and K equals to 24. Three types of customer in Table I form a community, and each customer stands for various sizes of household. The production capacity of each customer's DER follows the basis in Fig. 3, according to the database of CAISO [21] that solar generations are able to work from clock 6 to 20 a day in summer. Depending on the different DER configurations, the G for each DER is calculated as the basis times a uniform distribution. To represent the environment of low and high DER production capacities among the community, $\mathcal{U}(0.2, 1.2)$ and $\mathcal{U}(0.8, 1.8)$ are two uniform distributions used for scenario 1 and 2 respectively. Each customer has multiple fixed, non-interruptible and interruptible loads. The grouped fixed loads are designed based on a basis of load profile, which is showed in Fig. 3. They are calculated by multiplying the basis with a uniform distribution, which represents various preferences and different sizes of households. Parameters of non-interruptible, interruptible loads and weights are listed in Table II. Customers connect to different power distributions lines (e.g., branches from multiple feeders) uniformly. In the experiment, we assume there is no blackout situation and design the assigned capacity of each power distribution line (T^c) as the number of connected customers times 150 kW, which is slightly larger than the maximum value in the basis of load profile.

Price indicators are provided as known values via various forecasting methods [22] and the agreed contracts as discussed in Section II-D. To make the experiment environment more realistic, we assume F-DREV acquires P^b based on the predicted fuel cost from a conventional generator, which produces sufficient energy to support loads for 3600 residents including both non-customers and customers of F-DREV under its output capacity constraints from 100 MW to 500 MW. With a quadratic fuel cost function that is widely used in thermal power plants [23], P^b is calculated as $a + b(3600 \times \text{load basis}) + c(3600 \times \text{load basis})^2$ with the coefficients $(a, b, c) = (240, 7, 0.007)$. The values are between 0.9 and 5.4 cents per kWh. λ is set to 0.4 for P^s in (8). To illustrate the effect of different designs of P^u and P^l, two cases of these two price indicators are discussed. The first case of P^u is equal to $P^s + \frac{3}{4}(P^b - P^s)$, and P^l is equal to $P^s + \frac{1}{4}(P^b - P^s)$. In the second case, P^u is set to $P^s + \frac{5}{8}(P^b - P^s)$, and P^l is equal to $P^s + \frac{3}{8}(P^b - P^s)$. Since the design of P^u and P^l directly affects the distinction of the proposed fairness in each community, both cases are discussed in the evaluation of fairness performance in Section IV-E. For other performance evaluations, the first case of P^u, P^l is used. The utilized time variant price indicators, $\{P^b, P^u, P^l, P^s\}$, over 24 time steps are presented in Fig. 4. The price of P^e follows the battery degradation cost in [24] as listed in Table II.

The real experiment implementations are considered in the paper, where the spec of tesla home battery [25] is utilized for the vale of S^{max}, ηd^s and ηc^s. According to [26], S^{min} is set as 15% of S^{max}. The value of γ^e, ηd^e, ηc^e, $S^{e,max}$ and $S^{e,min}$ of each EV follow the summarized data from three types of EV fleet data based on a European scenario in [1], where $S^{e,min}$ is 20% of $S^{e,max}$. Values of these parameters are presented

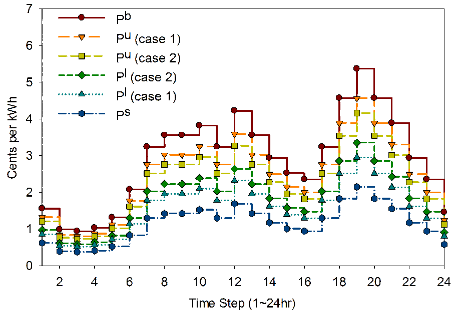

Fig. 4. Utilized P^b, P^u, P^l, P^s in experiment.

in Table II, which also lists $EV^{init}, EV^{end}, \alpha^e$ and β^e for the simplified driving behavior of each EV.

B. Comparison Schemes

Two comparison schemes are implemented to evaluate the performance of F-DREV. The first scheme, IM, manages loads individually without forming the community. It is similar to the approaches used in unmanaged distributed generators [27] and home energy management systems [3]. Trading is not available among customers, and choice variables are made based on the owned components, loads and fluctuated price indicator (P^b, P^s) individually for each customer.

The second scheme, DREV, fully coordinates the formed community without discriminating trading price for individual customer. That is, the trading price within the community in DREV is same for every customer. In the experiment, the trading price (P^r) in the compared DREV is chosen as the value that is able to achieve the least cost for each community. It should be the value that provides the same incentive (i.e., $P^b - P^r$ and $P^r - P^s$) for both customers who want to buy and who want to sell. If setting P^r as the value closer to P^b, P^r has more chance larger than P^b in different time steps. It decreases the willingness for customers buying from others, and increases the global cost. Similarly, if setting P^r as the value closer to P^s, lower incentive will be provided for customers selling to others and the global cost will be larger. Thus, the least-cost trading price is set to the value that satisfies $(P^b_t - P^r_t) = (P^r_t - P^s_t)$. To verify this, an experiment is conducted for 500 customers under scenario 1 of DER production capacity to show the global cost that achieved by DREV schemes with three different trading prices. As expected, the case with least-cost trading price achieves the smallest global cost as \$20549.15. The cases with the trading prices as the first case of P^u and P^l, which are mentioned in Section IV-A, achieve larger costs as \$20558.73 and \$20558.98 respectively.

C. Illustration of a Customer's Schedules and Interactions

We extract the information from a type 1 customer (the 87_{th}) out of 500 customers under scenario 2 (high DER production capacity) to present the schedule of storage, EV, and deferrable loads. The arriving time of the owned EV is time step 10 with initial capacity 8 kWh, and the leaving time step is 22 with required capacity 23 kWh. $\eta d^e, \eta c^e$ and γ^e follow the setting in Table II. Five interruptible loads and one non-interruptible load are requested with details listed in Table III. The determined operating time for each deferrable load, and the (dis)charging status of both storage and EV are presented in Fig. 5. Both storage and EV are operated between their maximum and minimum capacities, and EV is connected according to its arriving and leaving time. Deferrable loads are scheduled between their allowed operating time frame, and non-interruptible load maintains its continuity requirement. For example, interruptible load 5 is scheduled to operate at time step 11, 15 and 16, and non-interruptible load 1 is assigned to operate at time step 15 and 16.

To illustrate the interactions among customer's components, power grid, and the belonged community, Fig. 6 presents the amount of the total requested loads (includes fixed loads and scheduled deferrable loads), DER production capacity, the imported energy from both power grid and community, and the transferred amount to storage and EV from time step 3 to time step 13. Information over 24 time steps is also presented in the upper left part of the figure. Examples are shown in the Fig. 6 such as the customer imports power from the power grid for the requested load and charging the storage at time step 3.

TABLE III
REQUIREMENTS OF DEFERRABLE LOADS

	Interruptible load					Non-interruptible load
	no. 1	no. 2	no. 3	no. 4	no. 5	no. 1
α	10	15	5	21	1	8
β	13	22	17	24	20	21
γ	2	2	4	3	1	5
R	3	3	2	3	3	2

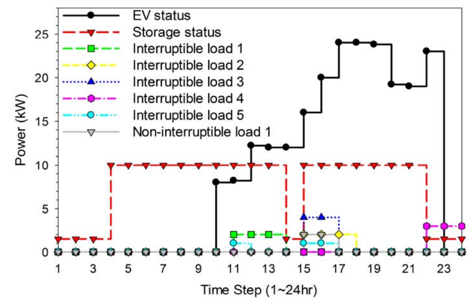

Fig. 5. The schedule of EV, storage, and deferrable loads.

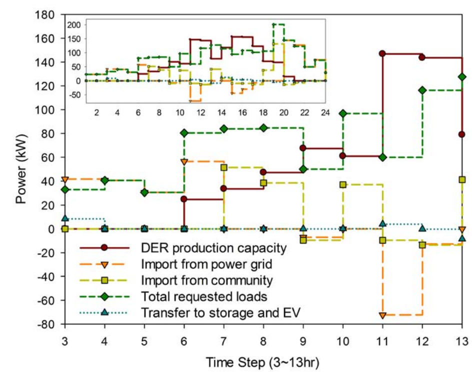

Fig. 6. Interactions among customer's components, power grid, and community.

TABLE IV
GLOBAL COST SAVINGS PERFORMANCE

	Scenario 1			Scenario 2		
Customer #	IM	DREV	F-DREV	IM	DREV	F-DREV
500	1.069	1.055	1	1.187	1.142	1
1000	1.067	1.054	1	1.184	1.140	1
1500	1.068	1.054	1	1.184	1.140	1

At time step 8, the requested loads are fulfilled by importing from community and the DER production.

D. Global Cost Savings Performance

To show that F-DREV minimizes the global cost with the customized trading prices for each community, the global cost savings performance is discussed with three schemes under two scenarios of DER production capacity. The global cost ratios to F-DREV are listed in Table IV. Comparing the F-DREV to DREV scheme, F-DREV achieves a lower global cost due to the distinction of different participation levels, where customers select different electricity usage and trading choices according to their customized trading prices. F-DREV is able to reduce the cost 5.4% and 14% more than DREV in scenario 1 (low DER production capacity) and scenario 2 (high DER production capacity). While no community is formed to fully coordinate and perform the trading among customers in IM scheme, the global cost ratios to F-DREV are larger in IM than in DREV. IM requires the cost 6.7% and 18% more than F-DREV under scenario 1 and scenario 2. The achievable performance is stable as the number of customer increases, and is promising with the growing DER production capacity.

E. Fairness Performance and Effect of P^u, P^l

Fairness performance is evaluated with 500 customers under scenario 2 (high DER production capacity) with IM, DREV, and two F-DREV schemes with two cases of P^u and P^l. Customers are clustered into 2 groups with the sorted fairness index, where customers in group 1 have higher participation levels than customers in group 2. The summation of the individual cost for each group in the four comparison schemes are presented in Fig. 7. Comparing the aggregate costs in group 1 and group 2, without the distinction between different participation levels from customers, the difference between these two groups is not obvious in IM and DREV scheme. There are no incentives for customers to increase their participate level. On the other hand, F-DREV maintains the proposed fairness by letting customers in group 1 (higher fairness indexes) achieve lower individual costs than other customers in group 2.

The degree of distinguishing different participation levels among customers depends on the difference of P^u and P^l. Two cases of P^u and P^l, mentioned in Section IV-A, are used to show their effect to the fairness performance in F-DREV. As shown in Fig. 7, as the difference between P^u and P^l decreases (i.e., P^u, P^l case 2), the difference of the aggregate cost between the two groups also decreases while the global cost increases. However, the global cost in F-DREV is still smaller than the cost in IM and DREV. Depending on the value of P^u and P^l, the individual costs in F-DREV for customers with smaller participation level (group 2) can be slightly higher or lower than their costs in DREV scheme, and are always less than their cost in IM scheme. A trade-off exists between the global cost and the degree of distinguishing different participation levels. It affects the individual cost for customers in group 2, and is a useful reference for service providers to design the value of P^u and P^l in their service plans. Although incentive for customers with lower fairness indexes (group 2) involving F-DREV depends on the difference of agreed P^u and P^l, the fairness index will be updated in every operation period (K time steps). Customers with lower fairness indexes could obtain higher fairness indexes in the future operation periods. Attractions of reducing individual cost can be expected by customers in the long term even if the individual cost for customers in group 2 is slightly higher in F-DREV than DREV. With the proposed fairness, customers have the incentives to not only use the F-DREV service, but also increase their participation level actively by equipping more DERs or adjusting the flexibility of their requested loads.

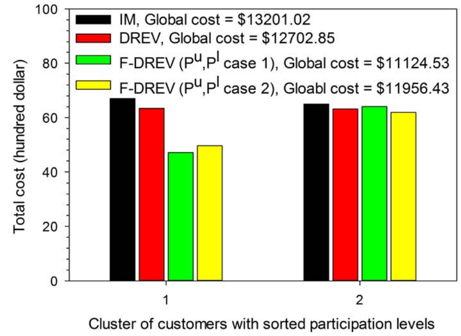

Fig. 7. Fairness performance and effect of P^u, P^l.

TABLE V
PERFORMANCE OF SMOOTHING FLUCTUATIONS

	IM	F-DREV case 1	F-DREV case 2	F-DREV case 3
T^u (kWh)	Nan	52000	51250	50500
T^l (kWh)	Nan	-24000	-22500	-21000
Max (kWh)	52861.61	52000	51250	50500
Min (kWh)	-26186	-24000	-24000	-24000
PAR	3.69	3.63	3.58	3.52
Global cost ($)	13201.02	11134.63	11149.45	11171.59

F. Performance of Smoothing Fluctuations

To evaluate F-DREV's ability to constrain the fluctuated penetration within the community, an experiment is conducted in 500 customers under scenario 2 by comparing IM and F-DREV with three different assigned T^u and T^l as shown in Table V. The value of maximum and minimum amount of total requested loads from power grid over 24 time steps, the peak to average ratio (PAR), and the global cost for the four compared schemes are summarized in Table V. The details of the requested energy from the power grid at each time step are presented in Fig. 8. As expected, F-DREV restricts the total requested loads from power grid with the determined T^u and T^l, and achieves lower global cost and lower PAR

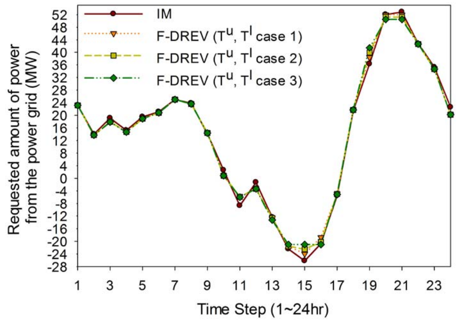

Fig. 8. Total requested energy from the power grid.

TABLE VI
EFFECT OF STORAGE

	Scenario 1			Scenario 2		
S^{max}	IM	DREV	F-DREV	IM	DREV	F-DREV
0 kWh	1.05	1.04	1.00	1.13	1.11	1.00
10 kWh	1.07	1.05	1.00	1.19	1.14	1.00
90 kWh	1.16	1.11	1.00	1.53	1.32	1.00

TABLE VII
EFFECT OF ELECTRIC VEHICLE

	Scenario 1			Scenario 2		
Customer types	IM	DREV	F-DREV	IM	DREV	F-DREV
All type 1	1.074	1.065	1	1.204	1.145	1
All type 2	1.069	1.054	1	1.186	1.140	1
All type 3	1.065	1.054	1	1.178	1.140	1

value than IM scheme. With the ability of smoothing the fluctuations, components within the community can be operated grid-friendly. A trade-off exists as the increased global cost when assigning the smaller difference between T^u and T^l. The revealed trade-off can be used as reference for F-DREV providers to determine the proper boundary (T^u, T^l) with local utilities in commitments.

G. Effect of Storage

The effect of storage in F-DREV is discussed with an experiment for 500 customers under both scenarios of DER production capacities. Based on the announcement from tesla that multiple home batteries can be installed together [25], up to 90 kWh for the 10 kWh battery, we compare three maximum capacity of storages: no storage (0 kWh), single home battery (10 kWh), and multiple home batteries (90 kWh). The global cost ratios to F-DREV scheme are listed in Table VI. Without any storage, F-DREV is still able to achieve the smallest global cost in the comparison schemes under both scenarios. When the capacities of involved storages become larger, the global cost can be reduced more. With the foreseeable growth and development in the storage and battery [28], the achievable savings can be expected.

H. Effect of Electric Vehicle

To discuss the effect of electric vehicle, an experiment is conducted with the 500 customers under both scenarios of DER production capacities. We compare the communities that are formed by all type 1, type 2 and type 3 customers (in Table I) respectively. The global cost ratios to F-DREV scheme are listed in Table VII. With the similar behavior of EV loads to interruptible loads, when more electric vehicles are involved in the community, more flexibility can be provided from customers' requested loads. Moreover, when EV has the V2G ability, it can be operated as a storage unit with specific connecting time and requirement. F-DREV is able to reduce the global cost more when more EVs with V2G ability are involved in the community.

I. Execution Time Performance

To estimate the computation time of executing F-DREV in modern cloud computing platform, a publicly accessible Linux server equipped 40 cores and 252 GB memory under low load is used in this experiment. This server's scale of resources is comparable to most provided instances from Amazon Elastic Compute Cloud [29]. The computation time for 500 customers is 9.28 seconds, and is 20.52 seconds for 1000 customers. For a larger size of community, such as 1500, the computation time is 32.5 seconds. It is significantly smaller than the day-ahead period (24 hrs), and is sufficient for the adjustment interval (following the 5 minutes real-time economic dispatch process) in checking and adjusting processes [12].

V. CONCLUSION

In this paper, a fair demand response with electric vehicles (F-DREV) is proposed for the cloud based energy management service. Communities are formed by involved customers owning various combinations of EV, DER, storage and multiple loads (fixed, interruptible and non-interruptible). For each community, incentive is maximized as the global cost is minimized by F-DREV for customers controlling their electricity consumption patterns, and the fluctuation is smoothed to operate EVs and DERs grid-friendly. Electricity usage choices and trading choices are combined and determined optimally for each customer via a binary linear programming model. Fairness is proposed as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community". It is attainable by customizing trading prices for each customer base on the fairness index. With the proposed fairness, customers are also encouraged to actively increase their participation level by equipping more DERs or adjusting the flexibility of their requested loads.

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