Customized Prices Design for Agent-based Local Energy Market with PV and Energy Storage

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***Abstract*—Distributed energy resources, especially residential photovoltaics (PV), have been playing increasingly important roles in modern smart grids over past years. Residential netload is closely tied with customers' activities and weather, such as load consumption and solar generation, which could potentially be leveraged to improve demand response by designing customized price incentives. This paper seeks to design customized prices for a local energy market (LEM) that consists of agent, PV, energy storage (ES), prosumers, and consumers. The LEM agent who owns a community-scale ES system is responsible for operating the market and facilitating the energy sharing within the community. A hierarchical energy trading infrastructure is considered, where the agent acts as the mediator between the utility grid and customers. A two-stage decision-making framework, including look-ahead ES scheduling and real-time customized prices design, is developed for agent's profit maximization. The customer's consumption behavior is modeled as a utility maximization problem. Numerical results of case studies with 10 residential customers show the effectiveness of the customized prices design.**

***Index Terms*—Distributed solar, local energy market, energy sharing, customized prices design.**

I. Introduction

The fast-growing installation of solar panels creates a potential to feed massive reverse power flow back into the grid, raising unexpected challenges to power system reliability [1]. Community solar [2] has shown to be an innovative local energy market (LEM) to address this challenge, which is gaining popularity across the U.S. in recent years. Allowing neighbors to share their excess PV generation, unused energy storage (ES) capacity, and spare roof space, etc., this novel business mode could benefit both customers and utility grids, by reducing the community's reliance on the utility grid, increasing the ability to participate in demand response (DR), achieving a better generation-load balance, and mitigating unexpected energy crises, e.g., the 2021 Texas power outage.

Extensive explorations have been conducted on designing and evaluating LEM and demand-side management, among which game theory has been widely used to address the interaction between different stakeholders, such as the Nash equilibrium-based game-theoretic approach [3], [4], coalition game [5], [6], leader-follower game [7], [8]. Other methods, such as auctions [9], machine learning-based decision-making [10], model predictive control [11], dynamic programming [12], and iterative algorithm [13], have also shown to be effective to promote the demand-side management. It is found that the pricing model plays a crucial role in a community energy market, which directly impacts the market participants' incentives of energy sharing and price-based DR. Most of existing works in the literature only focus on the unique price design, i.e., a single uniform pricing rate is applied to all participants. In practice, however, each residential customer has a preferred daily routine and consumption preference, which constitutes challenges for the energy retailer: how to promote the retailer's own profit while maintaining the customers' satisfactions with increasing diversities of consumption preferences?

Customized pricing for customers has been recently explored in the market design. For example, the state of Texas already offers customers different energy plans to choose based on their own preferences, such as flat rate, time-of-use (ToU), real-time price (RTP), discriminated price, reimbursed renewable, free night/weekend, solar buyback, etc. [14]. Besides, residential PV prosumers are also motivated to reduce their cost with the Feed-in-tariff (FiT) [15], which refers to the price rate at which the prosumers can sell their excess solar generation to the utility grid. Some interesting works regarding consumption preferences discovery and customized prices design have been implemented. For example, in Refs. [16], [17], the price-consumption response data is leveraged to estimate the consumers' preference. Yang *et al.* [18] proposed a bi-level programming-based customized prices design through appliances identification and consumers classification. Feng *et al.* [19] used a data-driven method and leader-follower game to design customized prices for consumers. Similarly, Ref. [20] also designed individualized price scheme structures for different customer groups.

While customized prices design for consumers has been explored in recent years, its application in the community solar market is still lagging behind. This paper seeks to design customized prices for both prosumers and consumers in a community-scale LEM, based on their PV generation and consumption preferences. A two-stage decision-making framework for the LEM agent, including look-ahead ES scheduling and real-time customized prices design, is proposed. The customers' consumption behaviors are modeled as a utility maximization problem.

The rest of the paper is organized as follows. Section II describes the proposed LEM, which consists of agent's ES scheduling, customized prices design, and customers' consumption models. Section III shows a case study with

10 customers to evaluate the performance of the customized prices. Concluding remarks and future work are discussed in Section IV.

II. Methodology

The overall structure of the proposed LEM is following Ref. [10]. The LEM consists of an agent who owns a community-scale ES system and $\mathcal{N}$ energy sharing customers (including both prosumers with PV panels and pure consumers). The market works in an agent-based trading mode: the market agent trades with all customers with internal customized prices; besides, the market agent is also responsible for balancing the supply and demand in the LEM with the utility price (i.e., ToU and FiT prices in this work). The LEM decision-making consists of two major steps: look-ahead ES scheduling and real-time prices design, which are briefly described as follows.

1) *Step 1 – Look-ahead ES scheduling:* The LEM agent determines the ES capacity scheduling based on the aggregated netload (i.e., load minus PV in this paper) of the community to promote the self-consumption of the solar generation and maximize its profit. Since the state of charge (SoC) of ES is time-coupled, the ES scheduling works in a look-ahead manner.
2) *Step 2 – Real-time prices design:* The LEM designs customized pricing schemes for different agents to fully utilize the customers' sharing elasticity. Since the solar generation of prosumers is weather-dependent, the elasticity derives from the load flexibility. The agent and customers are assumed to act rationally and strategically to pursue their own interest, i.e., maximizing their profit/utilities in this work. Since the trading in LEM occurs in each hour, the customized prices design and demand response occur in a real-time manner.

A. Capacity Scheduling

The primary goal of the LEM agent's ES scheduling is to maximize its benefit and promote renewable consumption in the LEM. The objective function of the agent is modeled as minimizing the trading cost with the utility grid C, since the energy sharing within the LEM (i.e., from prosumers to buyers) does not impact the aggregated netload NL of the LEM:

$$C = \sum_{t=h}^{H} \left[\pi_s^t \left(NL^t + x^t, 0 \right)^+ + \pi_f^t \left(NL^t + x^t, 0 \right)^- + c|x^t| \right] \tag{1}$$

$$NL^t = \sum_{i=1}^{\mathcal{N}} (l_i - pv_i) \tag{2}$$

$$-\Lambda / C_{rate} \leq x^t \leq \Lambda / C_{rate} \tag{3}$$

$$SoC_{min} \leq SoC^t \leq SoC_{max} \tag{4}$$

$$SoC^t = \begin{cases} SoC^{t-1} + x^t \cdot \eta, & x_i^t > 0 \\ SoC^{t-1} + x^t / \eta, & x_i^t < 0 \end{cases} \tag{5}$$

where we define $(\cdot)^+ = \max(\cdot, 0)$, and $(\cdot)^- = \min(\cdot, 0)$. The parameter H is the optimization window (i.e., 24 h), and h is the current time slot. The parameter C is the trading cost with the utility grid from the current time h to future H. The parameter x^t represents the battery charging/discharging schedule, and η is the (dis-)charging efficiency. The parameter Λ is an integer number, which denotes the nominal capacity of the ES. The terms of $-\Lambda/C_{rate}$ and Λ/C_{rate} are the lower and upper bounds of the (dis-)charging energy in each time slot, respectively, and C_{rate} is the maximum (dis-)charge rate of the ES. The parameter SoC^t is the SoC of the ES at the end of time slot t; SoC_{min} and SoC_{max} are the lower and upper limits of the ES, respectively.

B. Customized Prices Design

In a deregulated electricity market, customers are allowed to freely choose their desired pricing schemes. Building upon this, customized prices design is further proposed to fully incentivize customers' participation in DR and energy sharing, considering their varying consumption satisfaction and solar generation. A successful price-based DR program should be designed by following ***incentive compatible*** [21], which is a way that attracts the interest of customers to participate in, through the provision of incentives to change their original gross load while at the same time minimizing their discomfort.

To make the customized prices incentive compatible, the LEM agent should ensure that the customers gain more benefits compared with the previous pricing scheme. In this way, consumers are willing to accept the customized prices, since they can achieve higher utilities or lower costs with these prices. In this work, the following constraint is implemented to maintain incentive compatible:

$$\pi_f \leq \lambda_b \leq \lambda_s \leq \pi_s \tag{6}$$

The buying prices λ_b refer to the energy trade-in offer for sellers $\mathcal{N}_s$, while the selling prices λ_s refer to the energy charge for buyers $\mathcal{N}_b$, and $\lambda_b < \lambda_s$ is to ensure the agent's profit. Besides, λ_b and λ_s prices are constrained by the utility price, i.e., the FiT (π_f) and ToU (π_s).

Based on the discussion above, the profit maximization of the customized prices design is formulated as:

$$P = \begin{cases} \sum \boldsymbol{\lambda_s} \odot \boldsymbol{E_b} - \sum \boldsymbol{\lambda_b} \odot \boldsymbol{E_s} - \pi_s \Delta E - c \cdot |x|, & \Delta E \geq 0 \\ \sum \boldsymbol{\lambda_s} \odot \boldsymbol{E_b} - \sum \boldsymbol{\lambda_b} \odot \boldsymbol{E_s} - \pi_f \Delta E - c \cdot |x|, & \Delta E < 0 \end{cases} \tag{7}$$

where $\boldsymbol{E_b}$ and $\boldsymbol{E_s}$ denote the total demand set from buyers $\{[l_i - pv_i], i = 1 : \mathcal{N}_b\}$ and supply set from sellers $\{[pv_i - l_i], i = 1 : \mathcal{N}_s\}$ inside the community, respectively. The parameters $\boldsymbol{\lambda_s}$ and $\boldsymbol{\lambda_b}$ denote customized prices set for buyers and sellers, respectively. The parameter ΔE denotes the imbalance between supply and demand, and $\Delta E = \sum \boldsymbol{E_b} - \sum \boldsymbol{E_s} - x$, which needs to be balanced with the utility grid, and x is a known number which is already obtained from Eq. (1). A positive ΔE denotes that the agent has to purchase power, and a negative value denotes feeding negawatt back to the grid.

C. Customers Model

In this work, all customers are assumed to act rationally and strategically to pursue their own interest, i.e., aiming to find the best scheduling of their load across a predefined optimization window. The customers' objective could be to minimize the daily cost [4], [5], minimize the inconvenience of DR [13], or maximize the satisfaction level of consumption [22]. In this paper, the utility function from Ref. [10] is adopted, which describes the customers' consumption preferences as two parts: the satisfaction from consuming energy and the cost of trading energy.

$$U_i = \begin{cases} k_i \ln(1+l_i) - \lambda_s(l_i - pv_i), & l_i \geq pv_i \\ k_i \ln(1+l_i) - \lambda_b(l_i - pv_i), & l_i < pv_i \end{cases} \tag{8}$$

In (8), $k_i \ln(1+l_i)$ is the utility achieved by the customer i through consuming energy l_i. The logarithm $\ln(\cdot)$ function has been widely used in economics for modeling the preference of users due to its close relation to fair DR [23]. And $(1+x)$ is a typical modified form to avoid $-\infty$. Note that k_i is the combination of the utility weight coefficient and consumption preference parameter. A greater value of k indicates a higher willingness to consume more energy. In this work, the k is calculated based on the original generation, load, and the utility prices, i.e., ToU and FiT.

Since the solar generation pv cannot be used for DR, the sharing elasticity only derives from the load flexibility. The parameter l_i represents the aggregated power in the household i. However, if customer's behavioural characteristics, together with the appliance identification, could be obtained, then residential daily patterns could be leveraged for more accurate DR modeling. In this work, the appliances information is not available due to limited data availability. To streamline the model, the following constraint has been added to the gross load.

$$l_i \in [l_{min}, l_{max}] \tag{9}$$

where $[l^h_{min}, l^h_{max}]$ is the range of customer i's electricity consumption, which can be extracted from historical usage. It is derived from Eq. (8) that a higher selling price λ_s will result in a higher consumption for a buyer ($l_i \geq pv_i$), while a higher buying price λ_b will encourage a seller ($l_i < pv_i$) to trade more energy by adjusting consumption.

In the real-time customized prices design, for any given price λ_b or λ_s at each hour, the customer i adapts its consumption l_i^* as the best response to λ for maximizing its utility U_i:

$$l_i^* = \arg\max \quad U_i(k_i, l_i, pv_i, \lambda_b, \lambda_s) \tag{10}$$

Note that the optimal l_i^*, at which the consumer i achieves its maximum utility in response to a price set (λ_b, λ_s), can be found from Eq. (8),

$$l_i^* = \begin{cases} k_i/\lambda_s - 1, & l_i \geq pv_i \\ k_i/\lambda_b - 1, & l_i < pv_i \end{cases} \tag{11}$$

This optimal solution holds when the obtained value locates within the consumption constraint Eq. (9). Otherwise, the optimal solution l_i^* will always lie on the boundary due to its strict concavity. Thus, each customer has an existing and unique best response to any price designed by the agent. Besides, there is no coupled constraints between customers, thus each customer's response is independent with others. By substituting Eq. (11) into Eq. (7), the Hessian matrix of P is negative definite, thus there also exists a maximum profit in a bounded region $[\pi_f, \pi_s]$.

III. Case Study and Results

The developed LEM is evaluated with a case study containing 10 customers (7 prosumers with PV panels and 3 pure consumers) in Austin, Texas[1]. The ToU and FiT prices are adopted from Ref. [22], which are also illustrated in Fig. 3 as black dashed lines. We consider a maximum C_{rate} of 2, $SoC \in [0.05, 0.95]$ with an initial minimal value 0.05, and $\eta = 0.95$. The ES capacity is chosen to be 40 kWh in this work. To perform a break-even analysis and capacity optimization of ES, the annual operation should be considered, as introduced in Ref. [24]. It should be noted that other cost functions, ToU/FiT prices, load/PV dataset, and ES parameters could also be adopted in this work.

To evaluate the effectiveness of the proposed method, the following three scenarios are selected for comparison: (i) *Baseline:* represents the scenario with ToU and FiT prices, (ii) *SP:* represents the scenario with a single (uniform) hourly price, and (iii) *CP:* represents the scenario with customized hourly prices.

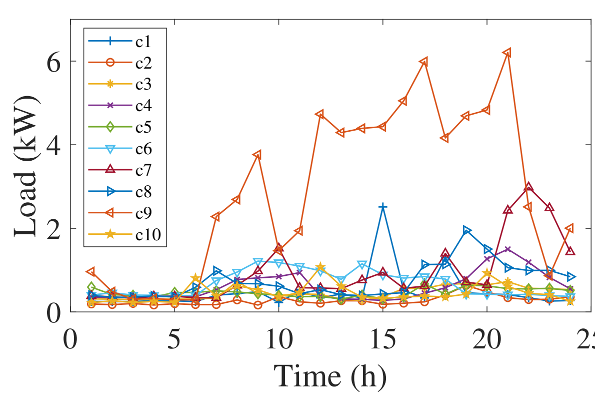

Fig. 1. Load of the community on November 6, 2018.

The load and solar data of the 10 customers (referred as c1-c10) on November 6, 2018 used in this study are shown in Figs. 1 and 2, respectively. It is observed that the highest hourly peak consumption corresponds to c9 with approximately 6 kW, followed by c1 and c7, with approximately 2-3 kW. Regarding the variability in consumption, c9 has the largest variation, followed by c1 and c7, while other customers have lower variations in daily consumption.

The customers with PV panels have similar daily PV generation trend curves with varying capacities due to strong spatial

[1]https://www.pecanstreet.org/dataport/

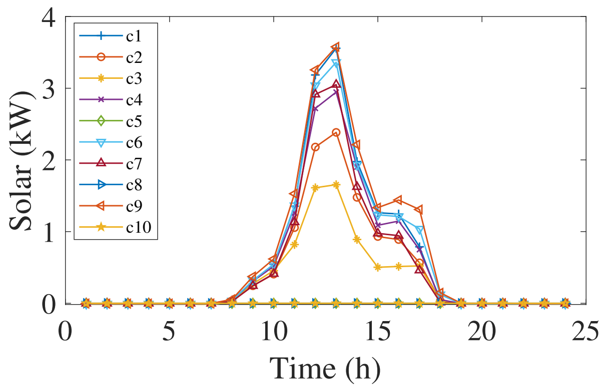

Fig. 2. Solar generation of the community on November 6, 2018.

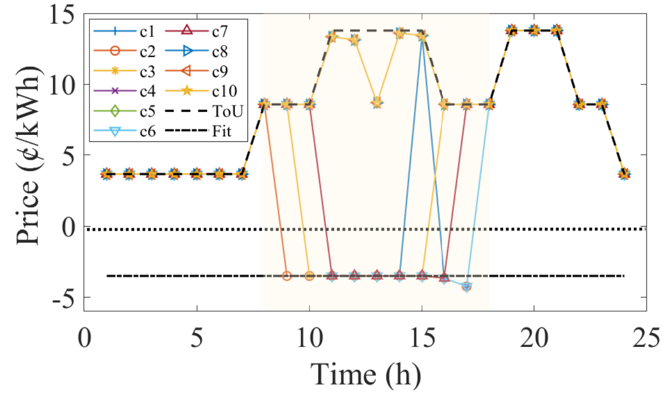

Fig. 4. The single uniform energy sharing prices of 10 customers.

correlations, and the daily maximum generation is ranging from 1.6 kW to 3.5 kW.

A. Results and Discussion

Figs. 3 and 4 show the customized prices design and single uniform prices design for the 10 customers, respectively. Positive values denote the prices designed for buyers, and negative values denote prices for sellers within the LEM. The two black dashed lines constrain the energy sharing prices, which are defined as the ToU (ceiling) and Fit (flooring) prices. In other words, only the buying prices (+) no higher than the ToU, and the selling prices (-) no higher than the FiT, are feasible for the LEM customers. Otherwise, the customers may switch to other retail agents or directly trade with the utility grid. The price transition from positive to negative values indicates the role of the customer is changed, from buyers to sellers, and vice versa. The peer-to-peer energy sharing periods are illustrated in shaded areas.

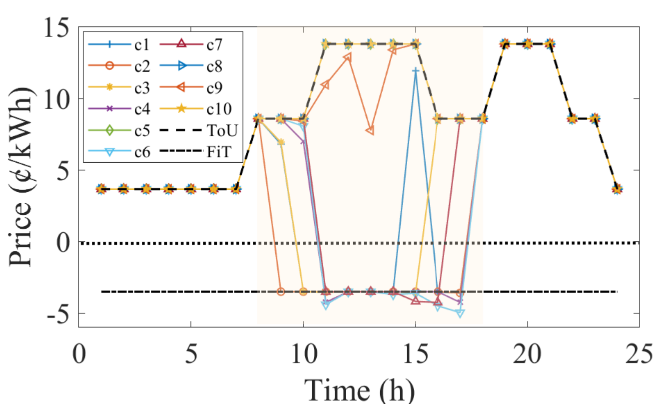

Fig. 3. The customized energy sharing prices of 10 customers.

The LEM agent designs different pricing schemes to encourage customers to participate in energy sharing, thereby maximizing its profit with the assistance of ES. Generally, the internal customized prices are same with the ToU and FiT during no/low solar generation periods. In Fig. 3, the customized prices vary for different customers at different hours based on their netload $l - pv$, consumption satisfactions parameters k, and demand response abilities $[l_{min}, l_{max}]$. It is found that c9 is offered the best buying price lower than ToU from hour 11 to hour 14. It is because c9 has the largest consumption, which directly affects the aggregated load of the community. Thus there is no need for the agent to send extra prices signals to other buyers. At hour 9, c1 and c3 are offered with customized prices, while at hour 10, c4 and c6 are offered. Besides, at hour 15, c1 is also offered with a customized buying price, due to the role change (from seller to buyer) with a sudden increase in consumption.

Most sellers are offered with selling prices that are same with FiT, since their excess energy has to be sold due to higher PV generation and lower consumption, otherwise, the excess energy has to be curtailed. Customers c4, c6, and c7 are offered with better selling prices at hours 11, 15-17, because those prosumers have higher consumption demand, as shown in Fig. 1, thus with higher flexibility to respond to the customized price signals. Thus, there exists a price discrimination with CP in the LEM, since each customer's contribution in the energy sharing is different. By comparing Fig. 4 with Fig. 3, it can be seen that with the uniform prices design, buying and selling prices are always the same. However, in the single prices design case, for the customer with the highest willingness of DR, its sharing elasticity is not fully utilized.

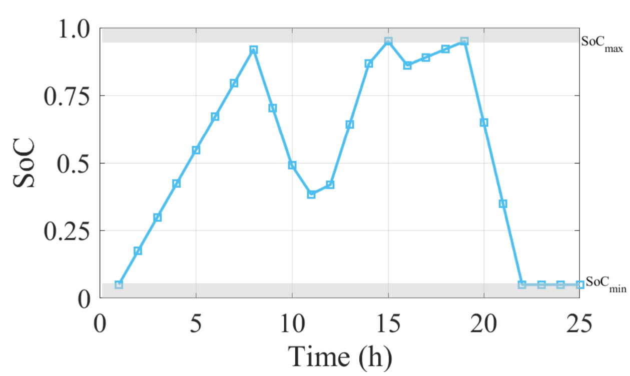

Fig. 5. State of Charge (SoC) of the ES.

The charging/discharging profile of ES is shown in Fig. 5.

The ES will arbitrage from the utility grid during night off-peak hours until 8 a.m., then release some stored energy when morning on-peak hours start (i.e., hours 9-11). Thereafter ES fully charges again with the excess solar generation in the noon, and then discharges in night peak hours until reaching its minimal capacity.

TABLE I
UTILITIES ($) OF CUSTOMERS AND BENEFIT ($) OF THE AGENT

	Customers' Utility ($)						
	CP	*SP*	*baseline*		*CP*	*SP*	*baseline*
c1	**6.1453**	6.1228	6.1136	c6	**5.9404**	5.9246	5.9220
c2	2.5498	**2.5531**	2.5495	c7	**11.245**	11.241	11.241
c3	**4.6365**	4.6327	4.6327	c8	9.6671	**9.6989**	9.6671
c4	**7.1308**	7.1225	7.1187	c9	**56.553**	56.522	56.426
c5	4.9918	**5.0159**	4.9918	c10	5.6305	**5.7740**	5.6305
Agent's profit *CP* ($)				7.3009			
Agent's profit *SP* ($)				6.5744			

Note: *CP* and *SP* indicate the customized pricing and single (uniform) pricing, respectively. **Bold values** indicate the customer earns a higher utility under this pricing scheme.

Table I summarizes the 10 customers' utilities and the agent's profit under the two pricing schemes and the baseline. The grey color highlights the pure consumers without PV panels. Compared with the baseline, at most scenarios both CP and SP cases yield higher utilities by following incentive compatible. In Table I, most prosumers are seen to have slightly higher utilities with the customized pricing (CP) scenario, while consumers gain more utilities with single uniform pricing (SP). This is because the benefit of implementing customized prices design is affected by the sharing elasticity, which depends on both solar generation and consumption flexibility. It is found that all consumers gain more benefits with the implementation of SP, while some flexible prosumers earn fewer utilities with SP. For consumers, since they are always short of electricity and have to purchase energy from others, their market power is relatively low. Similarly, for some excess prosumers, they also have low market power and have to sell their energy, otherwise the surplus energy will be curtailed. While for self-sufficient prosumers, such as c1, c4, and c6, the CP case benefits them more due to their higher sharing flexibility. The LEM agent monopolizes the market and earns a 11% profit increase by designing CP for customers. The profit could be further promoted with the increase of market participants, ES capacity, and solar installation.

IV. CONCLUSION

This paper proposed a customized prices design scheme to address challenges in peer-to-peer trading and demand response in a local community market (LEM). A two-step decision-making strategy was developed, including look-ahead energy storage scheduling and real-time customized prices design. The results of a case study with 10 customers showed that compared with the uniform pricing strategy, the customized prices can increase the LEM agent's profit while also maintaining the customers' consumption satisfactions.

This work could be extended in multiple directions. First, historical energy consumption data could be leveraged for resident behavior learning. With the historical data, a statistical study of consumption preferences for the customers could be conducted, such as on/off peak consumption periods, seasonal patterns, consumption statistics (e.g., mean, standard deviation, minimum and maximum, and quartiles), electricity elasticity, etc. In addition, more features of customers could be extracted using data mining techniques, to help the retailer perform demand-side management more precisely. Second, with aforementioned historical dataset, more accurate single-household netload forecasting and behind-the-meter solar power disaggregation/forecasting methods could be implemented, to better manage the uncertainty and further enhance the market efficiency. In addition, the current dataset only contains the aggregated load in the household. If customers' appliance identification could be obtained, more accurate forecasts could be obtained. Third, other entities could also be considered in the LEM, such as distributed energy resources owners, third-party owned ES, and market bidding stakeholders.

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