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Technical Aspects of Running Uncertain EDRP program in the Electricity Markets.

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ABSTRACT

Many studies have simply modeled responsive loads based on the elasticity definition and they have not considered a very important issue as uncertainty in their modeling. Considering uncertainty could make the model more realistic. This paper focuses on this important issue. A power model is proposed to simulate the customer's behavior enrolled on EDRP. The nonlinear behaviors of elastic loads are incorporated in modeling. The methodology is demonstrated through a practical case study on the Iranian power system. The obtained results on the proposed system demonstrate the great impact of running EDRP programs using proposed power model on the load profile of the peak day of the Iranian power system.
Keywords: Demand Response programs, Elasticity, Emergency demand response programs.

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INTRODUCTION

Demand response programs (DRPs) are being inclusive in the electricity markets throughout the world. They are used to refer to mechanisms used to encourage consumers to reduce demand, thereby reducing the peak demand for electricity. Since power systems are generally sized to correspond to peak demand and also extra capacity for forecasting error and unforeseen events. DRPs may also be used to increase demand at times of high production and low demand period.

Commercial and industrial power users might impose load shedding on themselves, without a request from the utility. Some businesses generate their own power and wish to stay within their energy production capacity to avoid buying power from the grid. Some utilities have commercial tariff structures that set a customer's power costs for the month based on the customer's moment of highest use, or peak demand. This encourages users to flatten their demand for energy, known as energy demand response, which sometimes requires cutting back services temporarily. 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"[1]. DR is the modification of consumer demand for energy through various methods such as financial incentives [2] and education. Usually, the goal of demand side management is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as nighttime and weekends [3].

Peak demand management does not necessarily decrease total energy consumption, but could be expected to reduce the need for investments in networks and/or power plants for meeting peak demands. An example is the use of energy storage units to store energy during off-peak hours and discharge them during peak hours [4].

In this paper, we focus on Emergency Demand Response Programs (EDRPs) as incentive-based programs. In EDRPs a significant amount of money (almost 10 times of the off peak electricity price) as an incentive payments provide to customers who reduce their load during reliability-triggered events; EDRPs may or may not contain penalties for non respondent customers. However, participation in such programs is voluntary. Running these programs had been very good results in USA. Figure 1 shows the implementation results of this program in New York Electricity Market in 2002 [5]. As it is shown, the ISO had been able to mitigate the price spark and turn prices back to its normal value. Also Peak load reduction is another result of EDRP implementation [6, 7].

Many researchers have modeled responsive load simply based on elasticity definition and they have not consider a very important issue as uncertainty in their model [7-10]. The previous models have two main defects. First the models are linear that could say customer behavior is not linear and could be more complicated than linear behavior in many real situations, and second is about demand elasticity which has modeled as a fixed value while there is some extent uncertainty in forecasted elasticity of demand. These

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problem have been solved in this paper because they could help the model becomes more realistic.

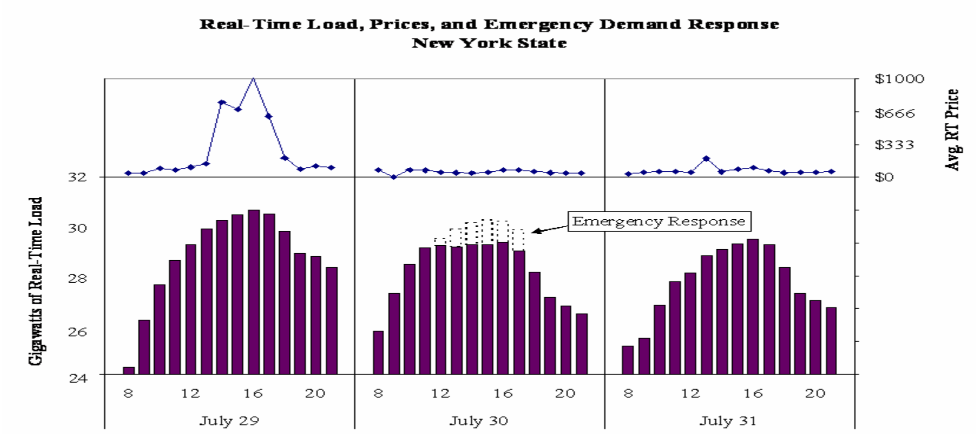

Figure 1: Impact of New York ISO emergency demand response during July 2002[5]

In this paper, a power model to describe price dependent loads is developed such that the characteristics of EDRP programs can be imitated. The remaining parts of the paper are organized as following: the definition of elasticity is reviewed in section 2. Section 3 is about elasticity uncertainty. Power modeling of DR based on the concept of price elasticity of demand is developed in section 4. Section 5 is devoted to simulation results where the impact of EDRP programs via proposed exponential model on load profile of the peak day of the Iranian power system in 2007 is investigated. Finally, the paper is concluded in section 5.

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.

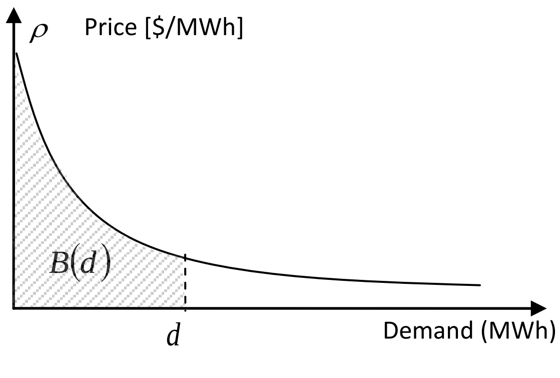

Figure 2: Demand curve

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

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

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

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

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:

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

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

Elasticity uncertainty

The expression for the probability density function of a normal distribution is always written as

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[\frac{-(x-\mu)^2}{2\sigma^2}\right] \tag{5}$$

Where μ is mean value and σ is standard deviation.

Typical normal density function curves are shown in Figure 3 for a given value of μ and three values of σ. Similarly since the value of σ determines the amount of spread or dispersion and therefore the shape of the curve, it is referred to as the scale parameter.

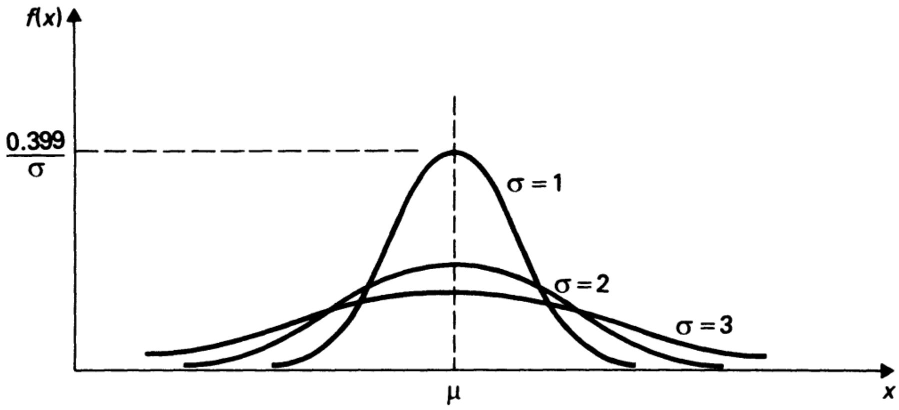

Figure 3: Normal density functions for three values of σ .

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It is extremely difficult to obtain sufficient historical data to determine the distribution describing the elasticity coefficient uncertainty. Published data, however, has suggested that the uncertainty can be reasonably described by a normal distribution. The distribution mean is the forecasted elasticity coefficient. The distribution can be divided into a discrete number of class intervals .The elasticity representing the class interval mid-point is assigned the designated probability for that class interval. This is shown in Figure 4, where the distribution is divided into seven steps. A similar approach can be used to represent a nun symmetrical distribution if required. It has been found that there is little difference in the end result between representing the distribution of elasticity coefficient uncertainty by seven steps or forty-nine steps. Here, we consider eleven intervals because our simulation showed that considering higher step numbers have no effect on the end result.

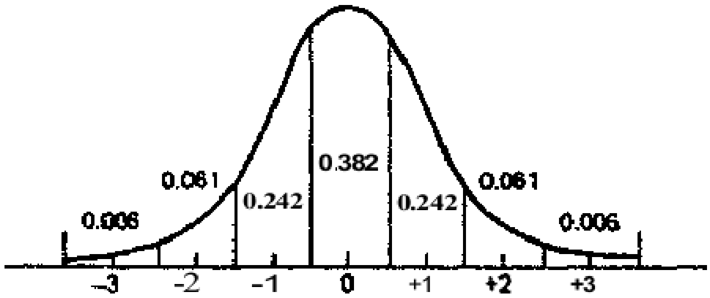

Figure 4: Seven-step approximation of the normal distribution

Power 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.

$$\Delta d_t = d_t - d_t^0 \tag{6}$$

Total incentive paid to customer in programs which contain incentive inc_t for load reduction in period t, will be as follows:

$$INC(\Delta d_t) = inc_t \cdot (d_t^0 - d_t) \tag{7}$$

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:

$$B[d_t] - d_t \cdot \rho_t + INC(\Delta d_t) \tag{8}$$

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

$$\frac{\partial B[d_t]}{\partial d_t} - \rho_t + \frac{\partial INC(\Delta d_t)}{\partial d_t} = 0 \tag{9}$$

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

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$$\frac{\partial B[d_t]}{\partial d_t} = \rho_t + inc_t \tag{10}$$

Substituting (9) to (3) and (4), a general relation based on forecasted elasticity coefficients is obtained for each time period t as follows:

$$\frac{\partial d_t}{d_t} = e_{t\acute{t}} \frac{\partial(\rho_{\acute{t}} + inc_{\acute{t}})}{\rho_{\acute{t}} + inc_{\acute{t}}} \tag{11}$$

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

$$\int_{d_t^0}^{d_t} \frac{\partial d_t}{d_t} = \sum_{\acute{t}=1}^{NT} \left\{ e_{t\acute{t}} \left[\int_{\rho_{\acute{t}}^0}^{\rho_{\acute{t}}} \frac{\partial \rho_{\acute{t}}}{\rho_{\acute{t}} + inc_{\acute{t}}} + \int_0^{inc_{\acute{t}}} \frac{\partial inc_{\acute{t}}}{\rho_{\acute{t}} + inc_{\acute{t}}} \right] \right\} \tag{12}$$

Combining the costumer optimum behavior that leads to (9), (10) with (11) yields the power model of elastic loads, as follows:

$$d_t = d_t^0 \prod_{\acute{t}=1}^{NT} \left[\frac{(\rho_{\acute{t}} + inc_{\acute{t}})^2}{\rho_{\acute{t}}(\rho_{\acute{t}}^0 + inc_{\acute{t}})} \right]^{e_{t\acute{t}}} \tag{13}$$

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

$$d_t = d_t^0 + \eta d_t^0 \left\{ \prod_{\acute{t}=1}^{NT} \left[\frac{(\rho_{\acute{t}} + inc_{\acute{t}})^2}{\rho_{\acute{t}}(\rho_{\acute{t}}^0 + inc_{\acute{t}})} \right]^{e_{t\acute{t}}} - 1 \right\} \tag{14}$$

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

Elasticity uncertainty based on details explained in the previous section could be considered in the equation number (14) as follow:

$$d_t = \sum_{i=1}^{ND} \left[prob_i \left(d_t^0 + \eta d_t^0 \left(\prod_{\acute{t}=1}^{NT} \left[\frac{(\rho_{\acute{t}} + inc_{\acute{t}})^2}{\rho_{\acute{t}}(\rho_{\acute{t}}^0 + inc_{\acute{t}})} \right]^{e_{t\acute{t},i}} - 1 \right) \right) \right] \tag{15}$$

Where *ND* is the number of class intervals, $prob_i$ *is* probability of class interval i^{th} and $e_{t\acute{t},i}$ is mid-point of class interval i^{th}.

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 [11]. Also the electricity price in Iran in 2007 was 150 Rials (Unit of Iranian currency). This load curve, shown in figure 5, 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).

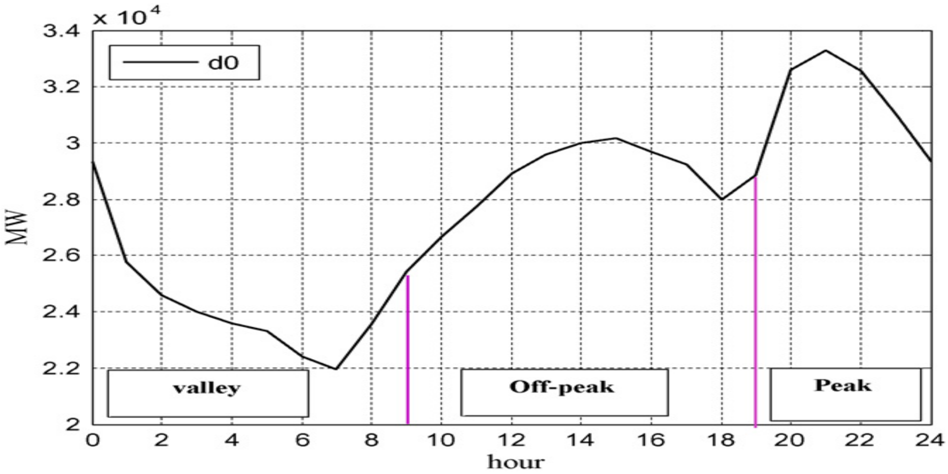

Figure 5: Initial load profile

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	0.014	0.016
Off-peak	0.014	-0. 10	0.012
Peak	0.016	0.012	-0. 10

The considered scenarios have been listed in Table 2.

Table 2: The considered scenarios

Scenario number	EDRP rates (Rials/MWh)	Incentive in peak periods (Rials/MWh)	Demand response potential (%)
1	Flat 160	400	10%
2	Flat 160	400	20%
3	Flat 160	400	30%

Figure 6 depicts the percent of load factor improvement in different scenarios. As seen, in scenario 1, increasing uncertainty through increasing σ leads to a bad result which is load factor decreasing, in scenario 2, we achieve to higher load factor when σ increases, in fact it is the main goal of system operator, and in scenario 3 we have both of the mentioned above results. From figure 6, we can understand that when σ is about 75%, slow increasing progress of load factor is stopped and it starts to decrease rapidly. It could be concluded that in low level of demand response potential, high uncertainty could lead to worse load factor values. Increasing in demand response potential mitigates this phenomena and even causes to correct and increase load factor. Increasing more in demand response potential cannot make this process better and may have destructive effect on it which has been discussed above.

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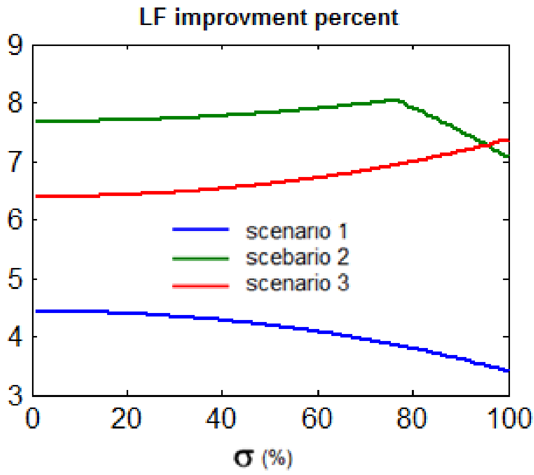

Figure 6: Percent of load factor improvement in different scenarios

Figure 7 shows scenario priority from load factor improvement aspect. As seen, for σ lower than 95%, scenario 2 has the highest priority and after that there are scenario 3 and 1, respectively. For σ higher than 95%, the priority of scenarios 2 and 3 is exchanged. But scenario 2 still has the highest priority.

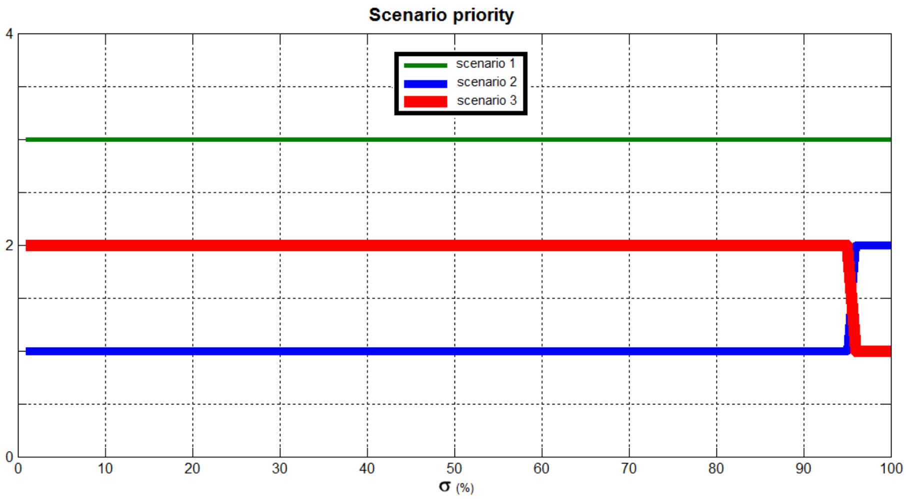

Figure 7: Scenario priority from LF improvement aspect

CONCLUSION

In this paper has been investigated the effect of considering uncertainty in demand response modeling. The customers' response to EDRP program has been model based on power function. This model can help sponsor's EDRP programs to simulate the behavior of customers for the purpose of improvement of load profile characteristics as well as satisfaction of customers. The studies were carried out on Iranian power system. Validate of the proposed technique showed by many simulation results.

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Nomenclature

0	Initial state index (Superscript)
i	Class interval index (subscript)
$t, \acute{t}$	Time period indices (subscript)
ND	Number of class intervals of normal density function
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
$e_{tt,i}$	Self elasticity in interval class i^{th}
$e_{t\acute{t},\iota}$	Cross elasticity in interval class i^{th}
$prob_i$	Probability of class interval i^{th}
inc_t	incentive payment for load reduction in period t
η	Demand response potential (%)

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