Including the Behavioral Aspects of Customers in Demand Response Model: Real Time Pricing Versus Peak Time Rebate

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***Abstract*— Demand response (DR) programs enable the demand side to actively optimize its consumption in response to the dynamic prices. The flexibility of consumption can be a useful tool for the electricity market to resolve many of its operation and reliability issues. Several models have been proposed in the literature to explain the human behavior aspect of the customers. These models are based on the classical utility function, but some studies have shown that the price effect on the customer's decision in areas like energy efficiency and consumption reduction depends upon many behavioral characteristics and without considering such characteristics, the results are unrealistic. Thus, loss aversion plays a crucial role in the decision making. So, in this paper, the impact of two time based rate DR programs have been investigated on the peak reduction considering the loss-aversion and its impact on the perception of the customers. Real time pricing and peak time rebate are two competing alternatives for peak reduction. A modified price elasticity based DR model is proposed to simulate the price response of the customers in the presence of both DR programs. MATLAB software is used to implement the DR models. The models are examined on one of the summer days of 2014 in Connecticut. The data is reported by New England ISO. Two PTR cases are generated for this study, with and without considering the loss aversion. Under both scenarios, without considering the loss aversion, PTR has advantages over RTP, but considering the loss-aversion, RTP showed a superior performance. It is shown that the behavioral characteristics of the customers, loss-aversion in this case, is indispensable in the selection of the proper program.**

***Index Terms*— demand response, electricity spot market price, electricity market, time-of-use (TOU) pricing, price elasticity of demand**

I. INTRODUCTION

A. Motivation

DYNAMIC pricing has tremendous appeal on a theoretical level. It gives the demand side the efficient consumption incentive and potentially it can improve the overall welfare. But it used to be a consensus among the market players that most of the customers, except a few large ones, lack the financial incentive and the expertise needed for effective decision making in the complicated electricity market. For such reasons, the demand side has been kept shielded from the liberalized prices in the wholesale market. In this environment, the utilities and load aggregators purchase the electricity on behalf of the customers and charge them on a flat rate basis.

The flat rate reflects the average cost of electricity plus a premium that compensate the retailer for the risks associated with buying variable price electricity and selling it at a fixed rate. therefore, with this setup, small customers are insulated from the spot price and the demand is determined only by the cycle of their activities [1].

The design and size of the electricity network is commanded by the aggregate peak of the demand-side cyclic behaviors. It makes the network overdimensioned for the off-peak periods. Dynamic pricing can help to modify customer behavior patterns in order to shift the demand from peak time to off-peak time and smooth out the load profile.

Ordinarily, due to the technical complication and highly capital intensive infrastructure of dynamic pricing programs, the utilities were reluctant to invest on these programs. But The US government and the energy sector, in response to the environmental challenges of the traditional electricity generation, adopted a very aggressive approach to create the required infrastructure for the demand response (DR) and energy efficiency programs. According to 2010 FERC survey, advanced metering penetration reached approximately 8.7 percent in the US [2].

Many initiatives have also been proposed for smart grid. The mobility-on-demand (MoD) project is proposed to integrate electric vehicles into the design and construction of modern cities. The Tennessee valley authority (TVA) is constructing a smart grid information processing architecture. Xcel energy is trying a smart grid city in Boulder, CO. It has launched different kinds of dynamic pricing pilots [3]. Moreover, many utilities launched pilot programs to study the feasibility and technical challenges of time-based DR programs [4-8].

There is a consensus among the behavioral scientists that the assumption of the classical economics about the people being always rational about the price is not right [9-10]. In this paper, the effect of two time based rate programs will be examined on the demand response. The loss-aversion is one of the behavioral characteristic of human beings, thus, its effect on the customers perception of the different programs will be examined.

B. Literature review and contribution

DR enables the demand side to actively engage in the optimization process and optimize its consumption in response to the dynamic prices. DR programs are divided into two main categories of time-based rate (TBR) and incentive-based programs(IBR). Each category is composed of several other programs as shown in Fig. 1. In [11-12], all these programs are explained in detail. The IBR programs have been used for many years, but mostly focused on large industrial and commercial customers. For example, ERCOT has emergency interruptible load program for large customers. SCE offers a variety of demand response programs such as automated demand response (Auto-DR), permanent load shifting (PLS), and scheduled load reduction program (SLRP) [13].

The customer's reaction vary to different DR programs, so, different models are proposed to explain the customer reaction function. Authors in [14-16] tried to model the demand response based on the demand-price elasticity concept. Demand-price elasticity is a concept borrowed from the consumer theory in microeconomics which reflects the relative change in the demand in response to the relative change in the price [17-18]. Authors in [19] modeled the customer reaction with linear optimization technique assuming the customers have access to the real-time electricity price. In this model, the objective function is maximizing the utility and minimizing the cost of electricity consumption.

Authors in [20] reviewed the recently-growing body of researches in psychology and behavioral economics to show that non-price interventions can be as powerful as the price in changing customer choices. They provided several recommendation in terms of energy policy.

Authors in [21] argue that psychologists believe that reward is a better tool for habit formation compared to the punishment. consequently, reward-wise programs tend to form better habits in the customers in terms of long run elasticity of demand. [22] surveyed 600 households in Sweden to study the behavioral patterns in energy consumption. According to their findings, there are many non-price incentives that affect the customer consumption decisions.

There are many papers that studied the price effect on the customer's decision about energy efficiency and consumption reduction. They suggest that the effect of the price is tied to many behavioral characteristics [20,23-24].

The study of the effect of behavioral characteristic in design of demand response programs is in its nascent stage. the researches in DR area mostly are interested in the impact of demand response on the system operation and reliability. They try to show the benefits of demand response to the utilities and the policy makers. This question that how to increase the efficiency of the demand response programs has not attracted enough attention yet.

In this paper, the impact of two time based rate DR programs have been investigated on the peak reduction. Then impact the loss-aversion is examined on the customers perception of the different programs.

C. *Paper Organization*

The paper will continue with the description of the loss aversion in section II and demand response model in section III. Section IV presents the results for a case study and discusses the results. Section V closes the paper with drawing conclusion from the provided discussion and results.

II. LOSS AVERSIOIN

It is a well established behavioral fact that the losses and disadvantages have greater impact on preferences than gains and advantages [25]. It results in a utility function that is steeper for losses than for gains. The classical assumption

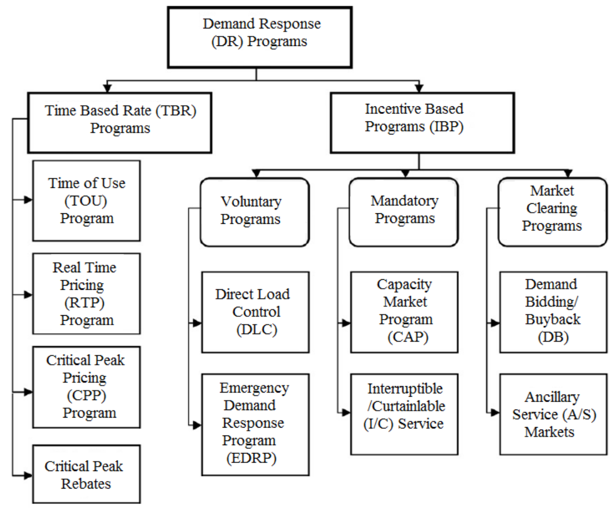

Fig. 1. Categories of the demand response programs

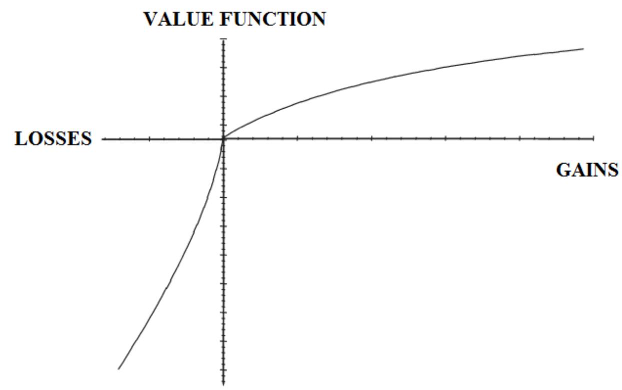

Fig. 2. An illustration of value function

which assumes a symmetry between the value of gain and loss simplifies the analysis of an individual choice, but it is not realistic. So, it can lead to over- or underestimated conclusions. Fig. 2 shows a simple illustration of a value function that can explain a large set of observations [26].

[26] introduces a model for risk aversion. The parameters of the model can be extracted from the observations of randomized trial. loss aversion is different in riskless and risky situation. Obviously the value function of loss aversion is steeper in risky situation. Both real time pricing and peak time rebates belong to the riskless situations.

In real time pricing (RTP), the utilities charge more during the peak periods, so, compared to the price of off-peak prices, any load that can be shifted to off-peak periods looks like a loss to the customer. On the other hand, peak time rebate (PTR) relies on rewarding the customers during the peak time based on their load reduction. Accordingly, any load that can be shifted to off-peak periods looks like a gain. So, even though in essence, they are the same behavior, namely shifting the flexible loads from peak period to off-peak period, their perceived value belong to the two different sides of the value function. In this context, the perceived value of a response is different from the nominal value of a response. The nominal value is a value expressed in monetary terms. The customers respond to the perceived value and not the nominal value.

Authors in [27] propose a model of price discrimination incorporating the loss aversion. This model can be used by utilities for profit maximization and also designing the most efficient dynamic pricing scheme.

Obviously, using the automated machines in the future reduces the dependence of demand response programs to such arbitrary-like non linear loss aversion value functions. However, in the absence of such provisions, the aforementioned behavioral characteristic should be considered in the utility function of the customers.

III. MATHEMATICAL MODELING

A. Demand response model

The demand for almost all goods and services rises as the price decreases. This change in the demand is not linear. To quantify this effect, the nonlinear demand curve can be linearized around a given point. It is defined as price elasticity of demand. In other words, the price elasticity is a normalized measure of change in the demand relative to the change in price. Fig. 3 shows how the demand elasticity can significantly affect the electricity price.

$$E = \frac{P_0}{d_0} \times \frac{\partial d}{\partial p} \tag{1}$$

Where E is the price elasticity, P_0 and d_0 are initial price and demand.

Price elasticity has two components: self-elasticity and cross-elasticity. For instance, between two competing commodities, if the price of one rises, its demand will change. One part of the change in demand is the shift of demand to the other competing commodity (cross-elasticity) and the other part is the change in its consumption (self-elasticity). Self- and cross-elasticity value for normal goods are negative and positive, respectively.

Demand response based on the price elasticity of electricity demand is formulated for each hour in the following subsections[30].

A. price elasticity model for one hour

Suppose customer's benefit for the i-th hour is as follows:

$$B(d(i)) = U(d(i)) - d(i).p(i) + \mathrm{P}(\Delta\,\mathrm{d(i)}) \tag{2}$$

Where $U(d(i))$ is customer's utility in *i*-th hour. This benefit can have different forms, for the simplicity, it's assumed to be in terms of dollar.

$$P(\Delta d(i)) = \lambda.R(i).\Delta d(i) \tag{3}$$

Where R(i) is an incentive payment; in this case, it is a reward paid for each kWh peak reduction. λ is a coefficient representing the real value of the nomianal reward or incentive payment.

It's assumed that every individual tries to optimize its benefit. So,

$$\frac{\partial B(d(i))}{\partial d(i)} = \frac{\partial U(d(i))}{\partial d(i)} - p(i) + \frac{\partial P(\Delta d(i))}{\partial d(i)} = 0 \tag{4}$$

Therefore,

$$\frac{\partial U(d(i))}{\partial d(i)} = p(i) + \lambda.R(i) \tag{5}$$

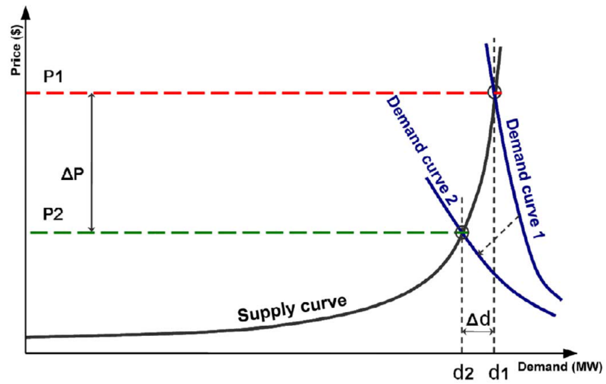

Fig. 3. Effect of demand variation on the electricity price

In the optimal point, the marginal utility is equal to the price of the electricity.

According to [31] , the Taylor series expansion can be used for quadratic customer revenue function, so,

$$U(d(i)) = U(d_0(i)) + \frac{\partial U(d_0(i))}{\partial d(i)} \times \Delta d(i)$$

$$+\frac{1}{2} \times \frac{\partial^2 U(d_0(i))}{\partial d^2(i)} \times (\Delta d(i))^2 \tag{6}$$

Where $\Delta d(i)$ is the customer demand change from $d_0(i)$ (the initial demand) to $d(i)$ (optimal point).

Assuming that the initial demand before implementing the DR program is optimal, the following relation should hold

$$\frac{\partial B_0}{\partial d(i)} = \frac{\partial U(d_0(i))}{\partial d(i)} - p_0 = 0 \tag{7}$$

$$\frac{\partial U(d_0(i))}{\partial d(i)} = p_0 \tag{8}$$

Using (5) and the definition of the price elasticity of demand (1),

$$\frac{\partial^2 U(d(i))}{\partial d^2(i)} = \frac{\partial p}{\partial d} = \frac{1}{E} \times \frac{p_0}{d_0} \tag{9}$$

Plugging (8) and (9) into the Taylor series expansion gives

$$U(d(i)) = U(d_0(i)) + p_0.\Delta d(i)$$

$$+\frac{1}{2}.\frac{1}{E(i)}.\frac{p_0}{d_0}.(\Delta d(i))^2 \tag{10}$$

Equation (10) can be rewritten and expanded as follows:

$$U(d(i)) = U(d_0(i)) + p_0.\Delta d(i)[1 + \frac{\Delta d(i)}{2 \times E(i) \times d_0}] \quad (11)$$

Expanding $\Delta d(i) = d(i) - d_0(i)$ and then plugging (11) into (5) gives

$$p(i) + \lambda.R(i) = p_0(i) \times [1 + \frac{d(i) - d_0(i)}{E(i) \times d_0(i)}] \quad (12)$$

$$p(i) + \lambda.R(i) = p_0(i) + p_0(i) \times \frac{d(i) - d_0(i)}{E(i) \times d_0(i)} \quad (13)$$

So, the customer's consumption can be represented as follows:

$$d(i) = d_0(i) \times \left\{ 1 + \frac{E(i) \times (p(i) - p_0(i) + \lambda.R(i))}{p_0(i)} \right\} \quad (14)$$

B. price elasticity model for 24 hours

The cross-elasticity between hours i and j is defined as:

$$E(i,j) = \frac{P_0(j)}{d_0(i)} \times \frac{\partial d(i)}{\partial p(j)} \ , \quad i \neq j \quad (15)$$

The demand response model for 24 hours of a day can be obtained by combining self- and cross-elasticity of demand as follows:

$$d(i) = d_0(i) + E(i) \times \frac{d_0(i)}{p_0(i)} \times (p(i) - p_0(i) + \lambda.R(i)) \quad (16)$$

$$+ \sum_{\substack{j=1 \\ j \neq i}}^{24} E(i,j) \times \frac{d_0(i)}{p_0(\mathrm{j})} \times (p(\mathrm{j}) - p_0(\mathrm{j}) + \lambda.R(j)) \ , \ i = 1, 2, ..., 24$$

The change in the demand in equation (16) comes from two sources, one source is the self-elasticity which is reflected by the first term and the other source is cross-elasticity which is reflected by the second term. The model represents both price and reward responsive demand.

B. Customer Base-line load calculation

In PTR, the payment is based on the difference of metered peak time load on PTR event day and estimate of the counterfactual, namely, the original amount of demanded load of the customer before applying PTR program. This estimation is referred to as the customer baseline load (CBL). there are many methods employed by utilities to estimate the CBL. [28] compared 21 different models for CBL calculation. One of the famous and easy to implement CBL model is referred to 3/5 baseline model. It uses the average of the load for each customer across the highest three out of five non-event weekdays for weekday event and three of the highest five weekends for weekend event.

The effectiveness of PTR largely depends on the accuracy of CBL estimation. Indeed, inaccuracy in the estimation of CBL will lead to over- or underpayment to customers and it can distort the intention of PTR. In this paper, a similar counterfactual load profile is used for both PTR and RTP.

IV. NUMERICAL RESULTS

A. load profile

The study has been done on the reported hourly data of New England ISO [29]. This ISO provides the zonal information for all its serving areas including the real time price of the electricity in the spot market. For this study,the load profile of Connecticut in August 18th, 2014 is selected for this study. The real time spot market price is used for RTP program.

TABLE 1: SELF AND CROSS ELASTICITIES

	Peak	***Off-Peak***	***Low***
Peak	-0.10	0.01	0.01
Off-Peak	0.01	-0.10	0.008
Low	0.01	0.008	-0.10

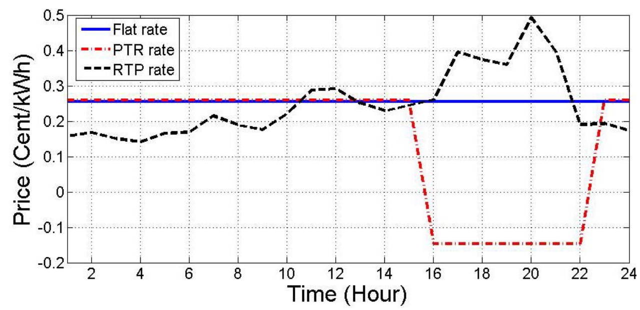

Fig. 1. different pricing scheme

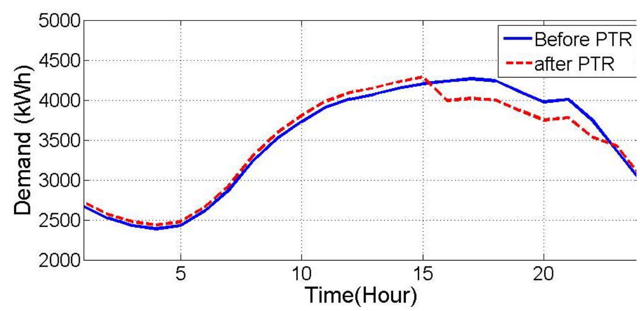

Fig.2. demand profile before and after PTR program

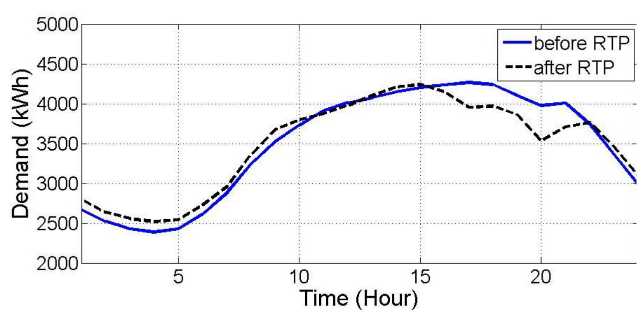

Fig.3. demand profile before and after RTP program

TABLE II: PEAK REDUCTION SCENARIO DATA

Pricing Policy	Price ($/kWh)	Total Cost (M$)	Total demand (kWh)	Peak (kWh)
Flat rate	0.2583	2.162	83,655	28,568
RTP	Dynamic	2.119 (Δ=-1.99%)	83,431	26,936 (94.29%)
PTR[1]	0.2583	2.124(Δ=-1.78%)	83,125	26,936 (94.29%)
PTR[2]	0.2583	2.100(Δ=-2.94%)	83,125	26,936 (94.29%)

PTR[1] is without considering the loss-aversion, PTR[2] is with considering the loss-aversion, and Rebate is 14.75 cent/kWh

TABLE III: EQUAL LOSS SCENARIO DATA

Pricing Policy	Price ($/kWh)	Total Cost (M$)	Total demand (kWh)	Peak (kWh)
Flat rate	0.2583	2.162	83,655	28,568
RTP	Dynamic	2.119 (Δ=-1.99%)	83,431	26,936 (94.29%)
PTR[1]	0.2583	2.119 (Δ=-1.99%)	83,087	26,821 (93.89%)
PTR[2]	0.2583	2.119 (Δ=-1.99%)	83,228	27,255 (95.40%)

PTR[1] is without considering the loss-aversion, PTR[2] is with considering the loss-aversion, and Rebate[1] is 15.80 cent/kWh and Rebate[2] is 11.88 cent/kWh

B. Results and discussion

Fig. 1 shows the considered pricing schemes in different RTP and PTR programs as well as the flat rate that represents the original pricing scheme before implementing DR program. It's assumed that the utilities choose the flat rate based on just the average cost of electricity. Therefore, based on the spot market data, the calculated flat rate is 25.83 cents. It is also assumed that in PTR program 14.75 cents is paid to the participant as a reward for every kWh reduction compared to the baseline. However, in RTP program, the hourly prices of the spot market is directly applied to the customers.

The load profile is divided into three categories, the low consumption, off-peak and peak periods. The low consumption period consists of hours 1 to 9. The off-peak period consists of hours 10 to 15, 23 to 24 and the rest is peak period. The price elasticity of demand for each period is shown in table I. these values are modified based on the length of the different consumption periods [30].

Figs. 2 and 3 show the changes of the demand profile in response to implementing PTR and RTP programs, respectively. in this paper, two scenarios have been considered with different scopes. Scenario 1 assumes that the utilities are interested in peak reduction. In this scenario, it is assumed that the utility is interested in 1632 kWh (5.71%) reduction of the electrical energy consumption in the peak period. Scenario 2 assumes that the utility wants to investigate how much peak reduction can achieve with the same amount of financial loss (42,200$).

For PTR program, two cases are studied. PTR[1] is a case without considering the loss aversion (λ=1). PTR[2] is the other case that loss aversion is considered. In this case, it's assumed that every dollar lost has twice the value of every dollar gained (λ=0.5). According to the results of the peak reduction scenario, shown in table II, both PTR and RTP programs reduce the utility revenue. Without considering the loss-aversion characteristics of the customers, the utility can achieve its target better with PTR (losing 37,700$ of the revenue) compared to RTP (loss of 42,200$). But considering the loss-aversion, RTP is better option than PTR (61,800$ loss in PTR[2]).

In the second scenario, the PTR rebate is increased to 15.8 cents per kWh to maintain the equal financial loss. Consistent with the results of the first scenario, without considering the loss-aversion, PTR can achieve 6.11% peak reduction compares to 5.71% peak reduction of RTP program. But considering the loss-aversion, the peak reduction could be reduced up to 4.6%.

The approach of this study to the loss aversion is very simplistic. Many theoretical loss-aversion indices are introduced for different setups that can be adopted to modify the utility function, but theoretical discussion and complexity of such indices are beyond the scope of this study.

By developing the smart grid technologies, with higher penetration of DR programs, it is expected that web and mobile applications to be developed to assist the customers in the decision making. in such environment, more small customers will participate in this market and as a result the effect of the behavioral characteristics will be underlined. As it is shown in this study, the optimum electricity pricing is highly dependent upon the precise modeling of the human intervention and by increasing the number of participants specially small customers in DR programs, such behavioral impacts have to be taken into the consideration more seriously.

V. CONCLUSION

The prospect of the demand response programs have created new horizons for the electricity market to engage the customers in the decision making process. TBR DR programs have shown an outstanding capability to assist the system operators in improving several of the operation and reliability indices. There are variety of proposed TBR programs, selection of the proper program hinges on many economic, policy and technical factors. On top of the aforementioned factors, there are many behavioral characteristic that should be incorporated into the customer's utility function.

In this paper, the effect of loss aversion is studied on the outcome of two of TBR programs under two scenarios. Real time pricing (RTP) and peak time rebate (PTR) are two competing alternatives for peak reduction. Two PTR cases are generated for this study, with and without considering the loss aversion. Under both scenarios, without considering the loss aversion, PTR has advantages over RTP, but considering the loss-aversion, RTP showed a superior performance.

It can be concluded from the results that the behavioral characteristic are indispensable in the selection of the proper program among these two competing programs.

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