A Decentralized Privacy-Based Market Scheme for Responsive Demands

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***Abstract*—In this work, a market-based control scheme is proposed to minimize the billing costs of responsive demands (RDs) with the minimum impact on their privacy and satisfaction. For this purpose, the RDs are modeled as agents who bid to the day-ahead and real-time electricity markets through their energy management systems. In the model, the financial compensation provided by the market motivates the RDs to shift their load to off-peak periods. Since dissatisfaction is caused by the deviations from the reference consumptions, the RDs' bids are dependent on the level of satisfaction that the consumers are willing to accept. In order to maintain the satisfaction and privacy of consumers in the demand response (DR) programs, a decentralized DR-based algorithm is developed considering the competition-based participation of consumers by a performance-based reward and recognition (PRR) strategy. Different numerical results verify the effectiveness of the proposed scheme.**

***Keywords*—Decentralized electricity market; Demand response; Multi-agent system; Performance-based reward and recognition; Privacy and satisfaction; Responsive demand.**

NOMENCLATURE

A. Indices (Set)

c (C)	index (set) of customers
d (D)	index (set) of demand
i (I)	index (set) of demand response
j (J)	index (set) of suppliers
t	index of time

B. superscripts

dem	demand
discom	discomfort of customers due to participation in demand response program
DR	demand response
ini	initial value
m	local market
sup	supplier

C. Parameters and variables

λ	offering/bidding price
β, γ	parameters of Q-learning algorithm
d	demand
P	offering/bidding quantity
D	total demand
ψ	coefficient of discomfort in the dissatisfaction function of customer

I. INTRODUCTION

A. Aims and Motivation

Advanced information, communication, and other developed technologies are leading the power system towards the new age of smart grid. These developments made the DR 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 take part in the DR programs more than before.

In other words, DR programs can motivate customers towards modifying their load demand voluntarily in reaction to the electricity price values in the market. It can increase the number and participation of RDs in the smart grid. Since it is difficult for customers to negotiate directly with the independent system operator, a linking agent/market is required to manage the customers and to provide different DR programs for each single responsive demand.

Although essential technologies for information and communication are currently available, the interconnections of these paradigms are seriously affected by severe privacy concerns of individual consumers [1], [2].

Moreover, without participating in DR programs, in a fixed-rate tariff, each consumer tends to operate its appliances when the highest comfort level is achieved based on its personal preferences [3].

It causes the customers to have inertia against participating in DR programs, aiming to have the maximum satisfaction while using the electricity. In particular, each consumer incurs a discomfort by reshaping its demand from the desired pattern (without DR) to a modified pattern (with DR).

According to the above description, this work aims to develop a decentralized market-based scheme to enable the consumers to contribute actively in day-ahead and real-time electricity markets through a competition-based approach, considering the consumers' satisfaction. In addition, a PRR strategy is proposed to ensure the privacy of individual consumers while participating in DR programs.

Moreover, the proposed work determines the optimal bidding strategies of individual responsive demand, considering the uncertainties associated with the customers' behaviors and the prices of the upper-level market. To this end, the bids of RDs are cleared based on the market supplies and customers' bids. An agent-based system is presented where each RDs optimizes its bidding strategy based on the market outcomes.

In the proposed market-based scheme, individual RDs take part in the market and submit their consumption bids. The objective function of each customer minimizes the billing costs during 24 hours.

B. Literature Review

With the deployment of intelligent devices and communication infrastructure in smart grids, the demand side is able to play a dominant role in the energy management task and balancing demand and supply [4].

All DR providers attempt to shape the load patterns of their consumers and achieve compensations for the expenditure saving imposed to system operator due to the load shaping [5]. Therefore, the DR providers motivate their consumers to change the consumption pattern, by price-based or incentive-based programs.

In [6], the interactions between utilities and active consumers have been reported in smart grids by modeling the DR as a non-cooperative game. In [7], a congestion game-based demand management approach is addressed.

In [8], linear supply functions are utilized for DR bidding. The incorporation of DR bids within a real-time regulation market is addressed in [9]. In [10], a residential DR program is addressed to optimize the time of use of appliances considering the electricity bills and customers' dissatisfaction cost.

In [11], a decentralized aggregated control approach is presented to manage the electrical appliances' operation mode through a potential game that models the interactions between the appliances.

In [12], decentralized and centralized controls strategies in smart grid are analyzed where the decentralized approach is modeled based on the game theory concept.

In [13], the DR problem is formulated as a coupled-constraint game. In [14], a billing framework is reported to find the minimum aggregated cost considering the consumers' privacy. In [15], a distributed framework is proposed to maintain the consumers' privacy.

Moreover, in [16] models a DR problem as a concave non-cooperative game, presenting distributed DR strategies to minimize the energy costs. In [17], a DR problem is formulated in a system with multiple Gencos and consumers.

In [18], a distributed framework is reported to determine the maximum social welfare of a Genco and customers. In [19], the DR program is modeled by a Stackelberg game among Gencos and consumers, proving that there is a unique equilibrium.

In [20], household energy scheduling is reported via Stackelberg game where the energy management system has been the leader and the utilities have been followers. In [21], an approach is addressed to optimize time-of-use pricing of a monopoly power market through a game-theoretic technique. In [22], a billing approach is reported to charge consumers for energy consumption via an aggregative game approach to model the consumers' behavior.

C. Contributions

According to the literature review, the contributions of the proposed work are as follows:

- Propose a market-based scheme to minimize the billing cost of RDs with the minimum impact on their privacy and satisfaction, by using an agent-based system powered by deep Q-learning with experience replay.
- Develop a decentralized DR-based algorithm considering the competition-based participation of consumers by a PRR strategy to maintain the satisfaction and privacy of consumers in the DR programs.
- Propose an approach to model each consumer's dissatisfaction cost based on the propriety, schedule, and appliances.

D. Paper Organization

Section II shows the mathematical model of the developed decentralized market-based scheme of RDs. Numerical results are presented in Section III, and finally, Section IV concludes the manuscript.

II. The Proposed Decentralized Market-Based Model of Responsive Demands

Game theory aims at modeling the conflicts and interactions between decision-makers and has been reported in the smart grid literature [16], [20]. In this work, the DR model with some local markets and several residential consumers is developed by means of a two-level non-cooperative game-theoretic problem. Fig. 1 illustrates the schematic of the proposed decentralized market.

In the first level of the decentralized market-based scheme, from the viewpoint of demand side, 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. In the second level, the local market will be cleared to find the most economic bids. At each hour, five stages are considered:

1. All individual customers define their demand bidding for the next hours, according to their necessities and past experiences.
2. The customers' bids are aggregated.
3. The aggregated bid is sent to the market.
4. The market is cleared.
5. The obtained prices are transferred to the customers.

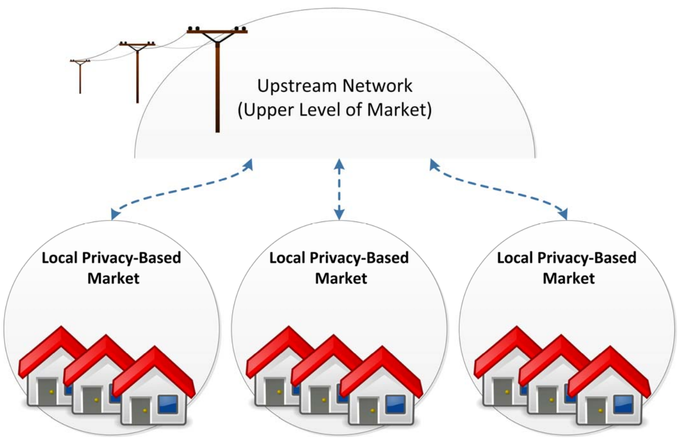

Fig. 1. The schematic of the decentralized market model and the upstream network.

It should be noted that the proposed approach computes the bids only or the next hour. It is due to the fact that 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 deep Q-learning with experience replay. 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.

Fig. 2 illustrates the Pseudo code of the proposed deep Q-learning with the experience replay. Based on the algorithm, previous and current states, previous action and its associated reward are all stored in a list known as experience replay.

A random part of the list will be employed to train during every episode, to avoid overfitting. Moreover, Fig. 2 shows how the algorithm predicts the future reward by finding the best possible Q-function, $Q^*(s|a)$.

The Q-value is the estimated reward of the potential state-action pairs that 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. It can significantly decrease the complexity of the model.

The optimal demand of consumer *c* purchasing power from the local market *m*, at time *t*, and $d_{c,t}^m$, can be formulated by (1) [17]:

$$d_{c,t}^m = \underset{d_{c,t}^m}{\arg\max}\, \omega_{c,t}(d_{c,t}^m) = \begin{cases} d_{c,t}^{\min} & (\beta_{c,t} - \lambda_t^m)/\gamma_{c,t} < d_{c,t}^{\min} \\ (\beta_{c,t} - \lambda_t^m)/\gamma_{c,t} & d_{c,t}^{\min} < (\beta_{c,t} - \lambda_t^m)/\gamma_{c,t} < d_{c,t}^{\max} \\ d_{c,t}^{\max} & d_{c,t}^{\max} < (\beta_{c,t} - \lambda_t^m)/\gamma_{c,t} \end{cases} \quad (1)$$

where λ_t^m denotes the price of the local market *m* at time *t*. $\beta_{c,t}$ and $\gamma_{c,t}$ represent time-varying parameters of the Q-learning algorithm; $d_{c,t}^{min}$ and $d_{c,t}^{max}$ are the minimum and maximum capacity of consumer *c* at hour *t*, respectively.

Various values of $\beta_{c,t}$ and $\gamma_{c,t}$ at different hours model the dynamics of consumer load:

$$D_t^m = \sum_{c=1}^{C} d_{c,t}^m \quad (2)$$

where D_t^m is the total demand from the local market *m* at time *t*. The accumulated consumers' welfare, obtained from the local market, ς_t^m, can be formulated as:

$$\begin{aligned} \varsigma_t^m &= \sum_{c=1}^{C}\left[d_{c,t}^{\mathrm{m}}\left(\beta_{c,t} - \lambda_t^m\right) - \frac{\gamma_{c,t}}{2}\left(d_{c,t}^{\mathrm{m}}\right)^2 \right] \\ &= \sum_{c=1}^{C}\left[\gamma_{c,t}\left(d_{c,t}^{\mathrm{m}}\right)^2 - \frac{\gamma_{c,t}}{2}\left(d_{c,t}^{\mathrm{m}}\right)^2 \right] \\ &= \frac{1}{2}\sum_{c=1}^{C}\gamma_{c,t}\left(d_{c,t}^{\mathrm{m}}\right)^2 \end{aligned} \quad (3)$$

Algorithm Deep Q-learning with experience replay

Initialize replay memory D
Initialize action-value function Q with random factors
for episode = 1, M **do**
  Initialize sequence $s_1=\{x_1\}$
  Initialize preprocessed sequence $\phi_1 = \phi\,(s_1)$
  for t=1,T **do**
    Select a random action a_t with the probability ρ
    Otherwise $a_t = \max_a Q^*(\phi(s_t), a; \theta)$ with the probability 1-ρ
    Implement a_t and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t$, a_t, x_{t+1} and preprocess $\phi_{t+1} = \phi\,(s_{t+1})$
    Store transition (a_t, r_t, ϕ_t, ϕ_{t+1}) in D
    Sample random part of transitions (a_i, r_i, ϕ_i, ϕ_{i+1}) from D
    Set $y_i = \begin{cases} r_i & \text{for terminal } \phi_{i+1} \\ r_i + \lambda \max_{a'} Q(\phi_{i+1}, a'; \theta) & \text{for non-terminal } \phi_{i+1} \end{cases}$
    Utilize a gradient descent step on $(y_i - Q(\phi_i, a_i; \theta))^2$
  end for
end for

Fig. 2. The Pseudo code for deep Q-learning algorithm

The dissatisfaction cost for each hour can be captured by the consumers' discomfort level based on the changes in the load demand in the DR program.

$$C_{t,d}^{dem} = \psi_{t,d}^{discom}\left| P_{t,d}^{dem} - P_{t,d}^{dem,ini} \right| \quad (4)$$

where $\psi_{t,d}^{discom}$ *is* the coefficients of the discomfort that denotes the discomfort of customer *d* because of changing the demand from the desired amount. These coefficients are based on the propriety, schedule, and appliances, and consequently, they are considered as private information for the consumers. A larger $\psi_{t,d}^{discom}$ means the lower flexibility to modify the demand in time t because of the lower preference of the customer d to modify its demand [23].

On the second level, the market is cleared based on the optimization problem presented in (5) that maximizes the social welfare.

$$\max\left(\sum_{d=1}^{D} P_{t,d}^{dem}\lambda_{t,d}^{dem} + \sum_{i=1}^{I} P_{t,i}^{DR}\lambda_{t,i}^{DR} - \sum_{j=1}^{J} P_{t,j}^{\sup}\lambda_{t,j}^{\sup} \right) \quad (5)$$

where $P_{t,d}^{dem}$, $P_{t,i}^{DR}$, and $P_{t,j}^{sup}$ represent the quantities of load, DR, and supply, respectively. Moreover, $\lambda_{t,d}^{dem}$, $\lambda_{t,i}^{DR}$, and $\lambda_{t,j}^{sup}$ denote the offering/bidding prices associated with each mentioned quantity.

In (5), the first two terms represent the demand and DR costs, while the third term denotes the income of suppliers. Since the electrical network has been ignored in this work, the hourly balance between demand, DR and supply can be considered by (6):

$$\sum_{d=1}^{D} P_{t,d}^{dem} + \sum_{i=1}^{I} P_{t,i}^{DR} - \sum_{j=1}^{J} P_{t,j}^{\sup} = 0 \quad (6)$$

Inequalities (7)-(9) denote the minimum and maximum limits of demand, DR and supply, respectively.

$$P_{t,d}^{dem,\min} \le P_{t,d}^{dem} \le P_{t,d}^{dem,\max} \quad (7)$$

$$0 \le P_{t,i}^{DR} \le P_{t,i}^{DR,\max} \quad (8)$$

$$0 \le P_{t,j}^{\sup} \le P_{t,j}^{\sup,\max} \quad (9)$$

III. Numerical Studies

In order to investigate the impacts of the proposed decentralized market framework, the results of the proposed model are compared to the ones with an aggregator-based approach. To this end, the prices of the electricity market on the upper hand have also been considered uncertain. In order to model the uncertainty, various scenarios have been generated by using the roulette wheel mechanism based on the historical data of the electricity market in Australia.

Then, the scenarios have been reduced by a backward-forward method. Fig. 3 illustrates the considered scenarios of the upper electricity market as the input of both, the proposed decentralized market and aggregator-based models. Fig. 4 compares the resulted energy prices for the lower level market (for the customers) in decentralized and centralized frameworks. Although the aggregator bids require the complete information about the customers, the resulted market prices in the proposed decentralized scheme are almost the same as the obtained prices by employing an aggregator. It means that the consumers can have their perfect privacy without paying more cost. Meanwhile, the proposed decentralized market scheme does not affect the upper market negatively.

Figs. 5-7 compare the expected electricity cost of 1000 customers who participate in the proposed decentralized market scheme with the centralized one in the second day, sixth day and seventh day of the simulated week. According to Fig. 5, in the second day of the week, the customers' costs of decentralized model are lower than the aggregated ones in most of the hours.

However, in both the sixth and seventh days, in many hours, the customers' costs in the proposed decentralized scheme are higher than the ones of the centralized model that is due to the higher discomfort costs of the customers in the weekend days.

Overall, participation in the proposed decentralized scheme makes a trivial higher cost compared to the aggregation-based model.

Moreover, proposed model was designed considering GAMS 24.0.2® framework on Intel® XEON X5690 3.47GHz and 256GB of RAM.

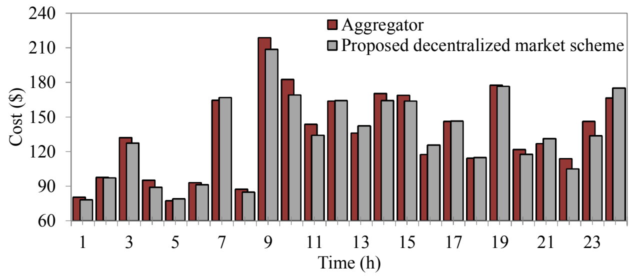

Fig. 5. The resulted expected electricity costs in centralized (aggregator) and decentralized market schemes for the second day.

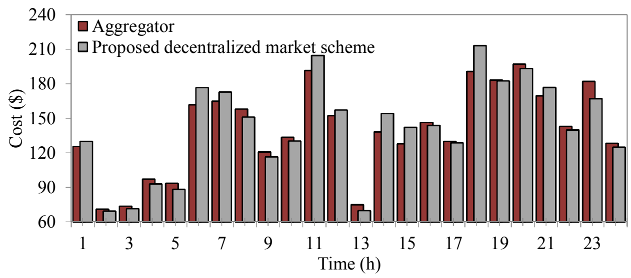

Fig. 6. The resulted expected electricity costs in centralized (aggregator) and decentralized market schemes for the sixth day.

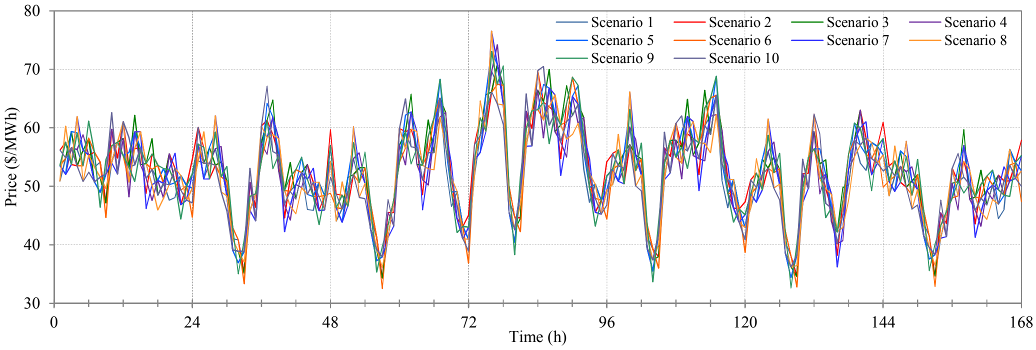

Fig. 3. The scenarios of energy prices of the upstream network.

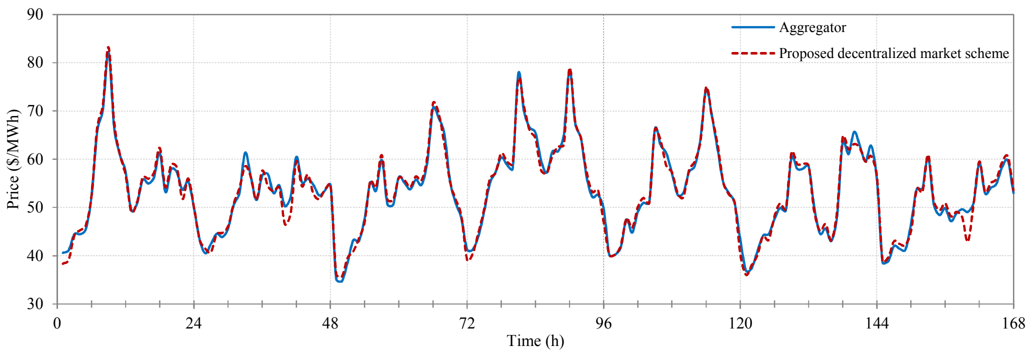

Fig. 4. The resulted energy prices in centralized (aggregator) and decentralized market schemes.

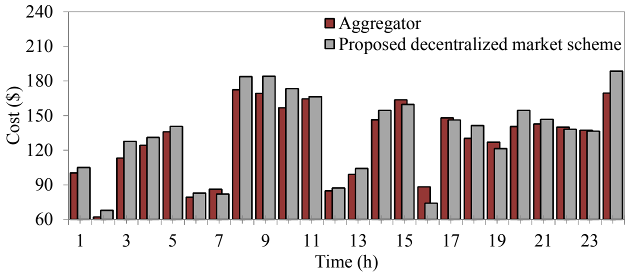

Fig. 7. The resulted expected electricity costs in centralized (aggregator) and decentralized market schemes for the seventh day.

IV. Conclusions

This work developed a privacy-based market scheme to minimize the billing costs of responsive demands with the minimum impact on their satisfaction. For this purpose, the RD was modeled as agents who bid to the day-ahead and real-time electricity markets through their energy management systems. In addition, an approach was proposed to model each consumer's dissatisfaction cost. To preserve the privacy of the consumers in the DR program, an algorithm was proposed to implement the DR framework in a decentralized fashion. To this end, a competition-based participation of consumers was modeled by a performance-based reward and recognition strategy. Results revealed that the billing cost of these customers could be considerably decreased compared to the uncontrolled method. In addition, the results were compared with a centralized aggregation-based method, where a DR aggregation entity directly buys the energy on behalf of RDs in the markets. The results demonstrated the effectiveness of the proposed decentralized market-based scheme.

Acknowledgements

This work was supported by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT-PAC/0004/2015 - POCI-01-0145-FEDER-016434, POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, and UID/EMS/00151/2013. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048.

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