Optimal Bidding Strategy of Responsive Demands in a New Decentralized Market-Based Scheme

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***Abstract*—In this paper, a market-based control scheme is proposed to determine the minimum billing cost of responsive demands with the minimum impact on their satisfaction. For this purpose, the responsive demands are modeled as agents who bid to the energy market. In the model, the financial compensation provided by the market motivates the responsive demands to shift their load to off-peak periods. Since dissatisfaction is caused by the deviation from the reference consumption, the responsive demands' bids are dependent on the level of satisfaction that consumers are willing to have. Numerical results reveal that the billing cost of these customers is meaningfully decreased compared to the uncontrolled approaches. In addition, the results are compared to the centralized aggregation-based approach, in which a demand response aggregation entity directly buys energy on behalf of responsive demands in the market. The results indicate the effectiveness of the proposed decentralized market-based scheme.**

Keywords—Agent-based system; bidding strategy; decentralized market-based scheme; demand response

I. INTRODUCTION

A. Motivation

Advanced information, communication and other developed technologies are leading the power system towards the new age of smart grid. These developments made the demand response as a fundamental element of power systems. In such situation, customers have access to the level of electricity consumption and the price/signal data through smart meters. On this basis, the customers are able to participate in the demand response programs more than before. This can increase the number and participation of responsive demands in the smart grid.

In one hand, since it is difficult for customers to negotiate directly with the independent system operator (ISO), a linking agent/market is required to manage the customers and to provide different demand response (DR) programs for each individual responsive demand. On the other hand, customers aim to have the maximum satisfaction while using the electricity. Without participating in DR programs, in a fixed-rate tariff, each consumer tends to operate its appliances at the times when bring the highest comfortable level during a day, on the basis of its personal preferences [1].

B. Literature Review

DR has been one of the key elements of smart grids. DR providers attempt to modify the load patterns of their consumers and achieve benefit for the expenditure saving imposed on the system operator due to the load shaving [2].

Therefore, a DR provider should motivate the consumers to amend their energy consumption profiles, by price-based or incentive-based programs. In [3], the interactions between utilities and consumers who participate in DR programs have been addressed by a non-cooperative game. In [4] was presented a framework based on supply function to bid the DR. The incorporation of DR bids into regulation markets has been presented in [5].

A market model was represented in [6] to design DR to match the power generation and shape the electricity demand. A distributed algorithm for a utility and its customers was reported in [7] to find the maximum social welfare. A DR management was modeled in [8] as an N-person concave non-cooperative game, and distributed DR strategies were developed to minimize the energy cost. In [9], a game-based demand side strategy was reported in smart grid considering grid congestions. A residential power schedule was proposed in [10] by considering Stackelberg game.

In [11], a DR program was presented for residential consumers to model the optimization problem including the electricity bills and consumers' discomfort cost to optimize the starting times of use of electrical appliances. In [12], a decentralized aggregated control model was presented to plan the electrical appliances. The interactions between the appliances were formulated by a game-theoretic form. In [13], a game theoretic model was reported to analyze both decentralized and centralized controls in a smart grid. The formulation of this decentralized framework was carried out based on a differential game, while the centralized model was on the basis of the optimal control.

The concept for DR programs was reported in [14] where billing mechanisms were designed to find the minimum aggregation cost of total system. In addition, a distributed framework was proposed to maintain the consumers' privacy. DR problem was formulated in [15] through a coupled-constrained game and it is converted to a decoupled game via dual decomposition methods.

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A distributed DR procedure was presented in [16] for smart grids to find consumption of all individual customers and the generation of all individual companies. By employing a dual decomposition technique, all the companies and consumers individually solve associated sub-problems to make the energy allocations. In [17], a billing mechanism was proposed to appropriately determine the tariff for the customers' consumption. A game framework based on the aggregation method is also employed to mathematically formulate the strategic behaviors of consumers.

In [18], the DR program was investigated via Stackelberg games between utilities and consumers to obtain the maximum income of all individual utilities and the payoff of all individual customers. Similarly, in [19], the DR problem was also considered in a system including multiple utilities and consumers.

C. Aims and Approach

In order to provide the required scalability, the bidding strategy of a large number of responsive demands is aggregated. Afterward, the bids are cleared based on the supply offers and load bids. The present paper aims to determine the optimal bidding strategies of individual responsive demand, considering the uncertainties related to the customers' behavior. To this end, an agent-based system is presented, where each responsive demand optimizes its bidding strategy based on the market outcomes. In the market-based control scheme, responsive demands individually take part in the market and submit their demand bid. The objective function of each customer minimizes the billing cost during twenty-four hours.

II. The Proposed Decentralized Market-Based Scheme

In the proposed market-based scheme, each customer takes part in the market by bidding its demand. By using a

Q-learning method, each customer learns how to setup its bid in different hours of a day. Q-learning iterations comprise 24 hours. At each hour, five stages are considered:

- All individual customers define their demand bidding for the next hour, according to their necessities and past experiences.
- The customers' bids are aggregated.
- The aggregated bid is sent to the market.
- The market is cleared.
- The obtained prices are transferred to the customers.

It should be noted that the proposed approach computes the bids only or the next hour. This is due to the fact that the each customer needs to update its energy status, and consequently its need/willingness to be charged, in each new hour. The employed machine learning method is based on a reinforcement learning technique so-called Q-learning. According to the technique, each customer is able to determine its optimum bidding strategy via its experiences resulted from the interaction with the electricity market. The Q-value is the estimated reward of the potential state-action pairs, which is modified at the end of each iteration of the process.

Because of the high numbers of agents that must be modeled, the Q-values are assumed independent of the states. This can significantly decrease the complexity of the model.

III. Bidding Framework

A. DR Agents

The DR agents will participate in the day-ahead market by placing bids that serve to express the willingness of the users to buy energy.

Throughout interaction with the market, agents will learn to place bids that will lead them to compete in the market with the other agents. Thus, the agents who are more willing to buy energy at a certain time-step will set higher prices for the same energy quantity demanded, being their need for energy consumption fulfilled in spite of the agents whose energy needs were set as low.

B. Demand Bids

Contrarily to what happens in the inflexible demand scenario, in which the DR-enabled customers do not express their willingness to buy energy according to their requirements, buying energy at the maximum price allowed in the market, the demand response program allows the customers to shift their energy consumption throughout the day.

Therefore, DR-enabled customers will set their bids according to their requirements at the present time-step. In order for the bids to express the customers' willingness to buy energy, a three-step approach similar to the one presented in [20] will be used.

The demand curve of all the DRs is a piecewise linear function defined in three different intervals, being its formulation presented below.

$$price(D) = \begin{cases} p_{max}, 0 \le D \le D_C \\ p_{state}, \ D_C \le D \le D_{int} \\ p_{int}, \ D_{int} \le D \le D_L \end{cases} \tag{1}$$

In which concerns to the definition of the variables presented above, D_C consists of the sum of the critical loads that must be mandatorily served at every time-step. As in [21], its definition consists of the formulation presented below.

$$D_C = P_{C,t} = \sum_{k=1}^{M} P_{C_k,t} \tag{2}$$

Where $P_{C,t}$ is the power consumption of all critical loads in time slot *t*, in kW, being C_k the critical load with index *k*. D_{int} is an intermediate point between D_C and D_L.. Moreover, D_s represents the sum of the all the controllable loads at a certain time-step, and its definition, also as in [22], is presented below.

$$D_S = P_{I,t} = \sum_{j=1}^{N} P_{I_j,t} \tag{3}$$

Where $P_{I,t}$ corresponds to the power consumption of all the controllable loads, being I_j the controllable load with index *j*. The controllable loads represent the loads that can be shifted in time.

The value of D_L corresponds to the demand limit at the referring time-step. This limit is a restriction on the amount of energy that customer is allowed to purchase at a certain time-step, being defined below.

$$D_C + D_S \leq D_L \tag{4}$$

In which concerns to the prices, p_{max} is the maximum price allowed in the market, i.e., the price that customers are willing to pay in a scenario in which the matching supply-demand quantity is not enough to serve the critical loads. The price p_{state} is the price that defines the urgency of the customer to buy energy. This price is based on the requirements of energy in every time-step, and it is defined below.

$$p_{state} = \frac{t_k \times (Dc + D_{TS})}{T \times D_L} \tag{5}$$

while T corresponds to the planning horizon during which a certain number of loads has to be served, t_k consists in the time range indexed by k, being $t_k \in T$ and $T = \{1, 2, \dots, 24\}$. The variable D_{TS} is related to the amount of shiftable loads that must be served during the planning horizon T. Thus, in case the consumers fail to buy enough energy to fulfill D_{TS} during the first time ranges of the planning horizon, consumers will be willing to buy energy at higher prices as the time range approaches to T. The price p_{int} is an intermediate point between p_{state} and 0. At every time-step, the value of D_{TS} is updated by diminishing its value, subtracting the amount of shiftable loads that had been previously served. The correspondent demand bid curve, with all of its parameters, is presented in Figure 1.

C. Actions

For the machine learning algorithm to converge to an optimal solution, different actions must be defined and considered. Those actions will be, similarly to the approach in [20], associated with p_{state}, being its formulation adapted to the one presented below.

$$p_{state} = B_1 + B_2 \times \frac{t_k \times (Dc + D_{TS})}{T \times D_L} \tag{6}$$

The actions are defined by a pair of variables, B_1 and B_2. The variable B_1 corresponds to the price that DR-enabled customers admit as low enough to buy energy at a certain time-step, even though no energy is urgently needed.

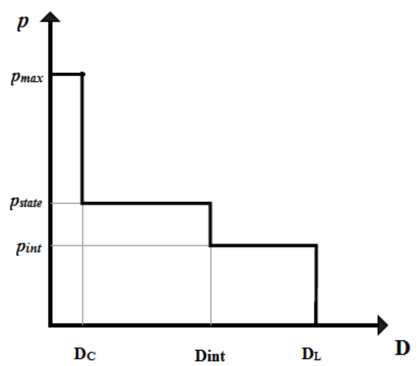

Fig. 1. DR bid curve.

Moreover, B_2 corresponds to the sensitivity to consumption urgency to the willingness to buy energy. By modifying the values of B_1 and B_2, the agent will learn how to place the optimal bid that will lead to the best possible reward.

D. Q-learning Algorithm

Since the state of the DR-enabled customer is already included in its demand bids, and also due to the fact that there is a high number of agents, the state will not be included in the Q-learning formulation. Therefore, as in [20], it will be used a simplified version of the Q-learning method as presented below.

$$Q_{t+1}(a_t) = Q_t(a_t) + \propto \times [R_{t+1} - Q_t(a_t)] \tag{7}$$

The Q-value to associate with action a_t is represented by $Q_t(a_t)$. The reward which is associated with the action is represented by R_{t+1}. The duration of every iteration is 24 hours, divided into hourly steps. The reward associated with the different actions is presented below.

$$R = -\sum_{t}^{24} p_t \times (E_t - w) \times \min(0, |E_{exp} - E_{prc}|) \tag{8}$$

The first term represents the sum of the cost of purchasing energy over the day, being p_t the market clearing price, and E_t the energy bought at its associated time-step.

In which concerns to the second term, it represents a penalty to be charged to agents whose amount of energy purchased throughout the day does not match their expected energy requirements.

The reward will be updated at every time-step, being its final value computed at the end of the day. The action defined by the bidding pair (B_1, B_2) will have an impact on the value of the obtained reward, being the agent's goal to determine which bidding pair maximizes the value of the reward.

E. ε-Greedy Policy

Due to the fact that no rule defines which action should the agent take, an ε-Greedy policy will be used for the agents to exploit the available information. By using this policy, agents will choose a random available action with probability ε, and the action that maximizes the reward with probability $1 - \varepsilon$.

F. Bid Aggregation

One of the crucial aspects of this decentralized model is to find a solution for the scalability problem associated with the centralized model. Therefore, to ensure scalability, the bids will be aggregated by horizontal summation of the demand bid curves.

G. Market Clearing

The market clearing will be performed at every time-step, being its goal to maximize the social welfare, matching demand with supply. The market clearing formulation for every time-step, considering the DR bids and supply, is presented below, as well as its restrictions.

$$max\left(\sum_{L} p_L^t \times E_L^t - \sum_{S} p_S^t \times E_S^t\right) \tag{9}$$

subject to:

$$0 \le E_x^t \le E_{max,x}^t, \qquad \forall x = \{L, S\} \tag{10}$$

$$\sum_L E_L^t = \sum_S E_S^t \tag{11}$$

where the prices p_L and p_S correspond to the bid price of the loads and suppliers at the time-step t, and E_L and E_S correspond to aggregated demand bids and supply volumes, respectively.

IV. Numerical Studies

A. Scenarios

To test the efficiency of the decentralized model, a comparison will be made between the model and a base case, in which there is no demand response approach, and also a centralized model.

B. Base case vs. Decentralized Model

The main goal of the optimal bidding strategy is to diminish costs of purchasing energy throughout the day, considering full load serving. In order to compare both scenarios, a fleet of five customers was analyzed, comparing not only the hourly energy cost, but mainly the daily energy cost.

The hourly cost per hour can be observed, for both scenarios, in Fig. 2. As noted in Fig. 2, without DR, the energy cost in peak hours reaches much higher values than in the rest of the day. For that, reader can note that the decentralized approach leads to a more uniform daily cost curve.

C. Centralized Model vs. Decentralized Model

Since the decentralized model solves the scalability problem associated with the centralized one, a comparison between both models will be carried out in order to compare the deviance between both models.

For a small fleet of 5 residential customers, it is possible to observe (as in Fig. 3) that both approaches lead to a more uniform cost curve.

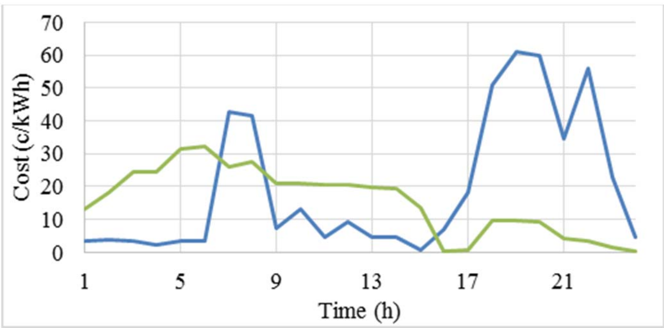

Fig. 2. Hourly energy cost, in c/kWh; in blue line the base case approach.; in green line the decentralized approach.

D. Results

To compare the quality in the three scenarios in which concerns the main goal, i.e., reducing the costs, a comparison between the final costs are presented in Table I.

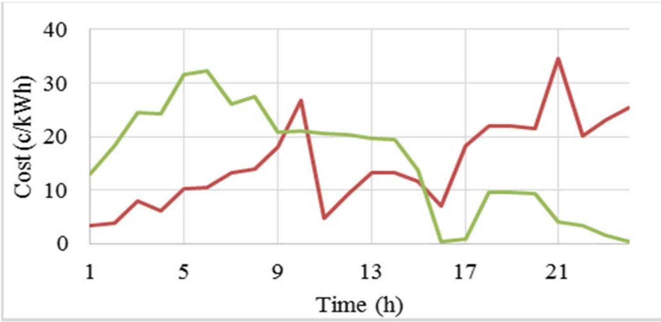

Fig. 3. Hourly energy cost, in c/kWh; in red line the centralized approach.; in green line the decentralized approach.

TABLE I. Daily Energy Cost

	Base Case	**Centr. Mod.**	**Dec. Mod.**
Daily energy cost (cents.)	464.324	361.228	372.913

As observed in Table I, both centralized and decentralized models lead to smaller daily costs comparing to a scenario without demand response penetration. In which concerns to the differences between the two different models that consider demand response, the centralized model has better results, as expect, due to the fact that the aggregator as perfect information that leads to the optimal cost reduction.

However, the results obtained in the decentralized approach are considerably good, since the deviation between it and the centralized model is not much, and its deviation from the base case is considerably enough to validate the decentralized approach as a good way for customers who participate in demand response programs.

V. Conclusions

The decentralized model for DR proposed in this paper leaded to appropriate results, not only by diminishing energy costs for the customers, but also by contributing to a more uniform load diagram. Moreover, from the results reported is possible to demonstrate that the centralized model under study has lesser cost (361.228 cents) compared with a decentralized model (372.913 cents), considering a small fleet of five residential customers under three possible scenarios, which is significant comparing both from the base case (464.324 cents). As future work, a more detailed comparison between the centralized and the decentralized models will be carried out, updating the model to a larger fleet to approximate the model to a real market situation as much as possible.

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