Retail Pricing and Day-Ahead Demand Response in Smart Distribution Networks

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Abstract :

This paper focuses on day-ahead (DA) retailing for fixed and Time-of-Use (TOU) price taker customers and DA real time pricing for active customers who participate in short-term markets. Customers' response to the offered hourly prices are modeled using an hourly acceptance function which includes decreasing linear probability density functions based on the hourly minimum and maximum retail prices allowed by market regulators. Furthermore, the retailer offers its active customers to participate in the DA demand response program and voluntarily reduce their real time consumption for offered incentives. Numerical studies represent the effect of implementing demand response programs on the total benefit of retailing.

Keywords: Day-ahead retail market, Demand response, Hourly acceptance function, Pricing, Smart power grid.

Nomenclature

$acc(P_{RT}(h))$	Acceptance of the real time price
$B_{fix}(h)$	Benefit resulted from selling electricity to the fixed price taker customers at $h-th$ hour ($)
$B_{TOU}(h)$	Benefit resulted from selling electricity to the TOU price taker customers at $h-th$ hour ($)
$B_{RT}(P_{RT}(h))$	Benefit resulted from selling electricity to the real time price taker customers at $h-th$ hour ($)
$B_{RT}^{EP+DR}(h)$	Obtained benefit through energy procurement for active customers and implementing DADRP ($)
$Fix(h)$	Hourly load consumption of fixed price taker customers (MWh)
$INC(h)$	Retailer's share from the hourly incentives paid by ISO ($)
$P_{RT}(h)$	Offered real time tariff at $h-th$ hour ($/MWh)
PF	Penetration factor (%)
$RT(P_{RT}(h))$	Hourly load consumption of real time price taker customers as a function of electricity price (MWh)
$TOU(h)$	Hourly load consumption of TOU price taker customers (MWh)

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1. Introduction

Smart power systems lean on four fundamental factors: Security, Quality, Reliability and Availability (SQRA) to meet the electrical needs of digital society based on convergence of energy, communication, internet, and electronic commerce [1]. Equipped with Advanced Metering Infrastructure (AMI), the smart power grid follows demand response (DR) programs based on dynamic and time-differentiated retail prices which produce large amounts of price responsive demand and result in significant SQRA and economic benefits such as electricity price reduction, transmission lines congestion resolving, security enhancement and improvement of market liquidity [2],[3]. Electricity markets and customers' participation in DR programs have been focused by many researches in recent years [2]-[10]. References [9]-[17] have studied pricing strategies and subsequent reaction of customers due to changes in the offered retail prices. Modeling customer response to the both groups of time-based and incentive-based DR programs has been presented in [13]. Ref. [14] has proposed a load management strategy that considers the power-purchase of energy of the consumers in a real-time pricing DR program optimizing the negotiation between the consumer and retailer. Considering DR patterns for different consumer types, price elasticity matrices have been developed in [15] to accurately model consumer behavior. Clustering similar demand patterns of customers has been addressed in [16] using large-scale sets of electric demand profiles.

In a complete competitive retail market, customers may have the right to switch to more profitable pricing programs offered by other retailers even in a short-term market such as DA one. Reference [10] has focused on fixed pricing pattern for monthly bilateral contracts and has modeled the customer response using a type of market share function. Based on the market share function employed in the recent paper, an hourly acceptance function has been proposed in [17] to model customers' demand in response to the varying hourly prices. Reference [11] has presented an acceptance function based on the acceptable energy costs for different clusters of customers. The latter model does not represent the percentage of the load, which customers may decrease, or purchase from other retailers according to the offered prices. A linear acceptance function has been proposed in [12] specifying the probability of accepting the offered Time-of-Use (TOU) prices by the end-users.

Retail energy providers should have precise evaluations from customers' demand as well as the wholesale price of the electricity in order to run their retailing activities in an economically optimized manner. Consequently, different forecasting approaches have been presented in many researches [18]-[20]. Ref. [18] has proposed several data mining approaches for electricity market price classification. Short term multiple load forecasting (STMLF) and the use of anthropologic and structural data within STMLF have been presented in [19]. Ref. [20] has focused on short-term gross annual electricity demand by applying fuzzy logic methodology using general information on economical, political and electricity market conditions.

The restructured power market provides divergent classes of customers with the requisite electricity power at some distinctive prices including predetermined fixed and time-of-use rates and also hourly varying cost. This paper models Day-Ahead (DA) retailing operations of a retailer for its customers who adopt three pricing patterns i.e. fixed pricing, TOU and Real Time (RT) pricing programs. The fixed and TOU price taker customers purchase energy at predetermined prices while RT price taker customers pay their electricity use at hourly varying prices which are offered by their respective retailer. Hereinafter, the former two groups of customers are referred to as inactive customers and the customers in the third class are called active customers.

The expected competition among energy providers in a competitive retail environment affect the offered retail prices to the active customers who keep the retail market under surveillance and may decrease their electricity purchase from their current retailer through supply all or a part of their electricity demand from other resources in order to manage the corresponding electricity bills. Here, the focus is on DA real time pricing as a time-based DR program for active customers and Day-Ahead Demand Response Program (DADRP) as an incentive-based DR scheme, both from the retailers' responsibilities. This paper does not focus on predicting procedure. Accordingly, it is considered that the retailer employs artificial neural networks (ANNs) as a forecasting approach to predict customers' demand as well as wholesale electricity prices with up to %10 error of price forecasting. As in a competitive retail market, the procedure addressed here allows these customers to adjust their effective demand according to the real time retail prices and/or change their retail energy provider even in a daily basis. Consequently, this paper proposes an hourly acceptance function. In order to represent the rational behavior of customers, the proposed acceptance function is composed of decreasing linear probability density functions supported by minimum and maximum DA retail prices which are allowed by market regulators.

Furthermore, in this paper the retailer plays the role of an enrolling participant who proposes its active customers to participate in a DADRP and reduce their energy consumption. DADRP allows customers to submit an offer concurrent with the DA energy market to curtail electricity consumption for the following day. The retailer forecasts DA wholesale prices. The predicted prices indicate the approximate maximum values for the prices which would be offered to ISO for the curtailed load by DADRP participants. The retailer suggests some prices less than the predicted values to participant customers in order to help customers in making imminent offers of load reduction.

The remaining parts of the paper are structured as follows. Section 2 presents the retailer's interactions with other market players. Section 3 discusses energy procurement for inactive customers. Section 4 is on the energy procurement and retail pricing for active customers. Section 5 is assigned to the day-ahead demand response program and section 6 represents numerical studies. Finally, section 7 concludes the paper.

2. Retailer's interactions with other market players

Smart distribution networks supply their customers with electricity of different quality levels and pricing patterns. In a real world competitive retail market there are some competitive retailers which try to partake in the retail market as more as possible. However, in this paper we focus on operation of one retailer that has an indirect competition interaction with others via sensitivity of customers to the proposed hourly price signals. A retailer is an economic enterprise which does marketing, wins electricity customers and encourages them to hold next contracts offering various demand response programs so as to gain profit. The smart power grid follows DR programs to establish bidirectional interrelations with customers in order to improve the system operation state, utilizing demand-side potential. DR programs are conducted in two groups of incentive-based and time-based programs [8].

One of the key roles of the retailer is to know local consumption market completely to be the final winner of the customer absorption game. In order to analyze different groups of customers, we suppose the retailer categorizes its customers to residential, commercial and industrial customers into fixed price takers, TOU and real time price takers groups.

Fig. 1 shows the interactions between a retailer and other market players in a smart distribution network. Distribution system company (DISCO) is responsible for calculating and managing SQRA indices in distribution networks and regulating distribution market, to optimize system's performance. The retailer purchases the demanded energy from the DA wholesale market and serves its customers in cooperating with DISCO. All inspection and maintenance operations of the system are performed by DISCO, which is aware of distribution system conditions, its strengths, weaknesses and contingency elimination tools such as maneuver points, etc. Fixed and TOU price taker customers, here called as inactive customers, wish to access to reliable, qualified, and inexpensive electricity but not engaging in price variations. They do not participate in short-term contracts and the retailer is obligated for supplying their consumption according to their contracts. The retailer should have a precise prediction of inactive customers' energy consumption.

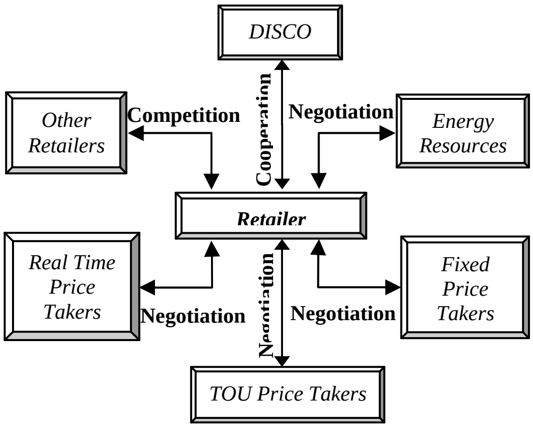

Fig. 1. The retailer's interactions with other market players in a smart distribution network

Real time price taker customers usually purchase a portion of their demand through bilateral contracts and then bid in day-ahead and spot markets to procure their needed surplus electric power. They wish to buy reliable and qualified electricity at dynamic prices in order to optimize electricity consumption and manage their electricity bills. These customers, here called as active customers, are aware of competitor retailers offers and have a good prediction about their hourly demand. They monitor other price alternatives and different provided services and usually participate in a variety of demand response programs.

Retailers plan for their marketing activities based on the wholesale energy prices. In DA energy market, they should have an acceptable prediction of DA energy prices, which directly affects the energy procurement plans and retail pricing for real time price taker customers. Here, it is considered that the retailer predicts the DA hourly wholesale prices with up to %10 error of price forecasting.

3. Energy procurement for inactive customers

The retailer is aware of its different classes of customers. Here, the residential, commercial and industrial customers are classified into fixed, TOU and RT price takers groups. Let $R^{Fix}(h)$ and $R^{TOU}(h), h = 1,2,...,24$ be the forecasted hourly load consumption of residential customers who adopt fixed and TOU pricing patterns, respectively. Also, $C^{Fix}(h), C^{TOU}(h)$ and $I^{TOU}(h)$ demonstrate the forecasted hourly load consumption of commercial and industrial customers who participate in fixed/TOU pricing patterns, respectively. As shown in Eq. 1, $Fix(h)$ includes energy consumption of customers from residential and commercial sectors.

$$Fix(h) = R^{Fix}(h) + C^{Fix}(h) \tag{1}$$

TOU price taker customers include customers from triple sectors of consuming groups. The hourly load consumption of these customers is formulated as:

$$TOU(h) = R^{TOU}(h) + C^{TOU}(h) + I^{TOU}(h) \tag{2}$$

Here, it is considered that the retailer has supplied a portion of previously predicted consumption of the inactive customers, typically 0.9 of it, through long-term contracts. Therefore, the surplus consumption which is necessary to be supplied in short term markets, $D(h)$, can be obtained as:

$$D(h) = 0.1 \times D_1(h) + \left(D_2(h) - D_1(h)\right) \tag{3}$$

Where $D_1(h)$ represents the inactive customer's consumption based on retailer's prior forecasts and $D_2(h)$ is the last forecast of their energy consumption at $h-th$ hour of the next day. The term $D(h)$ represents each of fixed/TOU price taker groups $\left(R^{Fix}(h), C^{Fix}(h), R^{TOU}(h), C^{TOU}(h), I^{TOU}(h)\right)$ in separate demand forecasting procedures for them.

Considering $p_w(h)$ as the forecasted DA wholesale price, the cost of energy procurement for fixed price takers would be $Fix(h) \times p_w(h)$. If the predetermined fixed price for residential and commercial customers be denoted by p^R_{Fix} and p^C_{Fix}, then the expected benefit through energy retailing for fixed-price taker customers will be obtained as:

$$B_{Fix}(h) = R^{Fix}(h) \times p^R_{Fix} + C^{Fix}(h) \times p^C_{Fix}(h) - Fix(h) \times p_w(h) \tag{4}$$

The obtained benefit of retailing for TOU price takers depends on predetermined peak, off-peak and valley TOU prices for triple sectors of residential $\left(p^R_p, p^R_o, p^R_v\right)$, commercial $\left(p^C_p, p^C_o, p^C_v\right)$, and industrial $\left(p^I_p, p^I_o, p^I_v\right)$ customers. Here, it is considered that commercial and industrial customers pay the energy at the same TOU prices $p^C_p = p^I_p$ and $p^C_o = p^I_o$ and $p^C_v = p^I_v$. The forecasted DA wholesale price directly affects the cost of energy procurement for the customers of TOU pricing class $\left(TOU(h) \times p_w(h)\right)$. Consequently, the retailer's benefit from energy procurement for TOU price taker customers will be acquired such as:

$$B_{TOU}(h) = -TOU(h) \times p_w(h) + R^{TOU}(h) \times p^R_{TOU} + \left(C^{TOU}(h) + I^{TOU}(h)\right) \times p^C_{TOU}$$

where,

$$p^R_{TOU} = \begin{cases} p^R_v & if \quad h \in \{valley\} \\ p^R_o & if \quad h \in \{off-peak\} \\ p^R_p & if \quad h \in \{peak\} \end{cases} \tag{5}$$

$$p^C_{TOU} = \begin{cases} p^C_v & if \quad h \in \{valley\} \\ p^C_o & if \quad h \in \{off-peak\} \\ p^C_p & if \quad h \in \{peak\} \end{cases}$$

The term p^R_{TOU} represents predetermined TOU rates of electricity at peak, off-peak and valley hours for residential customers, while p^C_{TOU} includes these prices for commercial customers.

4. Energy Procurement and Retail Pricing for Active Customers

This section is devoted to the energy procurement and real time pricing for active customers. The offered hourly prices $\left(p_{RT}(h)\right)$ will be optimized so as to maximize the expected obtained benefit through electricity retailing for this class of customers.

Active customers purchase a portion of their energy need in the DA market. In order to supply the active customers with electricity of hourly varying worth, the retail energy provider offers optimum DA prices and experiences subsequent demand side reactions. The customer's effective DA demand reflects their response to the offered prices. Therefore, as the effective demanded loads depend on the offered prices, it is required to supply requisite electricity and determine real time prices for it, simultaneously.

Let the demanded load of commercial and industrial customers who adopt real time pricing pattern be denoted by $C^{RT}(p_{RT}(h))$ and $I^{RT}(p_{RT}(h))$, respectively. Therefore, the total amount of the effective demand of RT-price taker customers is:

$$RT(p_{RT}(h)) = C^{RT}(p_{RT}(h)) + I^{RT}(p_{RT}(h)) \quad (6)$$

A demand value of $RT(p_{RT}(h))$ includes the total load of real time price takers composed of commercial customers' demand and industrial.

4.1. Acceptance function

The function of $RT(h) = F(p_{RT}(h))$ has been addressed in [10]-[12]. The probability density function according to which the retailer sets its equilibrium prices is usually defined as the market share or acceptance function [10]. Acceptance function is a decreasing function in which by increasing the offered price, the total confirmed demand would be decreased. Several factors such as long-term strategy of the retailer, risk attitude, the behavior of customers and the behavior of the competitors must be considered in determination of acceptance function [21]. In [12], two decreasing linear functions have been introduced as the models of customers' reaction against TOU offered prices. TOU pricing means to value electricity at two prices depended on time of energy consumption while real time pricing is constituted from offering 24 hourly prices. Here, for each hour of DA real time pricing a linear acceptance function is proposed based on the minimum and maximum retail prices allowed by independent system operator (ISO) which directly affect the customers' responses to the offered prices. If the minimum and maximum hourly retail prices be denoted by $p_{RT}^{min}(h)$ and $p_{RT}^{max}(h)$, then a linear acceptance function can be assigned to each offered price such as:

$$acc(p_{RT}(h)) = \frac{p_{RT}^{max}(h) + \varepsilon - p_{RT}(h)}{p_{RT}^{max}(h) + \varepsilon - p_{RT}^{min}(h)} \quad (7)$$

The proposed acceptance function depends on the minimum and maximum hourly retail prices, which are allowed by the market regulators. Maximum price acceptance by the active customers occurs at $p_{RT}(h) = p_{RT}^{min}(h)$. In other words, selling energy to the customers at the minimum hourly prices satisfies them completely.

Fig. 2 shows the proposed linear acceptance function for DA real time pricing. According to Eq. 7, $acc(p_{RT}^{max}(h) + \varepsilon) = 0$ and $acc(p_{RT}^{min}(h)) = 1$. It means that $p_{RT}^{max}(h)$ is the highest offered price in which $acc(p_{RT}^{max}(h))$ is above zero and customers do not accept the offered prices beyond $p_{RT}^{max}(h)$.Minimum retail prices $(p_{RT}^{min}(h))$ are the hourly prices at which the effective demands of active customers are equal to their initial demands; $RT_0(h)$.

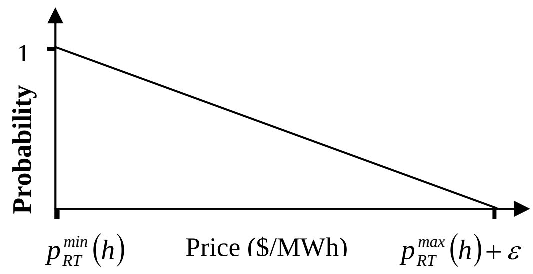

Fig. 2. The proposed hourly acceptance function

Therefore, the active customers' effective hourly demands will be as follows:

$$RT(p_{RT}(h)) = RT_0(h) \times acc(p_{RT}(h))$$
$$= RT_0(h) \times \frac{p_{RT}^{max}(h) + \varepsilon - p_{RT}(h)}{p_{RT}^{max}(h) + \varepsilon - p_{RT}^{min}(h)} \quad (8)$$

The offered hourly price affects customers' demand as it is demonstrated by Eq. (8). Offering $p_{RT}(h) = p_{RT}^{min}(h)$ attracts the maximum electricity demand while selling electricity at $p_{RT}(h) > p_{RT}^{max}(h)$ results in loosing demand.

4.2. Benefit function

Retailing benefit through supplying the effective demand of RT-price taker customers will be obtained as:

$$B_{RT}(h) = RT(p_{RT}(h)) \times (p_{RT}(h) - p_w(h)) \quad (9)$$

Neglecting the ignorable value ε and substituting Eq. 8 in Eq. 9 results in:

$$B_{RT}(h) = RT_0(h) \times (p_{RT}(h) - p_w(h))$$
$$\times \frac{p_{RT}^{max}(h) + \varepsilon - p_{RT}(h)}{p_{RT}^{max}(h) + \varepsilon - p_{RT}^{min}(h)} \quad (10)$$

The hourly benefit function (Eq. 10) would be maximized by $\frac{\partial B_{RT}(h)}{\partial p_{RT}(h)}$ which results in the optimum hourly prices as:

$$p_{RT}^{opt}(h) = \frac{1}{2}\left(p_{RT}^{max}(h) + p_w(h)\right) \quad (11)$$

The probability of accepting optimum hourly prices would be as $acc(h) = \frac{0.5\left(p_{RT}^{max}(h) - p_w(h)\right)}{p_{RT}^{max}(h) - p_{RT}^{min}(h)}$ and consequently, the retailer would receive active customers' effective demand as the following:

$$RT\left(p_{RT}^{opt}(h)\right) = \frac{0.5RT_0(h) \times \left(p_{RT}^{max}(h) - p_w(h)\right)}{p_{RT}^{max}(h) - p_{RT}^{min}(h)} \quad (12)$$

According to Eq. (10) and (12), the sequent retail benefit would be as the following:

$$B_{RT}^{opt}(h) = \frac{RT_0(h)}{4} \times \frac{\left(p_{RT}^{max}(h) - p_w(h)\right)^2}{p_{RT}^{max}(h) - p_{RT}^{min}(h)} \quad (13)$$

Therefore, the optimum retail prices and retail benefit will be dependent upon the maximum retail prices determined by ISO.

5. Day-Ahead Demand Response Program

DADRP allows customers to submit an offer concurrent with the DA energy market to curtail electricity consumption for the following day.

The offer would specify a proposed price in the range of 50 to 1000 $/MWh, the amount of curtailment (at least 100 kW per demand response asset), and minimum duration (up to four hours) over which the retail customer would be willing to reduce consumption. The offers less than or equal to the DA market hourly clearing prices will be accepted by the ISO.

According to the New-England energy market whose demands/prices data and retail regulations are utilized in this study, customers must enroll in DADRP through an enrolling participant such as local utilities, competitive electricity retailers and demand response providers. Due to the focus of the paper on the retail procedures, here the retailer plays the role of a trailblazer enrolling participant who proposes its active customers to participate in DADRP and reduce their energy consumption. It also suggests some prices for the curtailed load to be offered by customers. Each demand response asset should decrease at least 100 kW of its average recorded consumption.

The ratio of offer load reduction amount (L) in DADRP to the whole DA demands of active customers is called here as penetration factor (PF) which is dependant to the percentage of participating customers and their hourly load reduction (Eq. 14).

$$PF = \frac{L}{RT_0(h)} \quad (14)$$

Regarding the penetration factor, the obtained benefit through supplying not registered loads in DADRP can be updated as:

$$B_{RT}^{opt}(h) = (1 - PF) \times \frac{RT_0(h)}{4} \times \frac{\left(p_{RT}^{max}(h) - p_w(h)\right)^2}{p_{RT}^{max}(h) - p_{RT}^{min}(h)} \quad (15)$$

If the hourly offers are accepted, the retailer will be paid the hourly day-ahead wholesale price multiplied by the offer reduction amount $\left(RT_0(h) \times PF \times p_w\right)$. However, it is up to the participant customers and their retailer to work out an agreement on how the demand response payments will be shared. Here, it is considered that the retailer owns %30 of DADR program's payments. Therefore, the retailer's share from the incentive paid by ISO will be as:

$$INC(h) = RT_0(h) \times PF \times p_w(h) \times 0.3 \quad (16)$$

The obtained benefit through energy procurement for active customers together with implementing DADRP will be as:

$$B_{RT}^{EP+DR}(h) = B_{RT}(h) + INC(h) \quad (17)$$

Substituting Eq. (15) and Eq. (16) in Eq. (17) results in the total benefit obtained through energy procurement for active customers and gaining incentives for load reduction in DADRP as follows:

$$B_{RT}^{EP+DR}(h) = RT_0(h) \times PF \times p_w(h) \times 0.3 + \frac{RT_0(h) \times (1 - PF) \times \left(p_{RT}^{max}(h) - p_w(h)\right)^2}{4 \times \left(p_{RT}^{max}(h) - p_{RT}^{min}(h)\right)} \quad (18)$$

6. Numerical Study

In this study, the required data is extracted from the day-head of New England, Connecticut in May 2010 [22]. It is considered that the retailer supplies 30% of all Connecticut electricity demand of residential, commercial and industrial sectors which are categorized in three groups of customers, i.e. fixed and TOU price takers as inactive and RT price takers as active customers. The target day for the retail process is 26 May 2010.

Table 1 demonstrates participation share of customers in three pricing strategies. It is considered that 90% of demands in all sectors are supplied through bilateral long term. Therefore, the reminder portion of it (i.e. 10%) should be supplied in DA market.

Forecasting inactive customers' energy consumption, the retailer estimates the surplus electric energy to be procured in DA market (Eq. 3). Real time price taker customers send their demands to the retailer based on their load prediction. Fig. 3 shows requisite electric energy for three groups of customers through the next 24 hours.

Table 1. Participation of customers in three pricing strategies

Participant sectors		Inactive customers				Active customers
		Fixed	TOU			Dynamic Pricing
			valley	Off-peak	peak	
Residential	Portion (%)	50	50			-
	Price (¢/kwh)	11.5	8.0	10.6	14.1	-
Commercial	Portion (%)	30	50			20
	Price (¢/kwh)	11.6	7.5	10.6	13.6	To be optimized
Industrial	Portion (%)	-	20			80
	Price (¢/kwh)	-	7.5	10.6	13.6	To be optimized

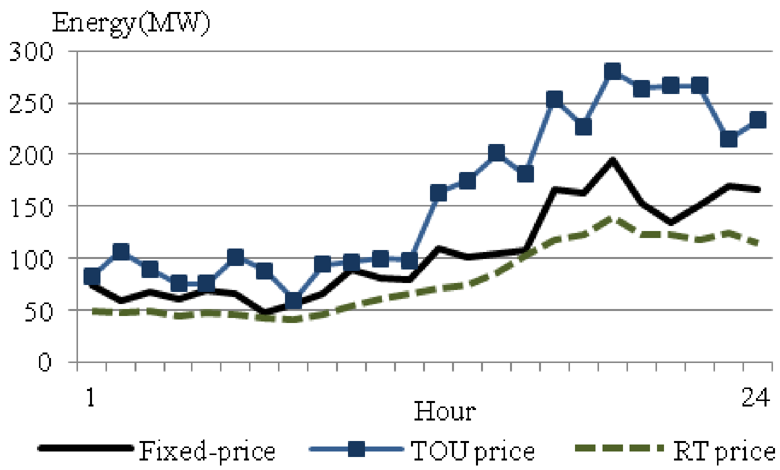

Fig. 3. Requisite electric energy to be procured for three classes of customers

The retailer purchases energy in order to supply its inactive customers' requisite electricity at predetermined fixed/TOU prices. Fig. 4 shows the hourly cost of energy procurement for them and consequent benefits.

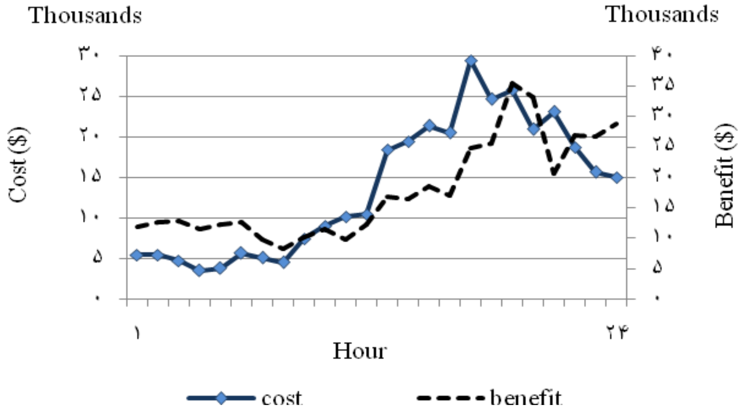

Fig. 4. Costs and benefits in energy procurement for the inactive customers (fixed and TOU price takers)

Retailing for RT-price taker customers includes retail pricing through energy procurement for them using DA wholesale market.

Fig. 5 compares minimum/maximum DA retail prices with the offered retail prices which are obtained based on the proposed hourly acceptance function.

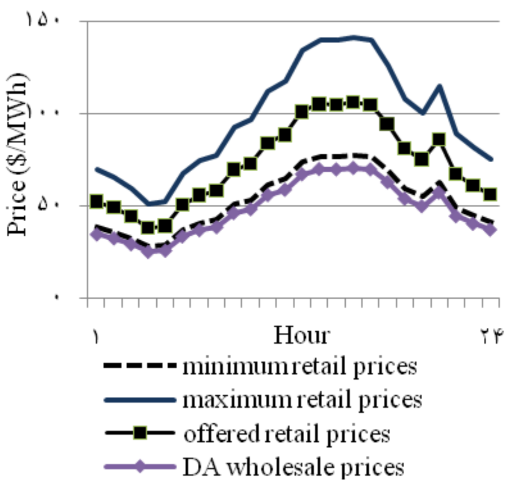

Fig. 5. Comparison of DA wholesale price, minimum, maximum and offered retail prices

Without offering DADRP to the active customers, $(PF = 0)$ they would demand electric energy at optimum DA prices. Fig. 6 shows the effective demands as well as subsequent energy procurement costs and benefits.

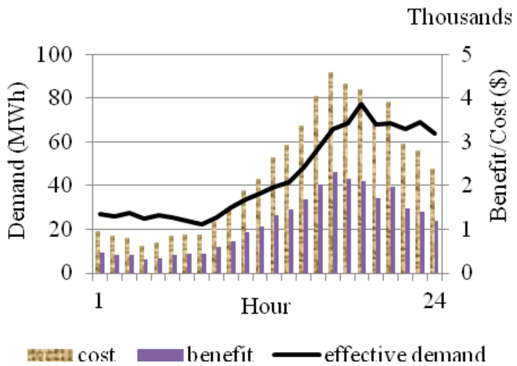

Fig. 6. Active customers' effective demand, hourly costs and obtained benefits through procurement electric demands $(PF = 0)$

The retail energy provider also offers participating in DADRP to its active customers and suggests the forecasted DA wholesale prices as the load curtailment incentive price. Here, it is considered that PF changes from 10% to 50% so as to analyze the benefits obtained by retailer through retailing and performing DADRP simultaneously. Fig. 7 presents the total hourly benefit in case of different participating rates.

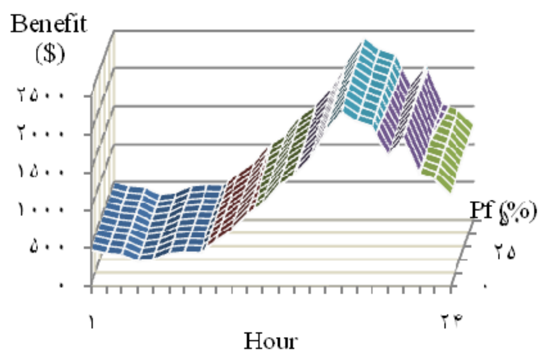

Fig. 7. The effect of different participating rates in DADRP on the total hourly benefit

Fig. 8 displays daily benefit of DA retailing accompanied with DADRP involving 0-50% of active customers' DA demand.

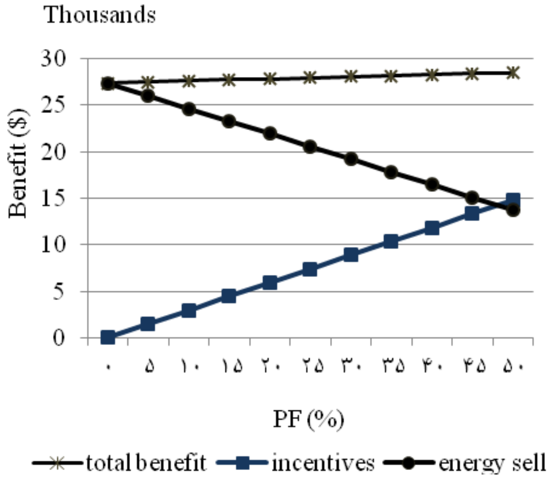

Fig. 8. Daily benefit of DA retailing accompanied with DADRP

As it can be seen in the figure, the total benefit obtained by retailer is composed of energy selling benefit and incentives from ISO subsequent to implementing DADRP. Greater participating rates (PF) eventuate much more benefit for the retailer (i.e. $\frac{benefit_{PF=0.5}}{benefit_{PF=0}} = 1.04$).

7. Conclusion

Smart grids are established based on bidirectional interactions between the power system operators and customers who may play as distributed energy resources in form of distributed generators or volunteer demand reducers. Demand response programs refer to mechanisms of encouraging customers to play active roles in energy markets.

In this paper, the retailer categorizes its residential, commercial and industrial customers in groups of fixed price takers, TOU and real time price takers. The latter group includes active customers who purchase a portion of their requisite energy in short-term markets and participate actively in demand response programs.

This paper discusses the problem of DA retailing for fixed and TOU price takers and DA pricing for active customers. Accordingly, it models customers' response to the optimum hourly prices and offer a participation in DADRP proposed by retailer. An hourly linear acceptance function is proposed in this paper which utilizes minimum and maximum DA retail prices allowed by market regulators to adjust hourly settings. Numerical studies demonstrate the effect of participation rate on the retail benefit. According to the obtained results, if the retailer's share of incentives is 30%, its total benefit will grow as more customers participate in DA demand response program. However, the proportion of incentive sharing between the retailer and customers, directly affect the resulted benefits and corresponding decisions.

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