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Effects of Time-Of-Use Demand Response Programs Based On Logarithmic Modeling for Electricity Customers and Utilities in Smart Grids

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Abstract

The focus of this paper is logarithmic modeling of time-of-use programs (TOU) as most prevalent priced-based DRPs**.** In this way, nonlinear behavioral characteristic of elastic loads is considered which causes to more realistic modeling of demand response to TOU rates. In order to evaluation of proposed model, the impact of running TOU programs using proposed logarithmic model on load profile of the peak day of the Iranian power system in 2007 is investigated.

Keywords

Demand Response programs; Elasticity; Time-of-use programs

Nomenclature

0	Initial state index (Superscript)
$t, \acute{t}$	Time period indices (subscript)
NT	Number of hours within period of study
d	Load (MW)
ρ	Price (Rials/MWh)
Δd	Demand change (MW)
$\Delta \rho$	Price change (Rials/MWh)
$B[d_t]$	Benefit of consumer at time period *t by* consuming d_t
e_{tt}	Self elasticity
$e_{t\acute{t}}$	Cross elasticity
η	Demand response potential (%)

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1. Introduction

A power system which is modern and intelligent is referred to Smart Grid. This system would have a wide range of advantages for electrical power industry. Smart Grid's characteristics will help customers to respond to changes in electricity price and vary their energy consumption during the day more effectively. In this new environment, even smallest customers would have the ability to participate in power market and to adjust their consumption with electricity price to reach the highest welfare. Enabled by Smart Grid infrastructures, each customer would be able to install his own electric plant and appear as a producer who sells power to the grid at times of extra production [1-3].

U.S. Department of energy defines Smart grid as today's grid joined by advanced metering and control devices such as Information Technology (IT), sensors, high speed, real-time two way communications, energy Storages, Distributed Generation (DG), In-home energy controllers, automated home energy use.

Enabled by smart infrastructures, each customer will pay the instantaneous market price (depending on market, price will be determined every hour, half an hour or every quarter). Smart grid enables the use of distributed generation in all voltage levels and with real time pricing and smart meters, even domestic customers would be able to install their own distributed generator. Domestic generators such as wind turbines or photovoltaic cells would help customers to reduce their energy bills and even sell extra to demand electricity to the grid.

Hybrid cars would be able to act as distributed storages, storing the energy at times of low electricity price and discharging the stored energy at times of high price. An in-home controller would be needed to control all of these actions. The controller receives energy spot price trough high speed connections and controls home appliances. In other words, it makes it possible for customers to use electricity as flexible as possible. For example the controller can be set to increase room temperature at times of high spot price, or to turn on washing machines at times of low spot price (2 or 3 am).
Some of Smart Grid's characteristics can be summarized as figure 1.

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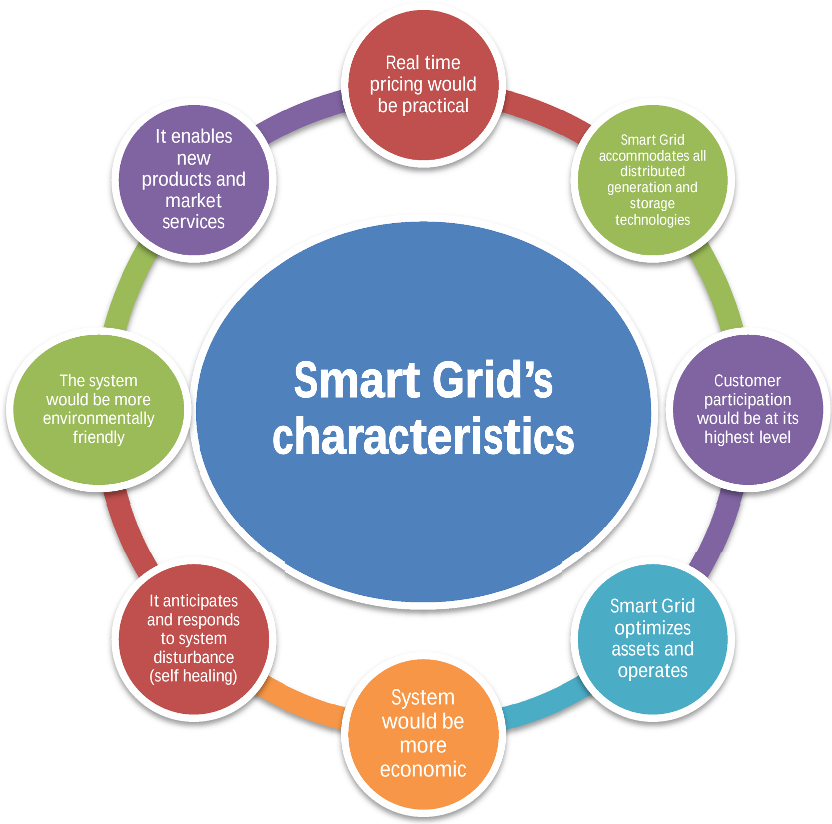


Figure 1. Smart Grid's characteristics

According to the U.S. Department of Energy (DOE) report, the definition of demand response (DR) is: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"[4]. According to DOE classification, demand response programs (DRPs) are divided into two categories as follows:

- **Price-based Options**
    - Time-of-use
    - Real-time pricing
    - Critical Peak Pricing

- **Incentive-Based Programs**
    - Direct load control
    - Interruptible/curtailable (I/C) service
    - Demand Bidding/Buyback Programs

- Emergency Demand Response Programs *
- Capacity Market Programs
- Ancillary Services Market Programs

Time of use programs (TOU) are the most prevalent priced-based programs. Most customers are exposed to some form of TOU rates, if only with rates that vary by six-month seasons. For instance, a summer-peaking utility may charge a higher rate for the energy use part of a bill than for the same amount of electricity consumed during the off-peak six months. This is a seasonal (time-varying) rate. More sensitive time-of-use rates establish two or more daily periods that reflects hours when the system load is higher (peak) or lower (off-peak), and charge a higher rate during peak hours. The definition of TOU periods differs widely among utilities, based on the timing of their peak system demands over the day, week, or year. TOU rates sometimes have only two prices, for peak and off-peak periods, while other tariffs include a shoulder period or partial-peak rate [5, 6]. Considerable researches have been done to introduce and extend linear economic modeling of DRPs [7-12]. This simple and widely used model is based on an assumption in which demand will change linearly in respect to the elasticity. Based on nonlinear behavior of real demand, those models don't be able to simulate demand responses accurately.

In this paper, a logarithmic model to describe price dependent loads is developed such that the characteristics of TOU programs can be imitated. Also Smart Grid as a new tool for better execution of TOU programs is introduced, modeled and analyzed. The remaining parts of the paper are organized as following: the definition of elasticity is reviewed in section 2. Logarithmic modeling of DR based on the concept of price elasticity of demand is developed in section 3. Section 5 is devoted to simulation results where the impact of TOU programs via proposed exponential model on load profile of the peak day of the Iranian power system in 2007 is investigated. The impact of Smart grid on TOU programs is discussed and it is shown that TOU programs would be executed more effectively in a smart grid. Finally, the paper is concluded in section 5.

2. Elasticity definition

Generally, electricity consumption like most other commodities, to some extent, is price sensitive. This means when the total rate of electricity decreases, the consumers will have more incentives to increase the demand. This concept is shown in figure 2, as the demand curve**.**

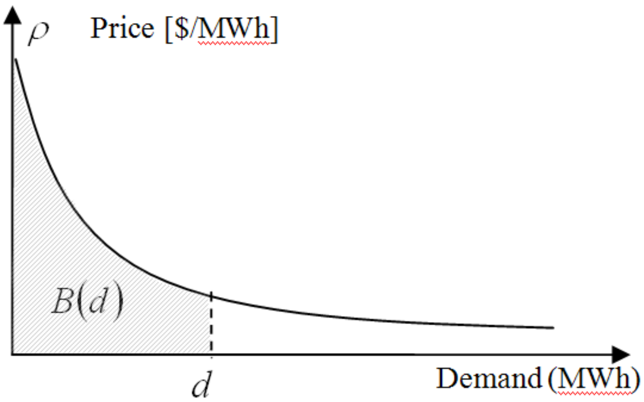


Figure 2. Demand curve

Hachured area in fact shows the customer marginal benefit from the use of d MWh of electrical energy. This is represented mathematically by:

$$B(d) = \int_0^d \rho(d).\partial d \tag{1}$$

Based on economics theory, the demand-price elasticity can be defined as follows:

$$e = \frac{\Delta d / d^0}{\Delta\rho / \rho} \tag{2}$$

For time varying loads, for which the electricity consumptions vary during different periods, cross-time elasticity should also be considered. Cross-time elasticity, which is represented by cross-time coefficients, relates the effect of price change at one point in time to consumptions at other time periods. The self-elasticity coefficient, e_{tt}, (with negative value) ,which shows the effect of price change in time period t on load of the same time period and the cross-elasticity coefficient, $e_{t\acute{t}}$,(with positive value) which relates relative changes in consumption during time period t to the price relative changes during time period $\acute{t}$ are defined by following relations:

$$e_{tt} = \frac{\partial d_t / d_t^0}{\partial \rho_t / \rho_t} \tag{3}$$

$$e_{t\acute{t}} = \frac{\partial d_t / d_t^0}{\partial \rho_{\acute{t}} / \rho_{\acute{t}}} \tag{4}$$

3. Logarithmic modeling of elastic loads

The proper offered rates can motivate the participated customers to revise their consumption pattern from the initial value d_t^0 to a modified level d_t in period t.

$$\Delta d_t = d_t - d_t^0 \tag{5}$$

It is reasonable to assume that customers will always choose a level of demand d_t to maximize their total benefits which are difference between incomes from consuming electricity and incurred costs; i.e. to maximize the cost function given below:

$$B[d_t] - d_t \cdot \rho_t \tag{6}$$

The necessary condition to realize the mentioned objective is to have:

$$\frac{\partial B[d_t]}{\partial d_t} - \rho_t = 0 \tag{7}$$

Thus moving the last term to the right side of the equality,

$$\frac{\partial B[d_t]}{\partial d_t} = \rho_t \tag{8}$$

Substituting (8) to (3) and (4), a general relation based on self and cross elasticity coefficients is obtained for each time period t as follows:

$$\frac{\partial d_t}{d_t^0} = e_{t\acute{t}} \frac{\partial \rho_{\acute{t}}}{\rho_{\acute{t}}} \tag{9}$$

By assuming constant elasticity for NT-hours period, $e_{t\acute{t}}$ = Constant for t, $\acute{t} \in$ NT integration of each term, we obtain the following relationship.

$$\int_{d_t^0}^{d_t} \frac{\partial d_t}{d_t^0} = \sum_{\acute{t}=1}^{NT} \left\{ e_{t\acute{t}} \left[\int_{\rho_{\acute{t}}^0}^{\rho_{\acute{t}}} \frac{\partial \rho_{\acute{t}}}{\rho_{\acute{t}}} \right] \right\} \tag{10}$$

Combining the costumer optimum behavior that leads to (8), (9) with (10) yields the logarithmic model of elastic loads, as follows:

$$d_t = d_t^0 + d_t^0 \prod_{\acute{t}=1}^{NT} Ln\left(\frac{\rho_{\acute{t}}}{\rho_{\acute{t}}^0}\right)^{e_{t\acute{t}}} \quad (11)$$

Parameter η is demand response potential which can be entered to model as follows:

$$d_t = d_t^0 + \eta d_t^0 \prod_{\acute{t}=1}^{NT} Ln\left(\frac{\rho_{\acute{t}}}{\rho_{\acute{t}}^0}\right)^{e_{t\acute{t}}} \quad (12)$$

The larger value of η means the more customers' tendency to reduce or shift consumption from peak hours to the other hours.

4. Simulation results

In this section numerical study for evaluation of proposed model of EDRP programs are presented. For this purpose the peak load curve of the Iranian power grid on 28/08/2007 (annual peak load), has been used for our simulation studies [13]. Also the electricity price in Iran in 2007 was 150 Rials[1]. This load curve, shown in figure 4, divided into three different periods, namely valley period (00:00 am–9:00 am), off-peak period (9:00 am–7:00 pm) and peak period (7:00 pm–12:00 pm).

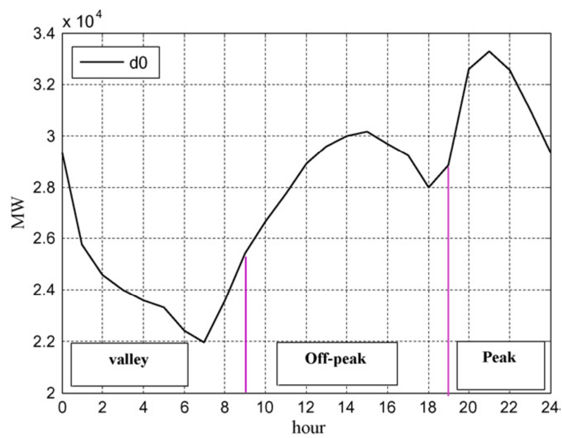


Figure 3. Initial load profile

[1]Unit of Iranian currency.

The selected values for the self and cross elasticities have been shown in Table 1.

Table 1: self and cross elasticities

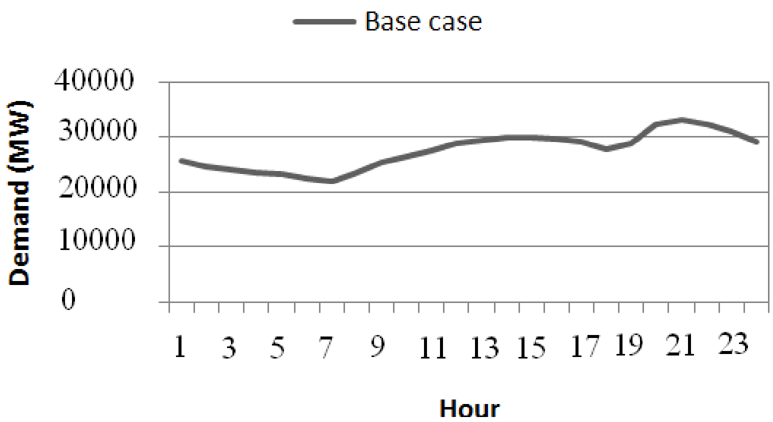
	Low	Off-peak	Peak
Low	-0.10	0.010	0.012
Off-peak	0.010	-0. 10	0.016
Peak	0.012	0.016	-0. 10

As it has been discussed in the introduction section, smart grid helps customers to be able to buy less energy from grid at times of high price, by shifting loads, using their own DG plant or even through discharging batteries of their hybrid vehicle charged during the last night. So Smart Grid's characteristics can be added to the proposed model as an increase in self and cross elasticities of demand between different time periods. It is assumed that in Smart Grid environment, demand response potential increases for 10% and reaches a portion of 40%. Elasticities between different time intervals are increased comparing to the case of non-smart grid. The increase is 10% for self elasticities and 100% for cross. In order to investigate about the effect of smart grid on the considered DR, different scenarios are considered according to Table 3.

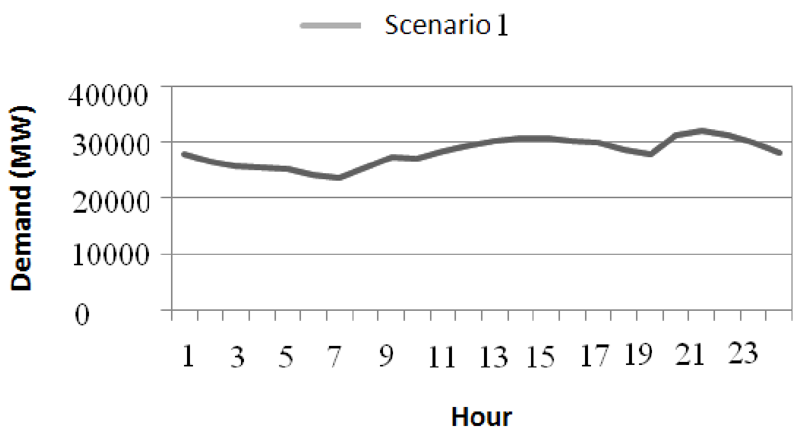
Table 3. The considered scenarios

Scenario number	TOU rates (Rials/MWh)	Demand response potential (%)
1	20, 80, 300 at valley, off peak and peak periods respectively	5%
2	20, 80, 300 at valley, off peak and peak periods respectively	10%

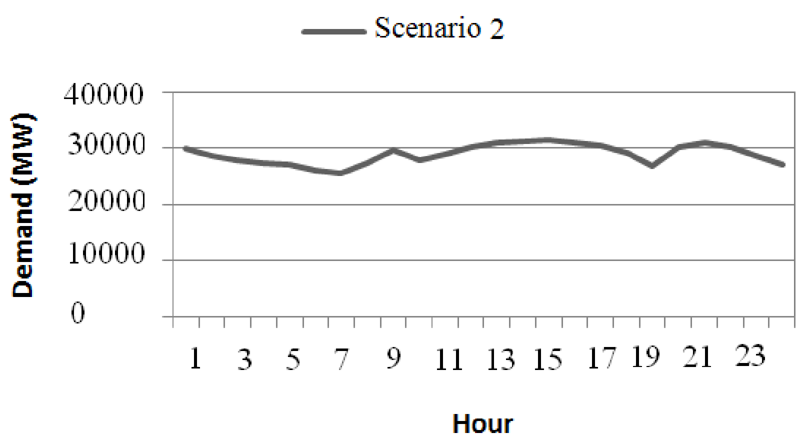
The impact of adopting scenarios 1 and 2 on load profiles have been shown all together in figure 4. As seen, the load of peak periods is reduced and shifted to other periods. Hence, the load of low periods is increased. By increasing the value of demand response potential according to scenario 1 and 2, the peak reduction and load shifting are increased.



(a) Base case



(b) Scenario number 1



(c) Scenario number 2

Figure 4. The load profile

(a) The base case (b) impact of adopting scenario 1 (c) Impact of adopting scenario 2

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Technical characteristics of the load profile in scenario 1 and 2 have been given in table 2. It is seen that the technical characteristics such as peak reduction, load factor have been improved by adopting scenario 1 and more in scenario 2 while daily energy change is positive. Also the values of peak to valley are improved.

Table 2: Technical characteristics of the load profile in scenarios 1 and 2 in comparison with the base case.

	Energy (MWh)	Energy change (%)	Peak (MW)	Peak reduction (%)	load factor	Load factor improvement (%)	Peak to valley (MW)
Base case	662268	0	33286	0	0.8290	0	11318
Scenario 1	679574.1348	2.6%	32108.7	3.5%	0.8819	6.4%	8308.4
Scenario 2	696880.2696	5.2%	31576.5	5.1%	0.9196	10.9%	5944.0

According to data reported in table 3 which are economical characteristics of the load profile in scenario 1 and 2, running TOU program is profitable for participated customers. Also by increasing demand response potential customers' profit is increased and it leads to more satisfaction of customers to participate in TOU program.

Table 3: Economical characteristics of the load profile in scenarios 1 and 2 in comparison with the base case.

	Bill in scenario 1 (Rials/day)	Bill reduction (profit) (%)
Base case	99340200	0
Scenario 1	81888685.2	17.6%
Scenario 2	80866450.5	18.6%

5. Conclusion

In this paper, a logarithmic model of demand response program has been introduced. It has been shown that this model could imitate customers' response to TOU program as prevalent DRPs. This model can help sponsor's TOU programs to simulate the behavior of customers for the purpose of improvement of load profile characteristics as well as satisfaction of customers.

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