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A Comprehensive Framework for Retailer's Financial Policy

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Abstract: This paper presents a comprehensive framework for retailers' financial policy which includes both electricity and demand response (DR) markets. Due to the existence of uncertainties in market environment, retailers may face with difficulties for purchasing electric energy from suppliers and selling it to their customers. If the selling price is not low enough, customers may choose a rival retailer. Demand Response Programs (DRPs) are introduced as a useful measure to mitigate a part of risks associated with these uncertainties. In this paper, a decision making framework is proposed which allows retailers to concurrently participate in energy market as well as the Demand Response Exchange (DRX) market to maximize their expected profit. This framework incorporates the elastic behavior of customers with respect to the electricity prices. Performance of the proposed approach is investigated through numerical studies using the Spain market data. The results show the efficiency and advantage of the proposed methodology.

Keywords: Contract design; Demand response exchange market; Electricity market; Retailer's financial policy

1. Introduction

A. Literature Review

In a competitive electricity market, Demand Response programs (DRPs) play an important role in improving market efficiency [1]. In the strategic plan of International Energy Agency (IEA), demand side activities are introduced as the first choice in all energy policy decisions, because of their potential benefits both at operation and economic levels [2].

DRPs invite electricity customers to motivate changes in energy consumption. Its potential to mitigate the electricity demand has made the use of DRPs more attractive to both customers and system operators [3, 4].consumption. In the market-based approach, all players are categorized in two groups: The first group is DR buyers and the second one is DR sellers. DRBs need demand response to improve their business and system reliability while, Demand Response Sellers (DRSs) are aggregators and customers who sell DR to enhance their benefit. This structure creates an efficient market for trading DR. As introduced in [5, 6], DRPs is treated as a tradable commodity in the pool-based market, where the demand response exchange operator (DRXO) collects both the aggregated demand and individualized supply curves. Then, it clears the supply and demand at a common price [5]. DRPs have implemented in many countries all over the world. DR resources are introduced as a measure to mitigate the risks of retailers. However, the concept of pool-based DR has been recently introduced which is named DRX. As above mentioned, DRX needs an operator to manage the pool market and find the equilibrium point of DR trading. DRX market is recently introduced and has not been implemented in real world markets.

Economic models of TBRPs and IBPs have been addressed in many researches in recent years [7-14]. Ref. [7] has discussed methods for customer and demand response policies in new electricity markets. Refs. [8, 9] have presented an economic model of price responsive loads based on the constant value of price elasticity. Market clearing programs are discussed in [10], which takes their economic benefits into account. In the authors' previous studies [11-14], an economic model of responsive loads has been derived.

DR beneficiaries include: Transmission System Owners (TSO), distributors, retailers, and aggregators. As a result of improving the network reliability, a TSO can benefit from DRPs [1], distributors can manage network constraints at the distribution level by using of DRPs [15]. A retailer purchases electricity from the pool market and sells it to his/her customers at fixed prices [16, 17]. When retailer buys electricity from suppliers, he/she may face with pool price uncertainties. Similarly, at the time of selling electricity to end-users, he/she may face with the demand uncertainty and also the fact that if the prices are not low enough, then the customers might change their retailer and buy from another entity [16]. Therefore, the retailers must manage the supply side contracts as well as the demand side.

Ref. [3] presents techniques for customers and retailers to participate in an electricity market. Profitability of the retailers with different price strategies is discussed in [18]. The optimal bidding in the power pool market for retailer is developed in [19]. Ref. [20] determines the retail electricity price using a capital asset pricing model. Interruptible contracts of price maker retailers are discussed in [21]. Refs. [16] and [22], present a stochastic programming model to determine the quantity of power which is purchased from the pool and forward contracts and also to determine the optimal selling prices to have a maximum profit from the viewpoint of a retailer. An integrated framework is presented in [23] to obtain the sale price to

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clients based on Time Of Use (TOU) rates and also to manage different contracts in order to determine the optimal energy procurement strategy within a medium-term period. An overview of risk management tools in power markets has been provided in [24]. Ref. [25], proposes a strategy for optimal price offering to end-users for maximizing the profit of a retailer which is based on load profile clustering methods. A method for determining the optimal demand function for a retailer has been presented in [26] which assumes that the retailer purchase electricity from both day-ahead and/or the regulation markets and sells it to his/her clients through fixed or real-time pricing contracts. Based on clustering techniques, an annual framework for optimal price offering by a retailer has been proposed in [27]. A bi-level programming method for solving the medium term decision making problem confronted by a retailer has been presented in [28]. In [29], a multistage stochastic optimization method was developed. Ref. [30] introduces a new portfolio-selection model (PSM) which is based on fuzzy value at risk.

B. Aim and Contributions

There is an important operational issue for any DRX market relating to dispatch timing [5]. Since the DRX market should be concurrent with the operations of an electricity market, the time horizon of DRX must coincide with time frame of electricity market. Note that, both time frames could be divided into different time scales such as day ahead, hour ahead, real time, etc. [5]. However, this paper addresses only the day-ahead time scale. As it was described in the previous subsection, retailers must purchase electricity from the wholesale market at volatile rates and sell it to their customers at flat rates. The market price uncertainties expose a retailer to financial risks. By reducing electricity demand during price spikes period, retailers may cover a part of these risks [4, 31]. They also should cope with demand uncertainties at the time of selling electricity to their clients. This paper provides a decision making framework for retailers, which determines their optimum level of involvement in electricity pool market and also deriving the optimum selling prices for end-users, as well as the optimal amount of involvement in demand response exchange market. Indeed, this framework allows retailers to determine the contract price with their clients and also to manage the portfolio of different contracts to maximize their expected profit. The reaction of clients to the selling price of retailer is modeled through a piecewise price quota function.

C. Paper organization

The rest of the paper is organized as follows. Section 2 explains retailers' decision making framework, the characterization of end-users and their acceptance function and also uncertainties which a retailer faces with them. The procedure of problem modeling and formulation is discussed in section 3. Section 4 is devoted to numerical study. Finally, concluding remarks are drawn in Section 5.

2. Decision Framework, End-Users Acceptance Function and Uncertainty Characterization

Fig. 1 depicts the outline of the proposed framework. The important point is concurrent participation of the retailer in both electricity and DR market in order to maximize his/her financial profit.

Demand response exchange operator must aggregate and sort demand response supply functions from various customers with different willingness of participation in DRPs. Then, DRXO determines the amount of DR and the price of per MWh of DR for each of DRSs.

Customers might have an elastic behavior with respect to the electricity prices offered by the retailers. If the retailers propose higher electricity prices to their clients, the chance of accepting these prices by the customers will be low; because, under the same conditions, the customer will prefer to have contract with other retailers with more favorable prices [32]. An acceptance function is defined as $\psi \rightarrow [0,1]$. This function shows the probability that the customer will accept the contract with retailers' suggested price. By increasing the price, the probability of acceptance will decrease. This means that the acceptance function should be decreasing.

The probability that the clients may choose a rival retailer if the selling prices are not low enough can be modeled by means of a piecewise price-quota function [16]. The retailer's ability to keep his/her customers has been modeled by the price-quota function in [33]. This function determines the amount of electricity which a customer accepts to buy based on the retailer's offered price [17]. Fig. 2 shows a parametric price-quota curve that is considered in this paper.

More details regarding the price-quota curve formulation is discussed in section 3.A.

Electricity retailers are intermediaries because they must purchase energy from suppliers and resale it to the final customers. Retailers must cope with a price and demand risk over a short term time horizon [34]. The main source of these uncertainties is the future pool prices. The customers' actual demand is another source of uncertainty which a retailer should cope with. Therefore, retailers must forecast the spot market prices as well as customers demand. If the higher price spikes have been forecasted, retailer might bids higher prices to enable more DR capacity. Considering that DR has its maximum capacity in the network, this constraint will limit the amount of purchased DR. In this situation, DR can omit a part of retailer's financial losses. If a retailer does not deliver the required load to customers, he/she will be penalized according to the energy not served which is not related to DR contracts.

Several methods have been introduced so far to forecast the demand and price of electricity. ARIMA models, wavelet transform model, and other approaches have been used to forecast both the electricity price and the demand [35-37]. Also, a hybrid method is developed in [38] which forecasts the electricity prices with reasonable error. In this paper, the ARIMA method is utilized for load and price forecasting.

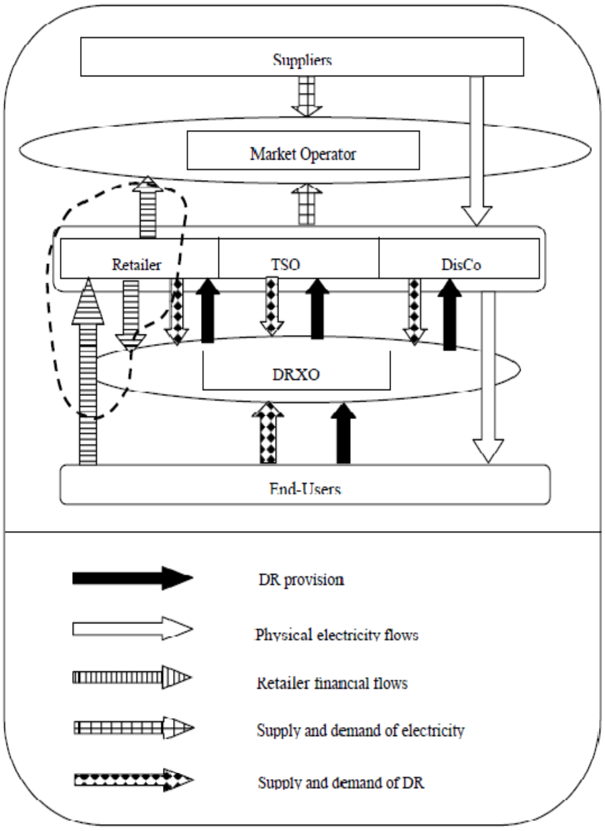

Fig. 1. General view of the proposed framework.

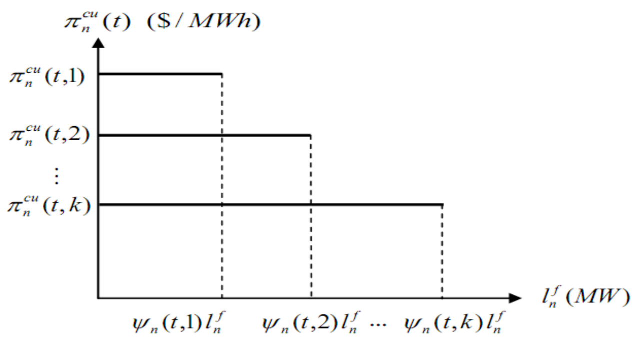

Fig. 2. Price-quota curve of the electricity supplied by the retailer.

The per unit daily price error is defined as:

$$e_d^p = \frac{1}{24}\left(\sum_{t=1}^{24}\frac{\left|\pi^s(t)-\pi^f(t)\right|}{\pi^s(t)}\right) \tag{1}$$

Also, the per unit daily load error is computed as:

$$e_d^l = \frac{1}{24}\left(\sum_{t=1}^{24}\frac{\left|\sum_n l_n^a(t)-\sum_n l_n^f(t)\right|}{\sum_n l_n^a(t)}\right) \tag{2}$$

3. Problem Formulation

In this section, the complete mathematical model of the problem is described which includes the price-quota curve, the objective function and associated constraints.

A. Price-quota Curve Formulation

The price quota curve can be formulated for each customer group in the considered time horizon as follows:

$$\pi_n^{cu}(t)=\sum_k \pi_n^{cu}(t,k)\times\delta_n(t,k) \qquad \forall t\in T,\ n\in\Gamma,\ k\in\Lambda \tag{3}$$

Taking into account the price-quota function, for each hour in the time horizon, one of the price blocks can be chosen by the retailer to sell electricity to the consumers. So, the value of δ in equation (3) will be equal to 1 for the selected price, and 0 otherwise. This constraint could be stated as the following equation:

$$\delta_n(t,k)\in\{0,1\}, \qquad \forall k\in\Lambda,\ t\in T,\ n\in\Gamma \tag{4-a}$$

$$\sum_k \delta_n(t,k)=1, \qquad \forall n\in\Gamma,\ t\in T \tag{4-b}$$

B. Objective Function

The retailers expected net profit is considered as an objective function which should be maximized through the optimization program. The income and the cost of the retailer can be categorized as following:

1) Expected revenue from selling electricity to the end-users,
2) Expected costs for buying electricity from suppliers in the day-ahead market,
3) Forward contract cost,
4) Expected cost/revenue from participating in the demand response exchange market, and
5) Expected cost/revenue from buying/selling electricity in the spot market.

Mathematical formulation of each of these income/cost resources is described separately at the following.

1) Expected revenue from selling electricity to the end-users

The expected income from selling energy to the end-users for a certain time horizon is defined by equation (5-a):

$$ER^{cu}=\sum_n\sum_t\sum_k \delta_n(t,k)\times\pi_n^{cu}(t,k)\times\left(\left(\psi_n(t,k)\times l_n^f(t)\right)-l_n^{DRX}(t)\right) \tag{5-a}$$

$$for \qquad t\in T,\ n\in\Gamma,\ k\in\Lambda$$

By considering the price-quota curve which is shown in

Fig. 2 and substituting it in the equation (5-a), retailer's income from selling electricity to end-users can be depicted as Fig. 3.
The expected income from selling energy to the end-users can also be expressed as the following:

$$ER^{cu} = \sum_{n}\sum_{t}\sum_{k} \delta_n(t,k)\times \pi_n^{cu}(t,k)\times \psi_n(t,k)\times l_n^f(t) \quad \text{(5-b)}$$
$$for \qquad t\in T,\ \ n\in \Gamma,\ \ k\in \Lambda$$

Equation (5-b) means that, end-user sells the DR that they have bought it. It should be noted that, both forms can be used to interpret the relation between DR and electricity prices and consequently the amount of retailer's revenue. Here, DR programs are contracts between retailers and customers which are traded in a day-ahead market. Retailers negotiate with DRSs to purchase DR in DA market, because they don't want to purchase electricity from wholesale market in high prices. So, instead of providing all forecasted electricity for customers, they negotiate with DRSs and cause load reduction with some incentives called as DR prices. Consequently, retailers' provided load and also customers purchased electricity are equal to $\left(\left(\psi_n(t,k)\times l_n^f(t)\right)-l_n^{DRX}(t)\right)$.

In addition to incentives which are paid to customers as DR prices, corresponding to the amount of load reduction, they have cost reduction in their electricity bill. So, equation
(5-a) will be utilized in these paper. More explanations about DR effective prices are given in the following of the paper.

2) Expected costs for buying electricity from suppliers in the day-ahead market

The optimal amount of the purchased electricity from day-ahead market is determined according to the forecasted prices and also the demand of customers. The amount of the purchased electricity is one of the decision variables which should be optimally determined. The expected cost of buying electricity from suppliers is described as the following equation:

$$\sum_{t}\pi^f(t)\times l_{DA}(t), \qquad \forall t\in T \qquad (6)$$

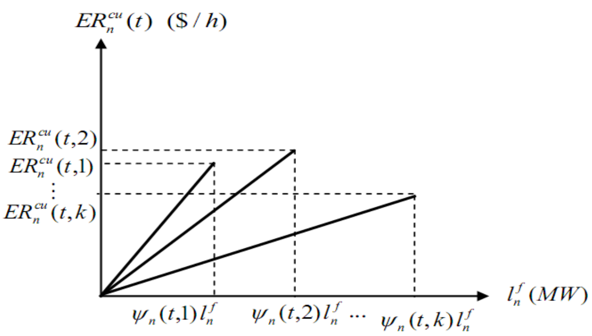

Fig. 3. Retailer's income from selling electricity.

3) Forward contract cost

Retailers can purchase a fixed amount of electricity through forward contracts. These contracts can consist of: peak, off-peak, and round-the-clock [23] as stated by equation (7):

$$C^{forward} = \sum_{t}\sum_{fc}\zeta(t,fc)\times p^{forward}(t,fc), \qquad \forall t\in T,\ \ fc\in N^f \qquad (7)$$

4) Expected cost/revenue from participating in the demand response exchange market

Demand response has many beneficiaries in the electricity market. DR buyers want to improve the reliability of their own electricity-dependent businesses and systems. Sellers of DR have the capacity to significantly modify their electricity demand. In this paper, it is considered that a retailer can participate in a pool-based DR market as well as the energy market. The cost of purchasing DR from DRX market can be stated as:

$$\sum_{n}\sum_{t} l_{R,n}^{DRX}(t)\times \pi_n^{DRX}(t), \qquad \forall t\in T,\ \ n\in\Gamma \qquad \text{(8-a)}$$

It should be noted that, by considering a linear curve for each demand response sellers' supply curve, the DR supply function can be defined for each group of customers as following:

$$\pi_n^{DRX}(t) = a^{cu,n} l_n^{DRX}(t) + b^{cu,n}, \qquad \forall t\in T,\ \ n\in\Gamma \qquad \text{(8-b)}$$

where $a^{cu,n}$ and $b^{cu,n}$ are constant coefficients. The coefficient $b^{cu,n}$ can be considered as $b^{'}(1-\theta_n)$ where, the coefficient θ_n is the customers' type and represents a customer's willingness to participate in DR programs. It takes a value between 0 and 1. By increasing the amount of θ_n, the cost of DR decreases because the customer has more willingness to participate in DR. Generally, higher amounts of $a^{cu,n}$ and $b^{cu,n}$ coefficients, denote the less willingness of DR sellers to participate in DR programs. On the other hand, decreasing the amount of these constant coefficients means that DR sellers have more willingness to participate in DRPs and so the cost of DR enabling will be decreased.

5) Expected cost/revenue from buying/selling electricity in the spot market

According to the difference between the amount of purchased electricity from both day-ahead and bilateral market and the amount of customers' actual load in the study time horizon, a retailer might sells his/her extra purchased electricity in a spot market or also might buy extra electricity to settle the end-users. The power that should be bought from the spot market is equal to:

$$\sum_t \left((l_{DA}(t) + \sum_n l_{R,n}^{DRX}(t) + \sum_{fc} p^{forward}(t,fc) - \right),$$
$$\sum_n \sum_k \delta(t,k) \times \psi_n(t,k) \times l_n^a(t)) \times \pi^s(t)$$
$$for, \ t \in T, \ n \in \Gamma, \ fc \in N^f, \ k \in \Lambda \tag{9}$$

C. Constraints

The maximization of the objective function is subjected to some constraints as following.

1) Balance

The total amount of the purchased electricity from suppliers and the enabled DR should be equal to the total amount of end-users demand. This constraint can be expressed as:

$$l^{DA}(t) + \sum_{fc} p^{forward}(t,fc) + \sum_n l_n^{DRX}(t) =$$
$$\sum_k \sum_n \delta(t,k) \times \psi_n(t,k) \times l_n^f(t) \tag{10}$$
$$for \ t \in T, \ n \in \Gamma, \ k \in \Lambda, \ fc \in N^f$$

2) Bounds on load and prices

The lower and upper bounds are considered on the amounts of the purchased load, DR capacity and all prices in electricity and DR markets to make the model more realistic. These constraints are stated as following:

$$0 \le l_n^{DRX}(t) \le l_n^{DRX,\max}, \qquad \forall n \in \Gamma, \ t \in T \tag{11}$$

$$l_{DA}(t) \ge o \qquad t \in T \tag{12}$$

$$\pi_n^{DRX}(t) \ge o \qquad \forall n \in \Gamma, \ t \in T \tag{13}$$

$$\pi_n^{cu}(t) \ge 0 \qquad \forall n \in \Gamma, \ t \in T \tag{14}$$

$$p^{forward}(t,fc) \ge 0 \qquad \forall t \in T, \ fc \in N^f \tag{15}$$

$$\zeta(t,fc) \ge 0 \qquad \forall t \in T, \ fc \in N^f \tag{16}$$

D. Complete Problem Formulation

The complete optimization model for maximizing the retailer's expected profit from participating in both electricity and DRX markets is developed as equation (17). In equation (17), $\pi_n^{DRX}(t)$ and $\rho^{db}(t)$ are DRSs' supply function and DRBs' demand function, respectively.

$$Max \quad \{RB\}$$
$$where,$$
$$RB = \sum_n \sum_t \sum_k \delta_n(t,k) \times \pi_n^{cu}(t,k) \times \left(\left(\psi_n(t,k) \times l_n^f(t) \right) - l_n^{DRX}(t) \right)$$
$$- \sum_t \pi^f(t) \times l_{DA}(t)$$
$$- \sum_n \sum_t l_{R,n}^{DRX}(t) \times \pi_n^{DRX}(t)$$
$$- \sum_t \sum_{fc} \zeta(t,fc) \times p^{forward}(t,fc)$$
$$+ \sum_t \left((l_{DA}(t) + \sum_n l_{R,n}^{DRX}(t) + \sum_{fc} p^{forward}(t,fc) - \right)$$
$$\sum_n \sum_k \delta(t,k) \times \psi_n(t,k) \times l_n^a(t)) \times \pi^s(t)$$
$$s.t.:$$
$$Constraints \quad (10-16)$$
$$\pi_n^{DRX}(t) = a^{cu,n} l_n^{DRX}(t) + b^{cu,n}$$
$$\rho^{db}(t) = a^{db} \times DR^{db}(t) + b^{db}$$
$$for \quad t \in T, \ n \in \Gamma, \ k \in \Lambda, \ fc \in N^f, \ db \in \Delta \tag{17}$$

4. Numerical Study

A. Load and Price Forecasting

The real data of Spain electricity market in 2002 has been used in this section for simulation studies [39]. The scheduling time horizon is considered to be 24 hours and an ARIMA model is utilized for price and load forecasting. Figs. 4 and 5 show the results of load and price forecasting. Both forecasted and real data are shown in these figures. Here, e_d^p and e_d^l values are equal to 9.7 and 1.4 percent, respectively.

B. Data and Assumptions

As described in previous sections, linear curves are considered as DRSs' supply functions. Three types of customer groups and therefore three types of DRSs are considered here according to their willingness to participate in DR. The common values for $a^{cu,n}$ and $b^{cu,n}$ is considered to be 1 and 5 for the first DRS, 3 and 8 for the second one, and 5 and 10 for the third one, respectively. Furthermore, the amount of DR capacity is considered equal to 15% (5% for each customer group) of network load for each hour. At the next step, the effects of "$a^{cu,n}$" and "$b^{cu,n}$" variations are evaluated and the results have been discussed.

For the sake of simplicity and without loss of generality, one retailer, one TSO and one distributor are assumed here as DR buyers. Linear demand functions are considered for DR buyers which are shown in Table 1.

The control variable for optimal determination of DRBs demand curve is considered to be b^{db}. In fact, it is assumed that DRBs change their DR demand function using b^{db}. The a^{db} coefficients are assumed to be equal to -10 for all DRBs.

An elastic behavior is assumed for customers for modeling their reaction when encountered with high prices. The elasticity is defined as the load sensitivity to price changes and is divided into self and cross elasticity. More details about elasticity can be found in [12]. In this paper, self and cross elasticity values are considered as shown in Table 2.

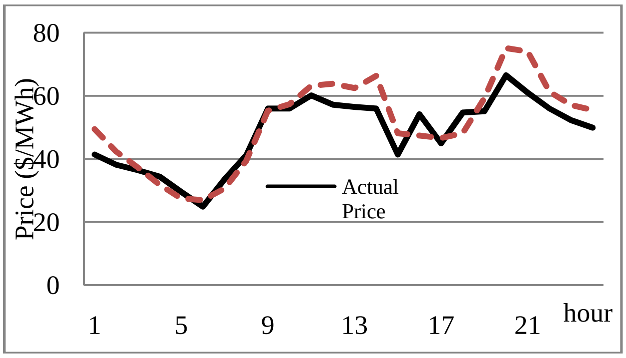

Fig. 4. Forecasted and real data of electricity price using of an ARIMA method.

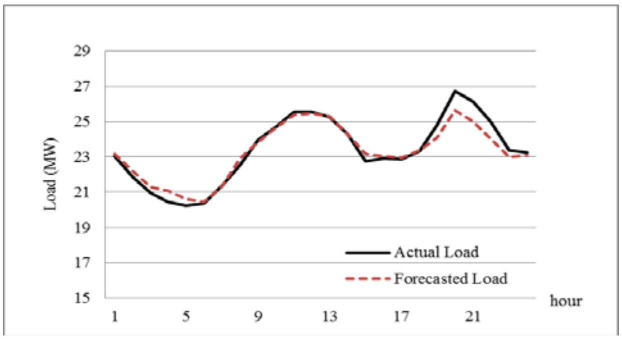

Fig. 5. Forecasted and real data of electricity demand using of an ARIMA method.

Table 1. Demand functions for DR.

DR buyers	DR demand function
Retailer	$\rho^R = a^R \times DR^R + b^R$
TSO	$\rho^{TSO} = a^{TSO} \times DR^{TSO} + b^{TSO}$
Distributor	$\rho^D = a^D \times DR^D + b^D$

Table 2. Elasticity values.

Self-elasticity	Cross elasticity
-0.2	0.012

Three stage tariffs will be considered for customer groups during a day. Hereinafter, the load elasticity concept is utilized to model the customers' reaction to price changes, and the introduced price-quota curve is not considered in numerical studies. Also, forward contracts are not considered in this section. These assumptions will not affect the generality of this study.

The amounts of purchased DR by a retailer are depending on the differences between electricity forecasted prices and selling contracts to consumers. As forecasted prices are higher than selling contracts, retailers will be more interested to purchase DR. However, if the selling contract prices be higher than forecasted prices, they will not be persuaded to purchase DRRs.

Also, in this work, the minimum up or down times are not considered for DR enabling in the network during the scheduling period. This means that, DRSs can change their supplied DR in each hour within the minimum and maximum capacity of DR. This assumption will not reduce the generality and accuracy of the proposed method.

C. Results Analysis

This subsection provides numerical results and their analysis. As mentioned in previous sections, by using of proposed framework, retailer determines the optimum amount of purchased load from DA market, contract price with his/her clients and the amount of purchased DR from DRX market in order to maximize his/her expected profit. Retailers' contracts with customers are considered to be as three-stage tariffs through a day. According to these assumed tariffs, the first time period include hours 2-8; the second one include hours 9-18, 23-24 and hour 1; and the last period include hours 19-22. These categorizes are according to the off-peak, shoulder and peak load times during a day. If a retailer proposes high contract prices to end-users, he/she may loss his/her customers. So, the contract prices should optimally be determined by retailers to maximize their expected profit. The contract prices between retailer and customers are 32, 56 and 71, respectively for each defined period. Also, the retailer should determine his/her DR demand curve optimally to purchase his/her desired DR from DRX market. The optimal amounts of b^R is achieved as shown in Table 3.

The amounts of purchased load are shown in Table 4. These are total amounts of load which is bought for all customer groups. Concurrently, the amounts of enabled DR are shown in Table 5. The sum of the values that are shown in Tables 4 and 5 is equal to the forecasted load which is illustrated in Fig. 5.

As it can be seen in Table 5, the amount of traded DR in hour 2 is higher than hour 20. Since the difference between forecasted and selling prices in hour 2 is comparatively more than the difference in hour 20, retailer expose to higher price risks in hour 2 in compare to hour 20. By this reason, retailer tries to mitigate his/her risk by using of enabling more DR in hour 2 than hour 20.Determined demand response prices are shown in Table 6 during a day.DR prices are varying according to the required DR in each hour. Furthermore, customers' incentives are in addition to the cost reduction in their electricity bill because of participating in DRPs and the consequent load reduction. If, it is assumed that customers buy electricity and resell it due to participating in DR, the price of sold load should be cumulated with the DR supply price to evaluate DR supply effective prices. This means that, if the real value of electricity for customers is not taken into account, the sum of electricity and above mentioned DR prices is remained for customers. Table 7, shows the effective price of DR per MWh.

The amount of retailer benefit by varying the amount of DR capacity is depicted in Fig. 6. In this figure, a_i and $b_i^{'}$ values are considered equal to 8 and 5 for all DR providers. The amount of DR capacity is considered to be a percentage of network load in each hour.

The amount of improvement in retailer's profit due to involving in DR market depends on the customers' willingness to participate in these programs and will vary by changing the DRSs' supply curves. Fig. 7 illustrates the expected profit of the retailer versus "$a^{cu,n}$" and "$b^{cu,n}$" coefficients. In Fig. 7, it is assumed that $a^{cu,1} = a^{cu,2} = a^{cu,3} = a$ and also $b^{cu,1} = b^{cu,2} = b^{cu,3} = b$.

Increasing the coefficients of DRSs' supply curves means that DR sellers have less willingness to participate in DR and so the price of DR enabling will be higher.

It should be mentioned that, since both the electricity and DR markets are considered to be day-ahead, retailer acts based on his/her forecasts of load and price. In fact, all the results of players benefit are the expected profit. For investigating the effect of spot market, the real data of load and price that have shown in Figs. 4 and 5 should be utilized. However, retailer acts according to load and price forecasted data to maximize his/her expected benefit. So, results of real benefits and therefore the spot market are not considered in numerical studies.

Table 3. The b^R values for each hour during a day.

Hours	b^R	**Hours**	b^R
2	23.941	**13**	21.881
3	19.319	**14**	23.944
8	22.368	**20**	16.086
11	21.905		
12	21.927	**at other hours**	–

Table 4. The amount of purchased load from DA market.

Hours	**Purchased load from DA market (MW)**	**Hours**	**Purchased load from DA market (MW)**
1	23.895	**13**	22.680
2	23.541	**14**	21.548
3	23.416	**15**	23.909
4	25.707	**16**	23.824
5	25.253	**17**	23.727
6	25.098	**18**	24.097
7	25.965	**19**	22.090
8	24.429	**20**	21.356
9	24.472	**21**	22.733
10	25.146	**22**	22.033
11	22.742	**23**	23.760
12	22.803	**24**	23.836

Table 5. Total traded DR during a day.

Hours	**Total traded DR (MW)**	**Hours**	**Total traded DR (MW)**
2	3.282	**13**	2.964
3	2.496	**14**	3.283
8	3.110	**20**	1.826
11	2.971		
12	2.978	**at other hours**	0

Table 6. Rated price of DR.

Hours	**DR price ($/MWh)**	**Hours**	**DR price ($/MWh)**
2	13	**13**	12
3	11	**14**	13
8	12	**20**	10
11	12		
12	12	**At other hours**	0

Table 7. Effective price of DR

Hours	**Effective price of traded DR ($/MWh)**	**Hours**	**Effective price of traded DR ($/MWh)**
2	45.38	**13**	67.95
3	43.38	**14**	68.95
8	44.38	**20**	81.13
11	67.95		
12	67.95	**At other hours**	0

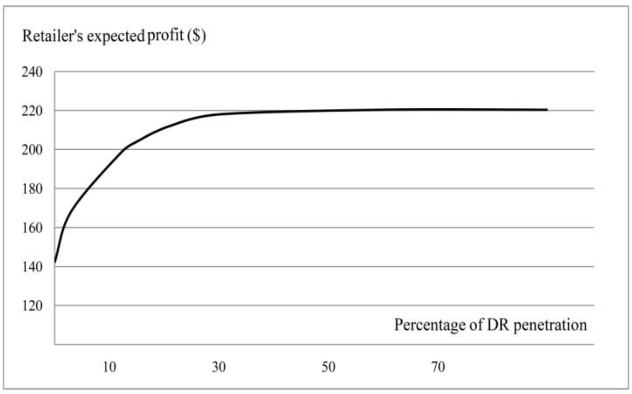

Fig. 6. Retailer expected profit by variation of DR penetration in the network.

The amount of DRSs' surplus from participating in DRX market is depicted in Fig. 8. Fig. 8 demonstrates the customers' surplus versus their DR supply functions coefficients.

Increasing the coefficients of DRSs' supply functions will increase the price of DR enabling and therefore will decrease the amount of purchased DR in the system. Indeed, DRSs can increase their profit in two ways: increasing the DR price or increasing the amount of enabled DR. However, by increasing the amount of DR supply function coefficients, the price of DR is increased and consequently the amount of traded DR is decreased. As it can be seen from Fig. 8, at first, increasing the price of DR is dominant factor and improves DRSs benefit, but when DR price tends to be much higher, the traded DR reduction as a consequence of higher prices is a dominant factor and reduces the profit of the retailer.

The market total benefit under the pool-based DR market will be higher than the conventional bilateral DR trading market. By considering the typical values of "$a^{cu,n}$" and "$b^{cu,n}$" coefficients, if a retailer involves in DRX market as well as electricity market, it's benefit will be equal to 222.328 ($) while if this retailer participates in electricity market and also in bilateral DR market, his/her benefit will decrease to 157.872 ($), because he/she should be responsible alone for DR enabling in DR bilateral market. Also, the customers' benefit is equal to 91.669 ($) and 4.396 ($) by participating in DR pool-based market and bilateral market, respectively.

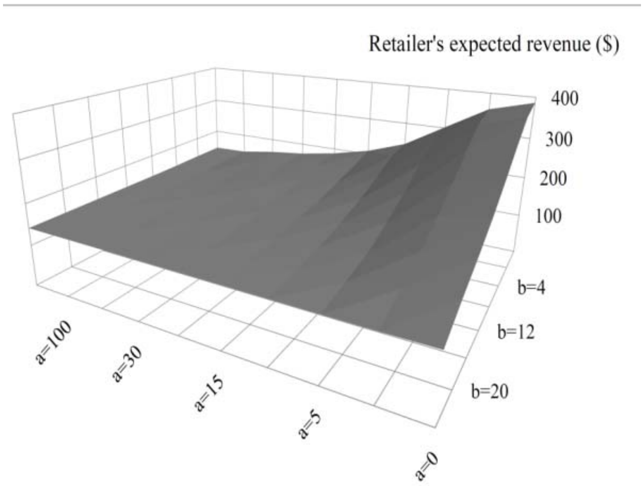

Fig. 7. Retailer's expected revenue by changing the amount of "$a^{cu,n}$" and "$b^{cu,n}$" coefficients.

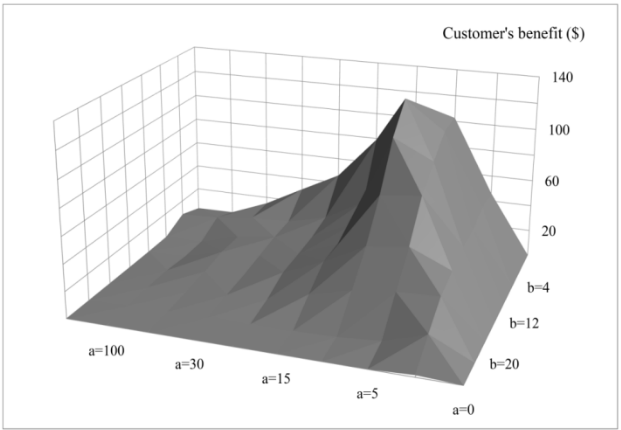

Fig. 8. The amount of customers' net surplus by participating in the DRX market versus the DRSs' supply curve.

5. Conclusion

In this paper a comprehensive framework is proposed for retailers: 1) to determine the optimal contract price with clients, 2) to determine the optimal amount of the purchased load from day-ahead market, and 3) to determine the DR demand curve which should present to DRX market. The main aim was to maximize the expected benefit of a retailer. A retailer participates in two markets simultaneously: electricity market and DR market. The elastic behavior of the end-users is considered as their reaction to high electricity prices. A case study using of Spain market data has been presented to demonstrate the usefulness and advantage of the proposed framework. The results show that using of this framework can have impressive effect on improving the expected benefit of a retailer. Furthermore, comparisons between the benefit of market players under DR pool and bilateral markets, show the advantage of the DRX market, where all players can have more benefit from participation in DRPs. Indeed, pool-based scheme for DR trading deals DR sellers with multiple buyers in a competitive way and therefore causes more profit for both group of buyers and sellers.

Nomenclature

Numbers

N	indicator for the number of customer groups
K	indicator for the number of price blocks
t	indicator for the number of hours of scheduling time horizon
m	indicator for the number of load and price intervals
db	indicator for the number of Demand Response Buyers (DRB)
fc	indicator for the number of forward contracts

Sets

Λ	set of price blocks
Γ	set of group of end-users

Δ	set of demand response buyers
N^f	set of forward contracts

Real Variables

$\pi_n^{cu}(t,k)$	the selling electricity price of the k^{th} block to customer group *n* at hour *t* (*\$/MWh*)
l_n^{DRX}	the quantity of sold DR by n^{th} customer group (*MW*)
l_{DA}	the amount of purchased load from day-ahead (DA) market (*MW*)
$l_{db,n}^{DRX}$	The amount of purchased DR from n^{th} DRS by db^{th} DRB (*MW*)
ER^{cu}	retailer expected revenue from selling electricity to customers (*\$*)
RB	the expected benefit of retailer (*\$*)
a^{db}	first coefficient of DR demand functions (*\$/MW²h*)
b^{db}	second coefficient of DR demand functions (*\$/MWh*)
DR^{db}	the amount of purchased DR by db^{th} buyer (*MW*)
$p^{forward}$	the amount of load in fc^{th} forward contract at hour *t* (*MW*)
p^*	price of DRX market equilibrium point (*\$/MWh*)
x^*	quantity of DRX market equilibrium point (*MW*)
$\psi_n(t,k)$	portion of load that the customer group *n* buy form the retailer at hour *t* if the retailer offer electricity price $\pi_n^{cu}(t,k)$
$C^{forward}$	cost of forward contracts

Binary variables

$\delta_n(t,k)$	binary variable which is equal to 1 if the selling electricity price for the customer group *n* at hour *t* is equal to the price of the k^{th} block, and zero otherwise.

Constants

p_n^{cu}	the amount of n^{th} customer group load (*MW*)
l_n^f	forecasted load of customer group *n* (*MW*)
$\pi^f(t)$	forecasted price of spot market (*\$/MWh*)
T	scheduling time horizon
$a^{cu,n}$, $b^{cu,n}$	the coefficients of n^{th} Demand Response Seller (DRS) supply curve ($a^{cu,n}$ in [*\$/MW²h*]and $b^{cu,n}$ in [*\$/MWh*])
θ_n	customers' type
$l_n^a(t)$	customers' actual load at hour *t* (*MW*)
$\pi^s(t)$	actual price of spot market at hour *t* (*\$/MWh*)
e_d^p	the per-unit daily price error
e_d^l	the per-unit daily load error
ζ	the price of fc^{th} forward contract at hour *t* (*\$/MWh*)
$l_n^{DRX,\max}$	maximum DR capacity of n^{th} DRS

Functions

ψ^n	acceptance function of customer group *n*
ρ^{db}	DR demand function from db^{th} buyer
π_n^{DRX}	DR supply function of n^{th} seller

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