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Abstract. Aggregating the Demand Response (DR) is approved as an effective solution to improve the participation of consumers to wholesale electricity markets. DR aggregator can negotiate the amount of collected DR of their customers with transmission system operator, distributors, and retailers in Demand Response eXchange (DRX) market, in addition to participate in the energy market. In this paper, a framework has been proposed to optimize the participation of a DR aggregator in day-ahead energy and intraday DRX markets. In this regard, the DR aggregator optimizes its participation schedule and offering/bidding strategy in the mentioned markets according to behavior of its customers. For this purpose, the customers' participation is modeled using a Supply Function Equilibrium (SFE) model. In addition, due to uncertainties of market prices and the behavior of consumers, an appropriate risk measurement, CVaR, is incorporated to the optimization problem. The numerical results show the effectiveness of the proposed framework.

Keywords: CVaR, day-ahead market, demand response exchange, DR aggregator, energy market, intraday market.

1 Introduction

In a competitive electricity market, demand response programs (DRPs) play an important role in improving market efficiency, reducing peak demand and price instability, and enhancing the reliability [1]. Most of independent market players (e.g. transmission system owner, distributors and retailers) can benefit from DR [2], [3], [4]. Moreover, by implementing the advanced smart grid infrastructure, DR share in system operation resources will be increased [5]. For this purpose, the regulatory bodies are changing market rules and regulations to support implementation of DR programs in electricity markets [6], [7]. From the market point of view, market players are divided into two sets: DR buyers and DR sellers.

DR buyers include retailers and distributors who need DR to improve their business and system reliability while DR sellers have the capacity to significantly modify electricity demand and sell DR to increase their profit [8].

DR sellers consist of large consumers which can meet the DR program requirements by themselves or a new market participant such as distribution system operators (DSOs), load service entities (LSEs), and DR aggregators which have the responsibility of managing customer responses. DR aggregators negotiate the amount of their consumers combined DR with TSO, distributors, and retailers.

As introduced in [8], DR can be treated as a tradable commodity in a market which is completely separated from energy market. In a DRX market, the DRX operator collects both the aggregated demand and individualized supply curves. Then, it balances the supply and demand at a common price to clear the market [8].

The literature contains some studies about demand-side players that bid to power markets [6], [7] and [9]. However, DR aggregation has not been discussed in the studies. It is obvious that simultaneous participation of DR aggregators in the energy and DRX markets has not been addressed thoroughly in the previous works.

The majority of the electrical energy is traded in day-ahead market. Hence, the market players have to submit their offers for entire hours of the day-ahead, several hours in advance. The offers have a degree of uncertainty due to the volatile nature of renewable based plants in the future smart grid. Therefore, participation in short timeframe markets for market players is crucial. In other words, from day-ahead market to the spot market, the market players can obtain some new data to update their preliminary offers in an intraday market [10], [11]. The intraday market is a corrector market that is closer to the operational hour; accordingly, that market allows market players to update their offers.

In this paper, the optimal participation of DR aggregator in intraday DRX market and day-ahead energy market is presented. For this purpose, the behavior of DR aggregator's customers has been modeled by Supply Function Equilibrium (SFE) method, unlike the previous studies that have considered constant DR demand curves [8]. On this basis, a new approach is developed for consumers' participating in DRX market. In addition, Conditional Value at Risk (CVaR) is incorporated to the model to tackle the uncertainties of market prices and the behavior of consumers.

The rest of the paper is organized as follows. In Section 2, the contribution to collective awareness systems is presented. Section 3 introduces the optimal participation of DR aggregator in DRX and energy markets. Section 4 is devoted to the case studies. Finally, Section 5 concludes the paper.

2 Contribution to Collective Awareness Systems

Recent advances in smart metering technology enable bi-directional communication between the utility operator and the consumers and facilitate the option of dynamic load adaptation. Toward this direction, DR provides incentives to major consumers, usually in the form of monetary rewards, to reduce their electricity consumption in peak periods. Since the importance of energy conservation and environmental protections are growing, DR can favorably affect the future smart grid [10], [11].

In this context, future collective awareness systems can positively affect future smart grid by obtaining precise information and the effective involvement of the consumers.

On this basis, improvements in collective awareness systems cause customers' behavior in demand side to play a crucial role in future smart grid. Although DR has been successfully applied in the industry sector [5], its application in the residential sector is a more challenging task. On this basis, some new market players (e.g. DR aggregators) should manage the customers' consumption.

Aggregators possess the technology to perform DR and are responsible for the installation of smart meters at end-user premises. Since each aggregator represents a significant amount of total demand in DR market, it can negotiate on behalf of home users with the operator more efficiently. Since these players are the link between customers and electricity markets, they have a critical role in moving towards future smart grid. In future smart grid, by supplementing the collective awareness systems and consequently increasing the participation of customers in DRPs, the players will have a more important role in the electricity markets.

3 Modeling the Optimal Behavior of DR Aggregator

DR aggregator aims to maximize its profit by participating in day-ahead energy and intraday DRX markets. On this basis, DR aggregator plays in DRX market as a DR seller and takes part in energy market as a *negative load* in demand side [12]. A schematic of DR aggregator presence in the mentioned markets is illustrated in Fig. 1. As it is shown, DR aggregator can participate both in intraday DRX market and day-ahead energy market. However, in the first case it has the role of a DR seller and in the second one it takes part on behalf of demand side.

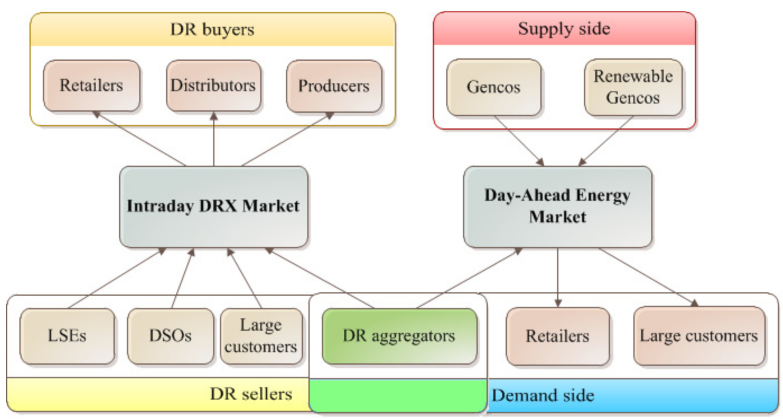

Fig. 1. Day-ahead energy and intraday DRX markets scheme.

3.1. Modeling the Supply Function of DR Aggregator's Customers

In order to obtain the optimal behavior of the DR aggregator, the behavior of its customers is modeled first. For this purpose, a new approach based on SFE method is developed for customers' supply function in order to maximize their benefit.

Based on this, the clearing price of DRX market, π^{DRX} , can be formulated as follows:

$$\pi^{DRX} = a_i .DR_i + b_i .(1-\theta_i) \quad (1)$$

where DR_i is the amount of DR purchased from i-th customer. The coefficient θ is the *customer type* and represents a customer's willingness to participate in DRPs. It takes a value between 0 and 1. By increasing the amount of θ, the cost of DR decreases because the customer has more willingness to participate in DRPs. Additionally, a_i and b_i are SFE coefficients applied to all customers [13].

Since, a balance should exist between the amount of sold and purchased DR [8], the balance between electricity load and supply has been considered. On this basis and by introducing the Required DR, *RDR,* it will be as:

$$RDR = \sum_{i=1}^{I} DR_i = \sum_{i=1}^{I} \frac{\pi^{DRX} - b_i (1-\theta_i)}{a_i} \quad (2)$$

$$\pi^{DRX} = \left[RDR + \sum_{i=1}^{I} \frac{b_i (1-\theta_i)}{a_i} \right] \Big/ \sum_{i=1}^{I} \left(\frac{1}{a_i}\right) \quad (3)$$

In this approach, each aggregator should maximize its benefit in the worst case. The worst condition for aggregators occurs when θ tends to 0. In this condition, aggregators have the least capacity to participate in DR, and their profit will be low.

Accurate estimation of consumers cost functions needs accurate investigation and data mining in various energy sectors. Ref [14] has investigated the utility function of consumers and the utility function has been proposed to be considered as quadratic.

Based on this, the consumers' cost functions have quadratic form as the following:

$$Pf_i = \pi^{DRX} \times DR_i - \mathrm{cost}_i (DR_i) \quad (4)$$

Participating in DRPs means that customers reduce their electricity consumption and will lose corresponding utility. Considering this fact, if the revenue of providing DR be less than their pre-existed benefit of electricity consumption, the customers will not be convinced to participate in DRPs.

Considering quadratic cost function for the consumers and combining (2) and (4) and by substituting $\theta=0$:

$$pf_i = \pi^{DRX} \times \left(\frac{\pi^{DRX} - b_i}{a_i}\right) - \left[\frac{am_i}{2} \times \left(\frac{\pi^{DRX} - b_i}{a_i} \right)^2 + bm_i \times \left(\frac{\pi^{DRX} - b_i}{a_i} \right) \right] \quad (5)$$

where am_i and bm_i are the customers marginal cost function coefficients. As can be observed from (5), SFE model is utilized for offering strategy of consumers [15].

On this basis, each seller can offer its a_i and b_i to increase its profit. Based on this, the expected clearing price of demand response can be formulated as follows:

$$\pi^{DRX} = \left[RD + \sum_{i=1}^{N^{DRS}} \frac{b_i}{a_i} \right] \Big/ \sum_{i=1}^{N^{DRS}} \left(\frac{1}{a_i} \right) = \left[RD + \frac{b_i}{a_i} + \sum_{i \neq j}^{N^{DRS}} \frac{b_j}{a_j} \right] \Big/ \sum_{i=1}^{N^{DRS}} \left(\frac{1}{a_i} \right) \tag{6}$$

3.2 Modeling the Uncertainty of Market Prices

In order to successfully participate in electricity market, DR aggregators have to forecast market prices. In this paper, two uncertain market prices are considered: day-ahead and intraday. For this purpose, Roulette Wheel Mechanism (RWM) technique is applied for scenario generation in each hour. In order to develop an accurate and appropriate model, market prices have been characterized by log-normal distribution in each hour [16]. Thus, considering μ and σ represent mean value and standard-deviation, respectively, the PDF of market prices is represented by (7):

$$f_{Pr}(Pr, \mu, \sigma) = \frac{1}{Pr\sigma\sqrt{2\pi}} \exp\left[-\frac{(\ln Pr - \mu)^2}{2\sigma^2} \right] \tag{7}$$

3.3 Incorporating Risk Management

Since the profit of DR aggregator is related to the uncertain behavior of its customers, it should manage its related risk. Conditional value-at-risk (CVaR) can be an appropriate technique to incorporate risk management into the problem. The formulation of CVaR is indicated in (8)-(9):

$$Max: \quad \xi - \frac{1}{1-\alpha} \sum_{s=1}^{S_N} \rho_s . \eta_s \quad , \quad \eta_s \geq 0 \tag{8}$$

$$-B_s + \xi - \eta_s \leq 0 \tag{9}$$

The parameter α is usually assigned within the interval of 0.90 to 0.99, which in this work is set to 0.95. If the profit of scenario s is higher than ξ, the value of η_s is set to 0. Otherwise, η_s is assigned to the difference between ξ and the related profit. The above formulated constraint is applied to unify the risk-metrics CVaR.

3.4 Objective Function of the DR Aggregator

In the pool based model, each DR aggregator manages its customers' responses and offers its price-quantity. The uncertain characteristic of the day-ahead energy and the intraday DRX market prices is fully considered. The aggregator offers a specified quantity in day-ahead market and gets accepted level of energy from day-ahead market for each hour. Then, it can update the offers in intraday market. The price scenarios utilized at the DRX market become more accurate. Moreover, in the proposed stochastic framework, risk aversion is implemented by restricting deviations of expected profit using CVaR technique. According to the above mentioned description, the objective function can be expressed as (10):

$$\text{Max } EP = \beta\left(\xi - \frac{1}{1-\alpha}\sum_{s=1}^{S_N}\rho_s.\eta_s\right) + \sum_{s=1}^{S_N}\rho_s\sum_{t=1}^{T}\left[\pi_{ts}^{D}.P_t^{D} + \pi_{ts}^{I}.P_{ts}^{I,sell} - \sum_{d=1}^{ND}\pi_{td}^{DRX}.DR_{td}\right] \quad \mathbf{(10)}$$

where, β is the weighting factor to achieve a tradeoff between profit and CVaR.

The first term indicates the CVaR multiplied by β. The next two terms represent the incomes achieved from selling energy in the day-ahead and intraday markets, respectively. Finally, the cost of buying energy from DRX market is represented in the last term. Eq. (10) is maximized considering the constraints described below:

$$P_{ts}^{Sch} = P_t^{D} + P_{ts}^{I,sell} - \sum_{d=1}^{ND} DR_{dts} \quad \mathbf{(11)}$$

$$-\sum_{t=1}^{T}\left[\pi_{ts}^{D}.P_t^{D} + \pi_{ts}^{I}.P_{ts}^{I,sell} - \sum_{d=1}^{ND}\pi_{td}^{DRX}.DR_{td}\right] + \xi - \eta_s \le 0 \quad \mathbf{(12)}$$

The total scheduled energy of the aggregator in both day-ahead and intraday markets is given in (11). Eq. (12) is related to incorporating the risk into the problem.

4 Numerical Study

In order to illustrate effectiveness of the model, some numerical studies are accomplished. It is assumed that DR aggregator's customers are clustered into four DR sellers which offer to the aggregator. The values of θ are considered as shown in Table 1 for each DR seller. A common load curve of a real-world system is considered [17]. The peak of typical load curve is considered to be 100MW.

Table 1. θ coefficient for DR sellers.

DR sellers	Seller 1	Seller 2	Seller 3	Seller 4
θ	0.9	0.7	0.5	0.3

When the hourly required DR is less than the sellers' capacity, a competition has been raised between sellers to sell DR. This competition occurs in a pool-based market. SFE coefficients (a_i , b_i) for each seller are obtained using the approach expressed in section 3.1. The amount of traded DR by each customer is indicated in Fig. 2. As it can be seen, each seller wins an amount of DR that is related to its willingness coefficient. Sellers 1, 2, and 3 can participate in DRX market in most hours, while seller 4 can participate only in peak times. Furthermore, in off-peak intervals, the traded DR between players is decreased.

Table 2 presents the effect of participation in the intraday DRX market on the DR aggregator's expected profit. The capacity of DR for offering to DRX market is supposed to limit up to 20%. As it can be seen in Table 2, an increase in DR aggregator's risk causes a reduction in its expected profits. Moreover, the participation in intraday DRX market can increase its profit.

The effect of DR participation level on the cost and income of DR aggregator is presented in Table 3. The maximum capacity of DR for participating in the DRX market is supposed to be 10%. As it can be seen in Table 3, the intraday DRX market encourages the aggregator to bid more quantities to the day-ahead market, because it expects to make the uncertainties up. On other hand, the prices of DRX market are more stable than those of the intraday market. As can be observed, the increases in DR participation level cause linear increases in the expected profits of the aggregator up to about 20% of DRP participation level. After this point, the impact of the intraday DRX market capacity on the aggregator's profit is decreased, thus its tendency for participating in the DRX market is saturated.

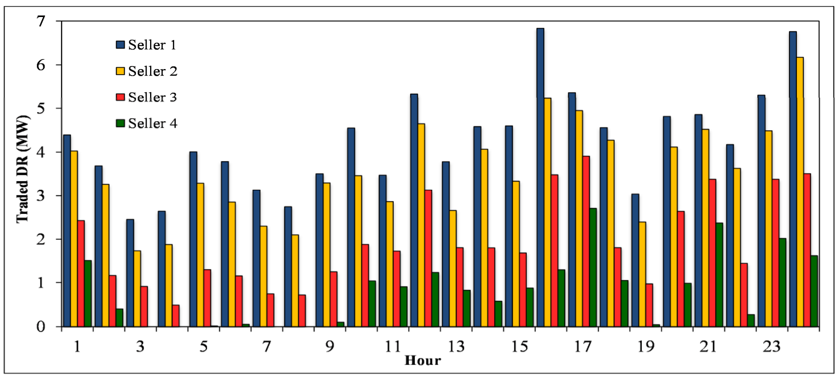

Fig. 2. Traded DR in DRX market.

Table 2. Effect of intraday DRX market on DR aggregator's profit and CVaR.

Case	Risk level (β)	CVaR ($)	Expected profit ($)
Without participation in intraday DRX market	0	8861.7	9421.5
	1	8989.8	9159.4
With participation in intraday DRX market	0	10059.6	10565.4
	1	10115.0	10126.1

Table 3. Effect of DR participation level on DR aggregator's costs and incomes.

DR participation level (%)	10	20	30	40	50
Income from day-ahead market ($)	6359.3	6932.7	7249.4	7278.2	7287.4
Income from intraday market ($)	4677.3	5775.9	5974.5	6043.1	6171.7
Cost from DR sellers ($)	2030.7	2582.5	2689.9	2711.6	2778.0
Expected profit ($)	9005.9	10126.1	10534	10609.7	10681.1

5 Conclusion

This paper investigated the impacts of intraday DRX market on optimal trading of a DR aggregator in a market environment. In this regards, the aggregator can participate in intraday market and use demand response resources a pool based DRX market in order to reduce its risk and maximize its profit. Behavior of consumers in selling DR was modeled using a new approach based on SFE method to maximize their benefit considering the amount of hourly required DR. In addition, the uncertain natures of day-ahead and intraday market price were modeled using RWM method. Furthermore, CVaR was applied as a risk measure that DR aggregator can specify its desirable weighting between the expected profit and risk. The results showed that establish of an intraday DRX market as an adjustment market may provide more opportunities for DR aggregators. The more application of DR could significantly increase the expected profit of DR aggregators and reduce their risks.

Acknowledgment. This work was supported by FEDER funds (European Union) through COMPETE and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and PEst-OE/EEI/LA0021/2013. The research also received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048.

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