OPTIMUM RETAILING STRATEGY IN COMPETITIVE ENERGY MARKET REGARDING PRICE ACCEPTANCE RATE

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ABSTRACT

Energy procurement for different classes of customers including fixed/time-of-use price takers (inactive customers) and real time price takers (active customers) from the viewpoint of a retail energy provider is addressed in this paper, concerning pool-based wholesale market as well as distributed generators as energy resources. Optimizing retail benefit function based on Genetic Algorithm approach, optimum retail prices are determined to offer to the active customers in day-ahead retail market. Retail prices are acquired with regard to their response against the offered prices, which is modeled using a price acceptance function. Furthermore, comparison between two retailing strategies of focusing on the active customers and concentrating upon the inactive ones are presented here using real energy market data.

***Keywords**: Competitive retail market, pricing, price acceptance function, energy resources, genetic algorithm*

INTRODUCTION

Developing bidirectional communications with customers and facilitating their attendance in the energy system environment are numerated as main causes to structure smart distribution systems. Achieving this goal, makes it possible to send/receive online information and commands so as to establish competitive retail markets and subsequently digital society.

Smart distribution system's customers purchase their requisite energy monitoring divergent retail contracts the offered prices. Each customer follows retail market changes as for its activities. Smart power grids support complete competitive retail markets enabling customers to select their desired energy provider concerning the provided pricing patterns, ancillary services and demand response (DR) programs. Enabling customers to change their retailer in short term and its effect on the customers' load profile has not been considered in load modeling and retail pricing addressed in previous researches. Some researches have focused on the switching right in long term [1,2]. However, it has been illustrated that a competitive market removes the switching barriers and allows the customers to select their desired energy provider [3].

Retailers need to model electric load profile to optimize their retailing activities. Therefore, modeling customers' reaction to the offered prices regarding other competitor retailers is a necessary step in retailing process. References [4-6] have presented customer load model in a retail environment. Pricing strategies in power markets [7-9] are other related subjects of research

Here, the retailer supplies triple groups of customers including fixed-price takers, time-of-use (TOU) and real time price takers, using pool-based wholesale market as well as distributed generators (DGs) in DA market. The retailer sells the energy to the inactive customers (fixed and TOU price takers) at predetermined rates, but offers the hourly energy prices to the active ones (real time price takers) in DA market to compensate for the remainder part of their electricity demand, which has not been supplied through long-term contracts. Consequently, to gain the maximum benefit, the retailer has to decide optimally about the energy resources and DA retail prices as well concerning the effect of the hourly prices on the active customers' load.

In this paper, modeling customers' load in competitive retail market is concentrated and using Genetic Algorithm (GA) the optimum hourly prices are determined concerning the active customers' response to the offered retail prices based on a type of price acceptance function presented in [5].

Energy procurement and retail pricing are conducted here using two strategies. The first retailing strategy is to focus on the inactive customers binding the retailer to procure their energy demand prior to the others. However, the latter strategy compels the retailer to prioritize the active customers to inactive ones.

In this paper, New England's energy market data are employed in numerical studies and three different DGs are assumed as well as the wholesale market.

The remaining parts of the paper have been structured as follows. Section 2 represents retailing for customers. Section 3 is assigned to the numerical studies. Finally, section 4 concludes the paper.

RETAILING FOR CUSTOMERS

Each retailer supplies divergent classes of customers. It is better to classify customers regarding their electricity consuming styles and load profiles or their accepted pricing patterns.

Accordingly, three different clusters of customers, i.e. fixed-price takers, time-of-use and real time price takers are considered in this paper. The first two groups are assumed as inactive customers and the latter is numerated as the active group. Inactive customers like residential and small commercial customers do not participate in short term markets and use long-term energy purchase contracts. However, the active customers monitor other pricing alternatives and different provided services and usually participate in long-term as well as short-term day-ahead (DA) markets. In case of considering retailer switching rights for the active customers (as is considered in competitive retail environments), the offered prices affect customers' load in DA market.

It is assumed that the retailer has purchased a portion of inactive customers' demand in long-term contracts. The surplus energy need for inactive customer is denoted by $D^{in}(h) = Fix(h) + TOU(h)$ which can be obtained through forecasting inactive customers' hourly demand including fixed price takers' demand $(Fix(h))$ and that of TOU price takers $(TOU(h))$. Similarly, active customers have to supply their surplus energy need in DA market $(D_0^a(h))$. The term $D_0^a(h)$ also denotes active customers' demand, which can be submitted to their current retailer in case of receiving fair offered prices from their viewpoint. It means that the retailer receives $D^a\big(P_{RT}(h)\big)$ as the active customers' demand affected by the offered retail prices $(P_{RT}(h))$ as presented by Eq. (1).

$$D^a\big(P_{RT}(h)\big) = D_0^a(h)AC\big(P_{RT}(h)\big) \tag{1}$$

The function $AC\big(P_{RT}(h)\big)$ known as the price acceptance function (PAF) represents the impact of the retail prices on the customers' demand. PAF reflects the effect of competition in retail environment on the retailer's electric load profile. Here, the PAF presented in [5] is used in modeling customers' response to the offered prices regarding no switching barrier in short term market (Eq. (2)).

$$AC\big(P_{RT}(h)\big) = 1 - \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{P_{RT}(h)} e^{-(0.5)(\frac{t+dp-DP(h)-m}{\sigma})^2}dt \tag{2}$$

where dp is decreasing point of the market share function represented in [10]. The related price at decreasing point is the highest offered price in which the acceptance rate equals one with a given tolerance (Eq. (3)).

$$dp = \{P_{fix} | AC(P) = 1 \,\&\, AC(P+\varepsilon) < 1\} \tag{3}$$

The term $DP(h)$ denotes hourly decreasing points which are proportional to hourly DA energy prices offered by the wholesale market $(P_w(h))$, as shown in Eq. (4).

$$DP(h) = c + P_w(h) \tag{4}$$

where c is a constant marginal benefit for the retailer influenced by some factors such as the local price caps and other retailers' pricing strategies. The applied PAF is shown in fig. 1.

The retailer has to supply $D^{in}(h)$ and $D^a\big(P_{RT}(h)\big)$ for its inactive and active customers, respectively. There are some energy resources like the wholesale energy market and the distributed generators, which can deliver electric energy to the power system to provide customers with the electric power.

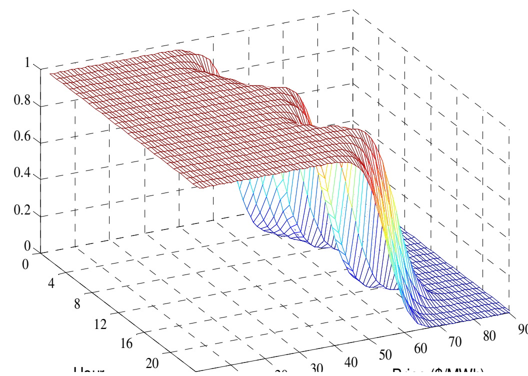

Fig. 1. Price acceptance function

If the hourly energy price from the $i-th$ energy resource is denoted by $P_i(h)$, then the cost of energy procurement will be as:

$$cost(h) = \sum_{i=1}^{n} E_i(h) \times P_i(h) \tag{5}$$

where $E_i(h)$ is the amount of energy purchased from the $i-th$ energy resource at $P_i(h)$ $^{\$}/_{KWh}$. If the retailer decides to supply $D(h)$ for its customers, then:

$$D(h) = \sum_{i=1}^{n} E_i(h) \tag{6}$$

Energy procurement process is followed by the energy sell procedure including determination of the retail prices for the active customers and billing for them as well as inactive ones.

The acquired benefit through retailing for customers, who need $D(h)$ KWh of electric energy and pay the average price of $p(h)$ $^{\$}/_{KWh}$ for it, is presented by Eq.(7).

$$B(h) = D(h) \times p(h) - \sum_{i=1}^{n} E_i(h) \times P_i(h) \tag{7}$$

Retailing strategies

Retailing strategy determines the energy purchase process and affects the final benefit, accordingly. Here, it is assumed that the retailer may adopt two different strategies, which can affect the energy purchase cost and subsequent retail prices. The retailing strategies differ in sequencing energy procurement for active and inactive customers and selecting the energy suppliers for them. The difference is built upon the assumption that there is limitation in the amount of energy to be purchased from some energy resources. This limitation can be emerged from DGs' limited outputs or distribution feeder loading, etc. Accordingly, here it is assumed that there are energy purchase cap in supplying energy from DGs, while there is no limitation in purchasing electric energy from the wholesale market as well as the flow of energy from the transmission system to the retailer's customers.

Adopting the first retailing strategy, the retailer uses inexpensive energy resources for inactive customers. Therefore, the hourly variations in the energy price are transferred to the active customers to distance inactive ones from the unforeseen price spikes, resulting in increasing the offered prices to the active customers.
However, the second strategy concentrates on the active customers at the first step of energy purchasing prior to inactive ones. Accordingly, inexpensive energy resources would be used to supply active customers' load and lower energy prices with higher acceptance rates are offered to them as for regarding the switching right for them. This strategy prevents partly from missing active customers because of offering high retail prices.
Retailing benefit is obtained as the following:

$$Max\, B_1(h) = Max\, B_1^{in}(h) + \underset{P_{RT}(h)}{Max}\, B_1^{a}(h) \tag{8a}$$

where,

$$B_1^{in}(h) = Fix(h) \times P_{Fix} + TOU(h) \times P_{TOU}(h) - \sum_{i=1}^{n} E_i^{in}(h) \times P_i(h) \tag{8b}$$

$$B_1^{a}(h) = D^a\big(P_{RT}(h)\big) \times P_{RT}(h) - \sum_{i=1}^{n} E_i^{a}(h) \times P_i(h) \tag{8c}$$

In Eq. (8), P_{Fix} and $P_{TOU}(h)$ denote the price of energy to be purchased to the fixed price takers and TOU price takers, respectively. The price $P_{TOU}(h)$ changes with the time of energy consumption based on the predetermined energy costs in peak, off-peak and mid-peak periods of day. The amount of energy to be purchased from the $i-\mathrm{th}$ energy resource for active and inactive customers are presented by $E_i^a(h)$ and $E_i^{in}(h)$, respectively. These values cover customers' demands as shown in Eq. (9).

$$D^{in}(h) = \sum_{i=1}^{n} E_i^{in}(h) \tag{9a}$$

$$D^{a}\big(P_{RT}(h)\big) = \sum_{i=1}^{n} E_i^{a}(h) \tag{9b}$$

$D^{a}\big(P_{RT}(h)\big)$ is dependent on the offered price which has been presented in Eq. (1). As mentioned before, offering unfair prices (from the viewpoint of customers) leads to decreasing active customers' demand.
Let assume that the retailer adopts the first strategy. Therefore, he/she has to prioritize inactive customers to the active ones. Therefore:

$$0 \le E_i^{in}(h) \le C_i(h) \tag{10a}$$

$$0 \le E_i^{a}(h) \le C_i(h) - E_i^{in}(h) \tag{10b}$$

where the term $C_i(h)$ represents the upper limit of energy purchase from the $i-\mathrm{th}$ energy resource regarding no cap for the wholesale market.
However, if the retailer follows the second strategy, he/she supplies the active customers' demand from the inexpensive resources at the first step and then cares for the energy demand of inactive customers. As a result:

$$0 \le E_i^{a}(h) \le C_i(h) \tag{11a}$$

$$0 \le E_i^{in}(h) \le C_i(h) - E_i^{in}(h) \tag{11b}$$

Genetic Algorithm in pricing and energy procurement for customers

Optimizing the benefit function (Eq. (8)) results in specification of the retail prices to be offered to the active customers as well as the amount of energy to be purchased from the wholesale market and DGs.
To this purpose, genetic algorithm (GA) is applied as an optimization method. GA approach searches for an optimal price operating on populations of individuals. Each individual chromosome represents a particular selection of the real time price corresponding to each hour of the next day. The GA-based real time pricing is structured as follows:

a. The initial population of prices is randomly generated.
b. Based on the objective function (Eq. (8) , (9)) and its constraints (Eq. (10) or (11) relating to the adopted strategy), a measure of fitness is assigned to each of individuals to estimate the probability of selecting each individual (price value) in forming the next population.
c. Applying the genetic operators of crossover and mutation, a new population is produced employing the selected individuals.
d. Repeat the above stages to reach an ignorable difference in the objective function value.

Table 1 demonstrates the adopted choices the basic GA parameters in real time pricing for the active customers.

Table 1. The adopted choices in GA method

GA parameters	Adopted options
Population size	20
Generations	500
Stall generation limit	100
Fitness scaling function	Proportional
Crossover function	Heuristic
Crossover fraction	0.8
Selection function	Roulette
Mutation function	Adaptive feasible

NUMERICAL STUDIES

In this paper, New England's energy market data ([11]) are employed in numerical studies and three different DGs are assumed as well as the wholesale market.
The wholesale market has no limitation while the first DG has variable capacity, the second DG and the third one have limited output, namely 20 and 15 MW each hour of a day. The energy prices from the resources are shown in fig. 2.

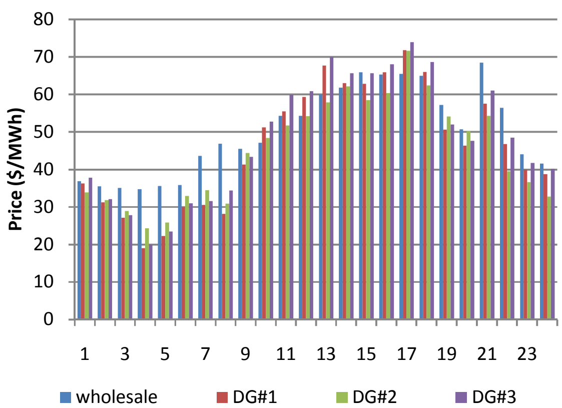

Fig. 2. Energy prices from the resources

Predetermined price rates for the residential and small commercial customers is assumed as shown in Table 2.

Table 2. Predetermined price rates (¢/KWh) for inactive customers

Customers	Fixed	TOU	
		Off-peak	peak
Residential	11.5	10.6	14.1
Commercial	11.6	10.6	13.6

The optimum hourly prices to be offered to the active customers and the subsequent acceptance rates on the basis of two retailing strategies are presented in Table 3.

Table 3. Optimum prices and the acceptance rates

hour	Optimum prices (¢/kwh)		Acceptance rates (%)	
	First strategy	Second strategy	First strategy	Second strategy
1	6.153	6.153	97.47	97.47
2	5.552	5.552	99.80	99.80
3	5.054	5.054	99.99	99.99
4	4.166	4.166	100.00	100.00
5	4.547	4.547	100.00	100.00
6	5.513	5.513	99.88	99.88
7	5.959	5.959	99.99	99.99
8	5.965	5.965	100.00	100.00
9	7.334	7.312	90.77	91.50
10	7.492	7.491	90.91	90.91
11	8.210	8.210	90.94	90.95
12	8.210	8.209	90.97	90.98
13	8.782	8.782	90.87	90.86
14	8.959	8.958	90.92	90.96
15	9.368	9.366	90.81	90.85
16	9.313	9.314	90.86	90.81
17	9.331	9.330	90.87	90.91
18	9.278	9.279	90.82	90.80
19	8.505	8.505	90.98	90.98
20	7.852	7.851	90.82	90.85
21	9.627	9.561	90.85	92.80
22	8.123	8.123	97.36	97.36
23	6.903	6.903	97.21	97.21
24	6.511	6.511	98.55	98.55

Retailing benefit function reflects the difference between the strategies more distinctly. Acquired benefit through retailing for the active customers is shown in fig. 3.

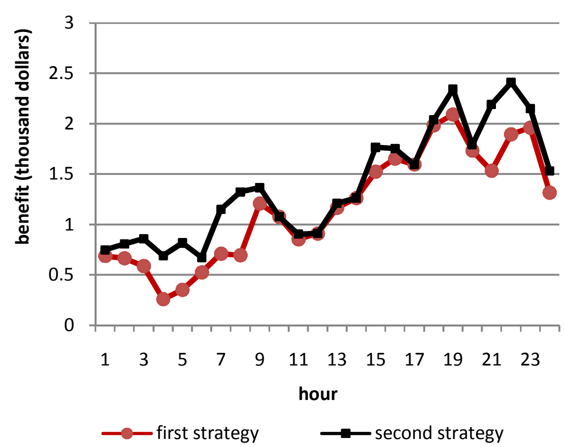

Fig. 3. The benefit of retailing for active customers

Total benefit from energy retailing for all customers is shown in fig. 4. As it can be seen in fig. 4, retailer's total benefit based on the second strategy is more than the benefit based on the first one.

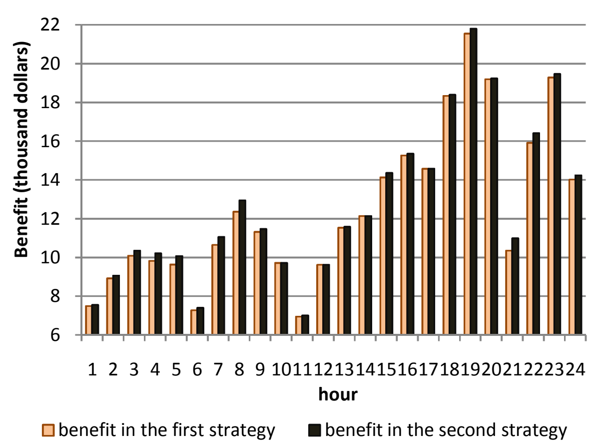

Fig. 4. The total benefit acquired through retailing strategies

Numerical results show that the retailer acquire 299944$ benefit through the first strategy, against 304805$, i.e. 1.02×299944$ through the latter one.
The results show that the second strategy is preferred to the first one from the viewpoint of benefit function in a competitive retail market, in which the switching barriers has been removed and the customers' confirmed demand is directly affected by the varying price acceptance rates.

CONCLUSION

This paper has focused on the retailing for different customers in a competitive environment. Active customers have been allowed to switch to another retailers in short term as it is allowed in competitive retail markets. Therefore, the offered prices affect the customers' submitted demand and subsequent retailing benefit. Furthermore, two different strategies, namely focusing on the inactive customers and concentrating on the active ones in supplying their demand from the available energy resources have been adopted here and the resulted difference in the final benefit has been shown. It was demonstrated that the active customers' switching right compels the retailer to employ inexpensive energy resources for them prior to inactive ones. This result has been obtained through retailing in one day. However, the retailing strategies would be better studied in long term retail activities, a subject of more research for further studies.

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