J Electr Eng Technol.2017; 12(5): 1719-1728
http://doi.org/10.5370/JEET.2017.12.5.1719

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Impacts of Demand Response from Different Sectors on Generation System Well Being

M. N. Hassanzadeh*, M. Fotuhi-Firuzabad and A. Safdarian†**

Abstract – Recent concerns about environmental conditions have triggered the growing interest in using green energy resources. These sources of energy, however, bring new challenges mainly due to their uncertainty and intermittency. In order to alleviate the concerns on the penetration of intermittent energy resources, this paper investigates impacts of realizing demand-side potentials. Among different demand-side management programs, this paper considers demand response wherein consumers change their consumption pattern in response to changing prices. The research studies demand response potentials from different load sectors on generation system well-being. Consumers' sensitivity to time-varying prices is captured via self and cross elasticity coefficients. In the calculation of well-being indices, sequential Monte Carlo simulation approach is accompanied with fuzzy logic. Finally, IEEE-RTS is used as the test bed to conduct several simulations and the associated results are thoroughly discussed.

Keywords: Demand-side management, Elasticity coefficients, Fuzzy logic, Generation system well-being, Time-varying prices

Nomenclature

$D^{k,t}$	Demand of load sector k at hour t (MWh).
$\rho^{k,t}$	Price of load sector k at hour t ($/MWh).
$A^{k,t}$	Incentive of program in the t hour $/MWh).
$\rho_o^{k,t}$	Initial price of load sector k in the t hour ($/MWh).
$D_o^{k,t}$	Initial demand of Load sector K in the t hour (MW).
$E^{(ik,jk)}$	Cross elasticity coefficients.
$E^{(ik,ik)}$	Self-elasticity coefficients.
$B(D^{k,t})$	Customers income of load sector K in the t hour ($).
$B_o^{k,t}$	Benefit of load sector K in t hour with nominal demand
ρ_o^k	Mean price for load sector K in 24 hours
up_j	Capacity of the jth in service unit in contingency c_i
cp_i	Capacity of available units in the ith contingency c_i
w_{i1}	First modifications factors associated with ith hour
$CLUS_i$	Capacity of largest units in ith hour
$Load$	System load at the given hour
m_{i1}	Set of in service units in ith hour which their single outage will not result in load interruption
$P(H)$	Healthy state probabilities
$P(M)$	Marginal state probabilities
$P(R)$	Risk state probabilities

† Corresponding Author: Center of Excellence in Power System Control and Management, Electrical Engineering Department, Sharif University of Technology, Iran. (Safdarian@sharif.edu).
* College of Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran (noandishan.sanat@gmail.com)
** Center of Excellence in Power System Control and Management, Electrical Engineering Department, Sharif University of Technology, Iran. (fotuhi@sharif.edu).
Received: June 12, 2016; Accepted: May 11, 2017

1. Introduction

Demand response is neither a new tool nor a complicated concept. It is referred to changes in consumers' usage profile in response to time-varying prices and/or signals indicating technical and financial condition in power industry. Although it has been known that flexibility in demand can bring several benefits, its realization has been postponed mainly because of technical barriers. These days, however, thanks to recent advances in communication systems and the smart grid paradigm, demand response has become very close to the realization phase. Demand response realization is counted as big step towards optimal electricity use and efficient power systems. There are different methods for activating demand response, which are used depending on the facilities and conditions. Various initiatives have been taken in the past two decades concerning demand response. References [1-3] discussed the application of different demand response and load modeling methods under different conditions. In [1], a study is carried out on demand response of intelligent systems based on the maximization of customer benefits or minimization of electricity costs using real time pricing. In [2], customers' response to real time prices was studied by maximizing customers' well-being. In [3], a study was carried out on the optimization of demand response using time of use (TOU) pricing method. A demand response model was also developed based on the average cost and consumption as well as time-dependent price differences. In [4], a practical pricing scheme was proposed to encourage different costumers to participate in demand response programs. Different studies were also carried out on the effect of application of demand response on both supply and demand sides. These studies covered a wide range of applications of the demand response. References [5, 6] discussed the economic planning issues considering the availability of demand response and examined its effect on power systems planning. [7], investigated the effect of demand response on the reliability of power systems considering load uncertainty. In that study, demand response was studied as load shift. [8], investigated the effect of demand response on different load sectors using the load shift method. It also studied the effects of load shift in different load sectors on system reliability at the production level. [9] and [10] examined the advantages of demand response in the agricultural and industrial sectors. They found out that the profitability of demand response varies in different sectors depending on the behavior and nature of loads in different sectors. In [11], industrial demand response modelling in smart grid was studied. It has been shown that demand response modeling has become a major technology to improve the reliability of system with reducing costumers costs. Although numerous studies have been carried out on demand response, majority of them have examined the partial effect of implementation of demand response programs on aggregate system load without considering the response from different sectors. In this paper, demand response potential from different load sectors is studies.

The use of demand response is anticipated to improve service reliability, prevent network congestion, mitigate environmental effects, improve system security, reduce network losses, and enable higher penetrations of intermittent energy resources [12-14]. In [15], a study was carried out on the impacts of demand response programs on reliability of wind integrated power systems considering demand-side uncertainties. They found out that demand response programs improve the reliability level and peak load carrying capability of new energy integrated systems.

Among the benefits, enabling higher penetrations of intermittent energy resources has attracted the attention of several researchers. This is mainly due to numerous advantages of using renewable energy resources. In this paper, demand response potentials in generation system well-being are evaluated. In the research, impacts of seven load sectors namely residential, agriculture, office, industrial, large user, government and commercial loads are studied. Another parameter that is taken into account in the implementation of demand response is demand sensitivity to the price of electricity. In the restructured electricity system, due to the economic issues and the electricity market, the price of electricity may change overtime and customers may be influenced by price variations. As a result, customers alter their energy use profile that can influence the status of the system [16]. Therefore, analysis of the effect of elasticity on the demand response is another parameter considered in this research. Various initiatives have also been taken concerning load elasticity in the demand response program. In [17], the authors investigated the effect of economic elasticity of load on the electricity market. In [18], load elasticity and its effect on load profile were calculated. In [19] and [20], load elasticity in the electricity market was modeled and simulated. The reported research indicated that load elasticity varies depending on the load sector. Moreover, some loads are flexible to prices while others are not. Demand response specifically influences the elasticity of load segments to reliability criteria within the framework of well-being. Different scenarios were used to study the use of demand response with and without encouragement and its effect on the system criteria. To this end, the sequential Monte Carlo method and fuzzy logic were used. The IEEE-RTS reliability test system is also used for assessment purposes.

2. Preliminary Basics

This section intends to briefly describe the major theoretical concepts applied in the developed model. In below, brief explanations over the considered model for demand response measures and well-being analysis are provided.

2.1 Demand response

Load elasticity is defined as the demand sensitivity to the price changes. It should be mentioned that elasticity coefficients are usually divided into two groups namely self-elasticity coefficients and cross elasticity coefficients. The former coefficients denote demand changes in response to electricity price variations at the same hour while the later coefficients represent demand response to price changes at different hours. [20]. In this section, we model how dynamic pricing and price elasticity affect the demand profile in different sectors and we show how the maximum benefit of customers can be achieved due to this response.

Modeling based on self-elasticity:

If load sector K changes its demand from $D_o^{k,t}$ to $D^{k,t}$ in response to incentive $A^{k,t}$, we have

$$\Delta D^{k,t} = D_o^{k,t} - D^{k,t} \tag{1}$$

So, incentive price for load sector k and the t-th hour will be as follow:

$$P(\Delta D^{k,t}) = A^{k,t}.\Delta(D^{k,t}) \tag{2}$$

Benefit of load sector K, $S(D^{k,t})$, for the t-th hour will be as:

$$S(D^{k,t})=B(D^{k,t})-D^{k,t}.\rho^{k,t}+P(\Delta D^{k,t}) \tag{3}$$

To maximize the load sectors K benefit, $\frac{\partial S(D^{k,t})}{\partial D^{k,t}}$ should be set to zero: i.e.

$$\frac{\partial S(D^{k,t})}{\partial(D^{k,t})}=\frac{\partial B(D^{k,t})}{\partial(D^{k,t})}-\rho^{k,t}+\frac{\partial P(D^{k,t})}{\partial(D^{k,t})}=0 \tag{4}$$

where

$$\frac{\partial B(D^{k,t})}{\partial(D^{k,t})}=\rho^{k,t}+A^{k,t} \tag{5}$$

The benefit function for load sector K in i-th hour is [19].

$$B(D^{k,t})=B_o^{k,t}+\rho_o^k\times\left[D^{k,t}-D_o^{k,t}\right]\times\left[1+\frac{D^{k,t}-D_o^{k,t}}{2.E^{ik,ik}.D_o^{k,t}}\right] \tag{6}$$

Where ρ_o^k is mean price for load sector K in 24 hours and is determined as follow:

$$\rho_o^k=\frac{\sum_{i=1}^{24}D_o^{k,t}\times P_o^{k,t}}{\sum_{i=1}^{24}D_o^{k,t}} \tag{7}$$

Considering (5) and (6) together we can have

$$\rho^{k,t}+A^{k,t}=\rho_o^{k,t}\times\left[1+\frac{D^{k,t}-D_o^{k,t}}{E^{k,t}.D_o^{k,t}}\right] \tag{8}$$

$$\rho^{k,t}-\rho_o^k+A^{k,t}=\rho_o^{k,t}\times\left[\frac{D^{k,t}-D_o^{k,t}}{E^{k,t}.D_o^{k,t}}\right] \tag{9}$$

Therefore, load sector K consumption will be:

$$D^{k,t}=D_o^{k,t}\times\left[1+\frac{E^{k,t}.\left[\rho^{k,t}-\rho_o^{k,t}-A^{k,t}\right]}{\rho_o^{k,t}}\right] \tag{10}$$

Where $D^{k,t}$ is demand of load sector k at hour *t* (MWh) and $\rho^{k,t}$ is price of load sector k at hour *t* ($/MWh) and $A^{k,t}$ is incentive of program at hour t ($/MWh) and $\rho_o^{k,t}$. is initial price of load sector k at hour t ($/MWh) and $D_o^{k,t}$ initial demand of load sector k at hour t (MW). Likewise, $E^{(ik,ik)}$ and $E^{(ik,jk)}$ are self and cross elasticity coefficients respectively and $B(D^{k,t})$ is customers income of load sector k at hour t ($) and $B_0^{k,t}$ is benefit of load sector k at hour t with nominal demand and ρ_0^k is mean price for load sector k within the 24 hours.

Modeling based on cross elasticity:

The cross elasticity for load sectors K between i-th hour and j-th hour is given by:

$$E^{ik,jk}=\frac{\rho_0^{k,jt}}{D_o^{k,it}}\times\frac{\partial D^{k,it}}{\partial\rho^{k,jt}} \tag{11}$$

If a constant cross elasticity for load sector K is assumed, the demand response to price variation could be defined as a linear function as follow:

$$D^{k,it}=D_o^{k,it}+\sum_{j=1}^{24}E^{ik,jk}.\frac{D_o^{k,it}}{\rho_o^{k,jt}}.\left[\rho^{k,jt}-\rho_o^{k,jt}\right];\ i=1:24 \tag{12}$$

If incentive in j-th hour for load sector K is $A^{k,jt}$ which can be positive in peak load hours and zero in others, energy price will be given by

$$\Delta\rho^{k,jt}=\rho^{k,jt}-\rho_o^{k,jt}+A^{k,jt} \tag{13}$$

Therefore

$$D^{k,it}=D_o^{k,it}+\sum_{j=1}^{24}E^{ik,jk}.\frac{D_o^{k,it}}{\rho_o^{k,jt}}.\left[\rho^{k,jt}-\rho_o^{k,jt}+A^{k,jt}\right] \tag{14}$$

Combining (10) and (14), we can have final model as follow:

$$D^{k,it}=\left\{D_o^{k,it}+\sum_{j=1}^{24}E^{ik,jk}\times\frac{D_o^{k,it}}{\rho_o^{k,jt}}\times\left[\rho^{k,jt}-\rho_o^{k,jt}+A^{k,jt}\right]\right\}\times\left[1+\frac{E^{ik,ik}\times\left[\rho^{k,t}-\rho_o^{k,t}-A^{k,t}\right]}{\rho_o^{k,t}}\right] \tag{15}$$

2.2 Well-being analysis

The well-being analysis is to evaluate the well-being of system in serving load via a set of probabilistic criteria. As displayed in Fig. 1. The degree of system well-being is quantified in terms of three indices namely healthy, marginal, and risk. The system is in the health state if there is additional reserve in available generation capacity to meet analytical criteria like loss of the largest available unit. In the marginal state, the system does not face problems in serving the load, but it lacks sufficient reserve to face

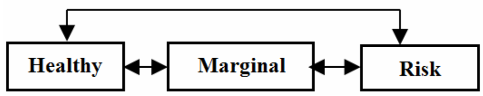

Fig. 1. Well-being model

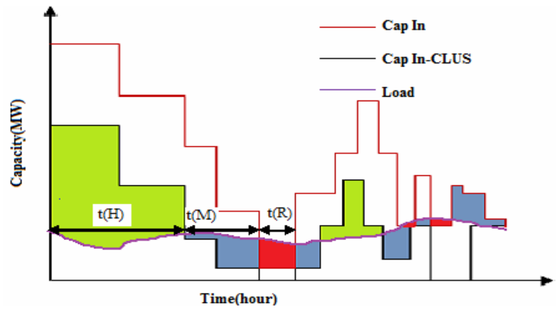

Fig. 2. Combined generating capacity and load

analytical criteria. Synonymously, in the marginal state, the generation capacity reserve is not enough to tolerate against the loss of the largest operating generating unit. In the risk state, the load is higher than the available generation capacity. Clearly, the system is always in either health state, marginal state, or risk state. The probabilities of the system being in any of the three states are considered as well-being indices.

There are analytical and simulation methods to estimate the well-being indices. Without loss of generality, this paper uses the sequential Monte Carlo simulation method for estimating the well-being indices. The method randomly samples the up/down state of generating units and calculates total available capacity of the generation system. Fig. 2 shows available generation capacity versus time for a typical generation system. This curve is known as cap-in curve. The capacity of the largest available unit is then subtracted from the cap-in curve to achieve cap-in-CLUS curve. Finally, comparing the two curves with the system load curve indicates if the system is in health, marginal, or risk state within each time interval. In the figure 2, $t(H)$, $t(M)$, and $t(R)$ represent the time during which the system is in health, marginal, and risk states, respectively. The probability of the system being in each of the states is finally calculated by summing up the associated duration times divided by the duration of simulation period.

3. Developed Methodology

This section develops a step-by-step procedure to include demand response impacts in generation system well-being assessment. The step-by-step process is described as follows:

Step 1: This step is to identify the system under study and prepare the required input data. The potential input data are load data associated with different load sectors, conventional generating units' data, and intermittent energy resources' data.

Step 2: In this step, sequential Monte Carlo simulation approach is used to determine up/down state of conventional generating units. The output of this step includes hourly available generation capacity during the simulation period.

Step 3: The data associated with the energy use of different load sectors, i.e., residential, commercial, etc., is employed to calculate hourly load of the system. At the end of this step, hourly total load profile of the system is achieved.

Step 4: In this step, in order to study the effect of demand response on the indices of the system well-being, load elasticity and time of use pricing are used.

The reaction of consumers in response to time-varying prices, i.e., hourly prices, is captured via price elasticity coefficients [17]. It should be mentioned that elasticity coefficients are usually divided into two groups namely self-elasticity coefficients and cross-elasticity coefficients. The former coefficients denote demand changes in response to electricity price variations at the same hour while the later coefficients represent demand response to price changes at different hours. It is worth mentioning that self-elasticity coefficients are always negative while cross-elasticity coefficients take positive values. At the end of this step, revised load profile associated with different load sectors and total load profile of the system after applying demand response are ready to be used in the next steps.

Step 5: In the above steps, hourly system load profile and hourly generation capacity are achieved. Hourly capacity of the largest available generating unit is the other information needed to start system well-being analysis. To this end, this step checks the up/down state of generating units during the simulation period and selects the capacity of the largest operating generating unit as the output.

Step 6: This step is to calculate well-being indices of the system based on the obtained hourly load, available generation capacity, and capacity of the biggest operating unit profiles. The well-being analysis is an iterative process as follows:

Step 6-1: The first time interval of the simulation period is selected. The available capacity of the generation system is compared with the system load during the selected time interval. If the load is more than the available capacity, system is assumed to be in the risk state within the selected time interval. Otherwise, if load is less than available capacity minus the capacity of the largest available unit, system is in the health state. Finally, if neither of the conditions is encountered, system is in the marginal state.

Step 6-2: The well-being indices are calculated by dividing the number of time intervals belong to each state by the total number of selected and analyzed time intervals.

Step 6-3: The termination criteria are checked in this step. Convergence of the indices, total number of selected and evaluated time intervals, and CPU time are the major termination criteria utilized in the literature. In case either of considered termination criteria is encountered, the study is done and calculated indices are reported. Otherwise, the well-being analysis proceeds to the next step. The stopping criterion is as follow:

$$\frac{\sigma(x)}{E(x)\times\sqrt{N}} \le 0.05 \tag{16}$$

where x is the P(H), N is the number of sampling years, $E(x)$ is the mean value function, and $\sigma(x)$ is the standard deviation function.

Step 6-4: In this step, the next time interval is selected and system state during the selected time interval is determined. The iterative procedure proceeds from Step 6-2.

The well-being indices that will be calculated by the above process are imposed to essential defects since system state is determined according to crisp criteria. In such a situation, even minor fluctuations in system load may trigger big changes in the well-being indices. This is more obvious especially when the largest collaborative unit is substantially bigger than other units. This issue can be solved by means of Fuzzy logic approach. In this approach, a specific membership function is used to determine to what extent the selected time interval belongs to the health and marginal states, and it is divided between the health and marginal states based on the membership function. For instance, consider a time interval during which the system does not have enough reserve to cope with the outage of the largest available unit. However, the system can tolerate the loss of smaller collaborative units, the system is assumed to be partly in the health and marginal states during the time interval. To determine the share of each system state, two correction parameters, introduced in [24], have been used. The first parameter represents the proportion of the number of available units whose failure does not lead to loss of load to the total number of the sharing units at that hour. The share of the health state increases as this parameter increases. The second parameter is the proportion of the value of load lost at each hour due to loss of the largest sharing unit at that hour to the size of the largest sharing unit at that hour. The share of health state increases as this parameter decreases. The above described procedure calculates generation system well-being indices considering demand response from different load sectors. The indices are also in the Fuzzy form which more effectively demonstrates system condition from the well-being viewpoint. In fact, this parameter demonstrates the effect of the largest available unit at each hour in load provision. To understand this better, consider a system with N generating units. Let available capacity value at hour i be cp_i. Assuming mc_i units out of N to be available and nc_i units to fail, the state at this hour can be represented as follows.

Where up_j is capacity of the j[th] in service unit in contingency c_i and cp_i is the available generation capacity within the i[th] contingency c_i and w_{i1} is the first modifications factors associated with the i[th] hour and w_{i2} is the second modifications factors associated with the i[th] hour and $CLUS_i$ is capacity of the largest unit in the i[th] hour and *Load* system load at the given hour. Likewise, m_{i1} is the set of in service units in the i[th] hour whose single outage will not result in load interruption and $P(H)$, $P(M)$ and $P(R)$ are probability of healthy, marginal and risk states.

$$up_1 \le up_2 \le \cdots \le up_{mci} \tag{17}$$

$$cp_i = \sum_{j=1}^{mc_i} up_{ij} \tag{18}$$

$$mc_i + nc_i = N \tag{19}$$

If $cp_i < Load$, the i[th] hour belongs to the risk domain. If $cp_i \ge Load$, the i[th] hour belongs to the comfort domain; i,e. healthy or marginal state. Modification factors in the i[th] hour are as follow:

$$w_{i1} = \frac{m_{i1}}{mc_i} \tag{20}$$

$$w_{i2} = 1 - \left(\frac{Load - (cp_i - CLUS_i)}{CLUS_i}\right) \tag{21}$$

Healthy and marginal state probabilities are calculated as follow:

$$P(M) = 1 - P(H) - P(R) \tag{22}$$

$$P(H) = \frac{\left(\sum_{j=1}^{N\times 8736} (j \perp cp_i \ge Load) \times w_{i1} \times w_{i2}\right)}{N\times 8736} \tag{23}$$

$$P(R) = \frac{\left(\sum_{j=1}^{N\times 8736} (j \perp w_{i2} = 0, w_{i1} = 0)\right)}{N\times 8736} \tag{24}$$

4. Test System Data

The original IEEE-RTS system with total installed capacity of 3,405 MW, 32 generators, single-state load model, and peak load of 2,850 MW, which is the sum of peak loads on all the buses, has been proposed in the initial plan [22]. The IEEE-RTS basic load model has been presented specifying load composition at each bus including the seven load sectors: residential, agricultural, official, industrial, residential, governmental, and commercial loads [23]. The system load has been presented in 8736 points in an hourly basis. The peak load in each sector is shown in Table 1 together with the related load factors. According to the research results, peak load and the factor vary for different sectors. This reflects effects of different response potentials from different sectors. Fig. 3 shows the load diagram for different sectors. In addition,

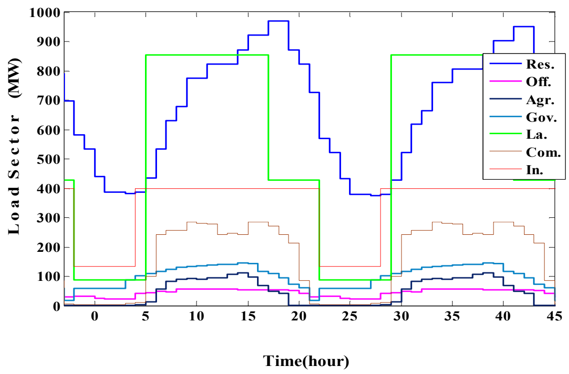

Fig. 3. Different load sectors profile

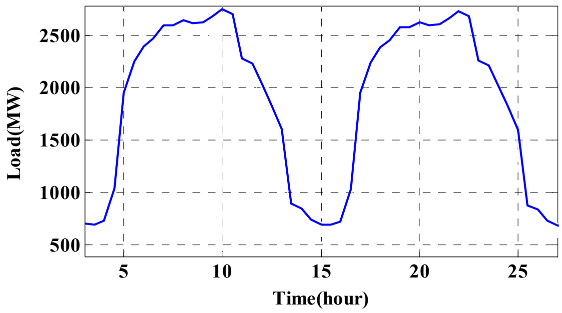

Fig. 4. IEEE-RTS system load profile

Table 1. Different load sectors Peak load and load factor IEEE-RTS

Sector	Load Factor (%)	Peak (MW)
Agricultures	38.38	113.1
Large User	63.44	855.01
Residential	57.48	968.99
Government	56.26	145.35
Industrial	83.42	399.01
Commercial	54.41	284.99
Office	61.73	57.02
System	63.80	2754.75

peak load hours and profile vary in different sectors. Each sector demonstrates a different behavior in terms of demand response. Load profile, which is the sum of that of all sectors, is depicted in Fig. 4. Results of the comparison of the above figures suggest that each sector has its own specific profile and its variations do not comply with the variation of aggregate system load.

5. Case Study

In order to study the effect of demand response on the indices of the system well-being using load elasticity and time of use pricing, the following scenarios are taken into account:

Scenario 1: In this scenario, the criteria of the system in question are calculated with and without the application of fuzzy method to demonstrate the efficiency of the fuzzy method in system well-being criterion. In this scenario, the calculations are made without considering demand response. The probability of health, marginal, and risk states is calculated and mentioned in Table 2. As displayed in the table, the health state probability value is increased from 0.951884 with the conventional calculation method to 0.979286 with the modified fuzzy based method. The marginal state probability is decreased. The risk state values, or LOLP, and the energy not served (ENS) values are the same in the two calculation methods. The annual amounts of served energy in the three health, marginal, and risk states can offer a better view of the used load serving quality. The total annual used energy value of the system is 15,375,179.76 MWh in the conventional calculation method while, 14,341,152.04 MWh of it is in the health state, 936,157.43 MWh in the marginal state, 97,870.29 MWh in the risk state, and 4,949.32 MWh is not served. In the method of calculation with the application of fuzzy method, the served energy value in the health state is increased by 578,613.98 MWh and reached 14,919,766.02 MWh. The served energy in the marginal state is decreased by the same amount. These values are displayed in Table 3. which can affect the calculation of the amount of reserve needed in the system and also make the amount of investment lower.

Table 2. Well-being indices with and without fuzzy logic

	E(Loss)(MWh)	P(R)	P(M)	P(H)
Normal	4949.32	0.004412	0.043704	0.951884
Modified	4949.32	0.004412	0.016302	0.979286

Table 3. Served energy with and without fuzzy logic

	E(Total) (MWH)	E(R) (MWH)	E(Margin) (MWH)	E(healthy) (MWH)
Normal	15375179.76	97870.29	936157.46	14341152.04
Modified	15375179.76	97870.29	357543.45	14919766.02

Table 4. Elasticity of different load sectors

	Peak Load	Off Load	Low Load	Peak Load	Off Load	Low Load
	Residential			Large user, Industrial		
Peak Load	-0.26	0.065	0.048	-0.13	0.054	0.039
Off Load	0.065	-0.26	0.04	0.054	-0.13	0.032
Low Load	0.048	0.04	-0.26	0.039	0.032	-0.13
	Commercial, Official, Governmental			Agriculture		
Peak Load	-0.21	0.020	0.015	-0.15	0.048	0.036
Off Load	0.020	-0.21	0.012	0.048	-0.15	0.03
Low Load	0.015	0.012	-0.21	0.036	0.03	-0.15

Scenario 2: In this scenario, demand response is considered based on self and cross elasticity coefficients of different load sectors. The values of the coefficients of different load sectors are given in Table 4. As displayed, loads are generally divided into the four groups of residential loads, large user and industrial loads, commercial, official, and public loads, and agricultural loads. Because official

and public load elasticity is not available, commercial load elasticity is used instead. Generally, measuring elasticity is a complex issue and estimating the elasticity coefficients is associated with many uncertainties. Cultural, economic, and political issues, climatic conditions, security and so on may affect elasticity coefficients. So far, lots of efforts have been made to estimate elasticity coefficients. Since estimating the coefficients is out of scope of this paper, we borrowed the coefficient values from relevant references. It should be considered that the elasticity coefficients are not estimated for individual consumers. Also, it should be noted that the coefficients represent the average behavior of consumers in the same sector. After demand response and the application of the fuzzy based method, the system well-being criteria are displayed in Table 5. As displayed, the reliability criteria are improved, but the improvement is different in different load sector responses. Residential loads due to the highest improvement where health state probability is increased from 0.979286 to 0.994786, and risk probability is decreased from 0.004412 to 0.0007938, that is, by about 82%. The unserved energy value is decreased from 4949 MWh to 738 MWh, that is, by 85%. After residential loads, large, commercial, and industrial loads have the highest effect, respectively, and official and agricultural loads have the lowest effect, respectively. With demand response from official sector, risk state probability is decreased by only 9%, and unserved energy value by about 10%, insignificant values as compared to those for residential and large user loads. The served energy value in all the three healthy, marginal, and risk states as well as the total annual value of energy used by the system are provided in Table 6. As observed, the total energy value is decreased by about 9.88% with residential demand response, and is decreased by 5.9% with large user demand response, and the lowest decrease concerns agricultural loads with 0.45%. In Fig. 5, the used energy decrease value and unserved energy decrease value are displayed in percent for the seven different load sectors. As observed, residential, large user, commercial, industrial, public, agricultural, and official loads, respectively, have the highest effects on improvement of system reliability. Figs. 6 to 8 display how different load sector responses affect the total load profile as compared to the system normal load without response. The figures well represent the values of the effects of

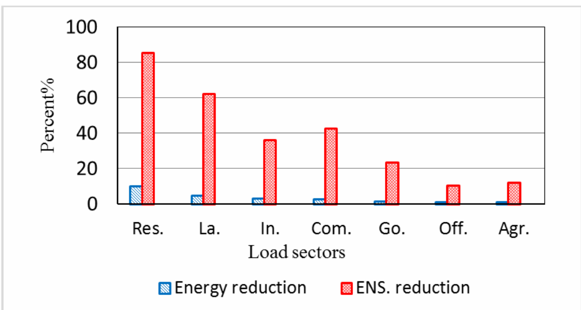

Fig. 5. Served and unserved energy reduction in scenario 2

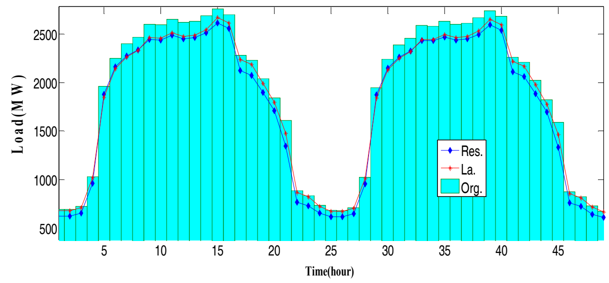

Fig. 6. Large and residential load sectors response in scenario II

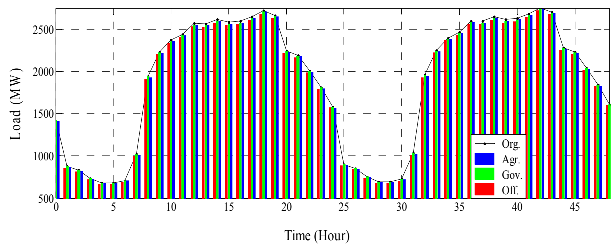

Fig. 7. Governmental, agriculture and official Load Sectors response in scenario II

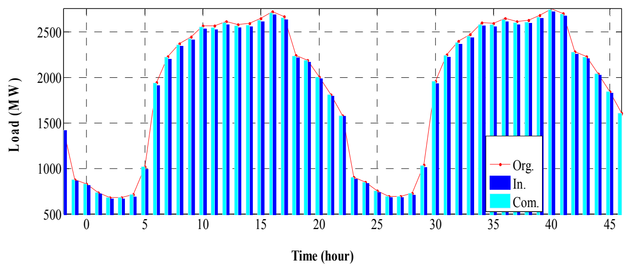

Fig. 8. Industrial and commercial load sectors response in scenario II

Table 5. Well-being indices with fuzzy logic in scenario 2

	P(Healthy)	P(Margin)	P(Risk)	E(Loss)(MWh)
Res-Elast	0.994786	0.00442	0.0007938	738.26
La-Elast	0.99003	0.008142	0.001828	1889.15
In-Elast	0.985227	0.011820	0.002953	3169.54
Com-Elast	0.98625	0.011066	0.002684	2856.87
Gov-Elast	0.982862	0.013648	0.0034898	3801.29
Off-Elast	0.980851	0.015141	0.004008	4443.72
Agr-Elast	0.981149	0.014915	0.0039361	4364.43

Table 6. Served energy(MWh) of three states in scenario II

	E(Healthy)	E(Margin)	E(Risk)	E(total)
Res-Elast	13751387.56	88808.84	16069.13	13856265.53
La-Elast	14469339.57	171245.94	38944.46	14679529.97
In-Elast	14703677.28	254169.20	64288.45	14951655.21
Com-last	14722865.19	236639.61	58054.93	15017559.73
Go-Elast	14819952.29	295394.91	76405.9	15191753.11
Off-Elast	14870105.03	330319.82	88430.41	15288855.26
Agr-Elast	14893303.1	325185.71	86812.78	15305301.6

different load sectors, and confirm the above items.

Sensitivity analysis: in this section, load responses in different load sectors have been examined through changing their self and cross elasticity. Self and cross elasticity values have been considered to be, positively and negatively, 50% as compared to those in the second scenario. The results appear in Tables 7 to 8. Fig. 9 displays the total system load profile with residential load sector response at three different levels of elasticity as compared to the total system normal load profile. Fig. 10 displays the health probability of the system for different load sectors with three different elasticity levels. As observed, residential and gross loads are the most sensitive to changes in elasticity. Unlike in the second scenario, industrial loads have higher health state probability than commercial loads at the third level of elasticity and lower health probability at the first level of elasticity, which demonstrates the higher sensitivity of this type of loads than that of commercial loads. Official loads are the least sensitive, and agricultural and public loads rank next. Fig. 11 displays unserved energy values for different load sectors relative to changes in load elasticity. As observed, residential, gross, and industrial loads have the highest changes, and official, public, and agricultural loads contain the lowest changes.

Table 7. Well-being indices with -50% of elasticity in scenario 3

	E(Healthy)	E(Margin)	E(Risk)	E(Total)
Res-Elast	14698941.07	266613.19	67358.0	15032912.33
La-Elast	14801660.5	286989.24	74785.4	15163435.24
In-Elast	14837626.8	322619.29	86113.7	15246359.87
Com-Elast	14765288.6	256390.42	64460.4	15086139.53
Go-Elast	14840224.5	306453.75	80185.3	15226863.58
Off-Elast	14879727.6	335235.57	90349.0	15305312.25
Agr-Elast	14911495.9	346408.14	94259.5	15352163.61

Table 8. Well-being indices with +50% of elasticity in scenario 3

	P(Healthy)	P(Margin)	P(Risk)	E(Loss)(MWh)
Res-Elast	0.998614	0.001225	0.000161	128.6
La-Elast	0.994346	0.004732	0.000922	904.27
In-Elast	0.988559	0.009271	0.00217	2259.42
Com-Elast	0.987318	0.010249	0.002433	2561.81
Go-Elast	0.983479	0.013178	0.003343	3610.64
Off-Elast	0.981137	0.014928	0.003935	4352.15
Agr-Elast	0.982332	0.014026	0.003642	3999.32

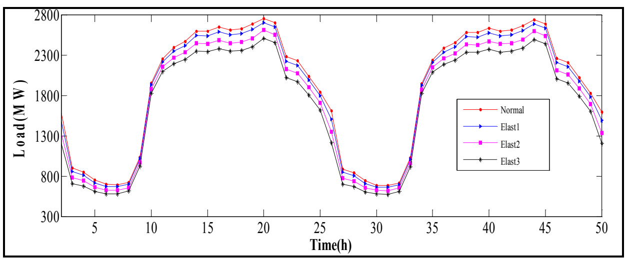

Fig. 9. Residential load Sector response in scenario 3

Scenario 3: In this scenario, the entire load is examined with the same elasticity. Load elasticity is considered as equal, and divided into five levels whose results are displayed in Table 9. The simulations are performed using the entire load elasticity with the same self and cross elasticity coefficients at the five levels as well as applying 5 and 10$ encouragement per MWh at peak load, and the results are displayed below in Tables 10. and 11. As observed, the load elasticity value in the total system load, even at a low amount, improves reliability to a great extent. At level one with self-elasticity of 0.05 and low cross elasticity, the health probability value is improved from 0.951884 to 0.991506 and risk probability, i.e., LOLP, is improved by about 67% since the value is decreased from 0.004412 to 0.001447. It should be noted that the improvement is significant since 39 hours of electricity service interruption within a year is reduced to about 13 hours when the proposed method is applied. Furthermore, the unserved energy value with level 1 elasticity is decreased from 4949.32 to 1465.28, displaying a decrease by 70 percent. Unserved energy is decreased by 1,128.22 MWh with 5$ per MWh encouragement and by 865.62 MWh with 10$ per MWh encouragement. Health state probability values are displayed in Fig. 12. for the three different states. As observed, the value of encouragement can be more effective for loads with low elasticity.

Table 9. Elasticity in scenario 3

	Peak load		Off peak		Low load	
Elast. Level	Level1	Level5	Level1	Level5	Level1	Level5
Peak Load	-0.05	-0.25	0.008	0.040	0.006	0.030
Off Peak	0.008	0.042	-0.05	-0.25	0.005	0.025
Low Load	0.006	0.030	0.005	0.025	-0.05	-0.25

Table 10. Well-being indices with fuzzy logic in scenario 3

	P(Healthy)	P(Margin)	P(Risk)	E(Loss)
Elast1	0.991506	0.007047	0.0014470	1465.28
Elast2	0.997036	0.0025508	0.0004132	365.25
Elast3	0.9991658	0.0007339	0.0001004	77.13
Elast4	0.999821	0.0001597	0.00001920	13.29
Elast5	0.999972	0.0000254	0.0000026	1.52

Table 11. Well-being indices with fuzzy logic in scenario 3

	P(Healthy)	P(Margin)	P(Risk)	E(Loss)(MWh)
Elast1A5	0.99301	0.005846	0.001144	1128.22
Elast2A5	0.998156	0.001615	0.000229	202.01
Elast3A5	0.999658	0.0003057	0.0000363	27.63
Elast4A5	0.999959	0.00003712	0.00000388	2.39
Elast5A5	0.999997	0.0000027	0.00000028	0.17
Elast1A10	0.994284	0.0048200	0.00022900	865.62
Elast2A10	0.998896	0.0009693	0.0001347	108.12
Elast3A10	0.999875	0.000112	0.000013	8.85
Elast4A10	0.999992	0.0000073	0.0000007	0.42
Elast5A10	0.9999998	0.00000022	~0	~0

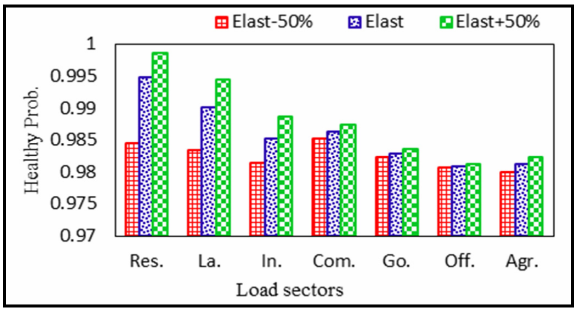

Fig. 10. Healthy probability with three different elasticity level

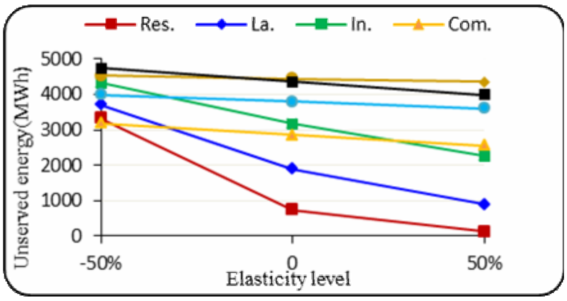

Fig. 11. Unserved energy values for different load sectors

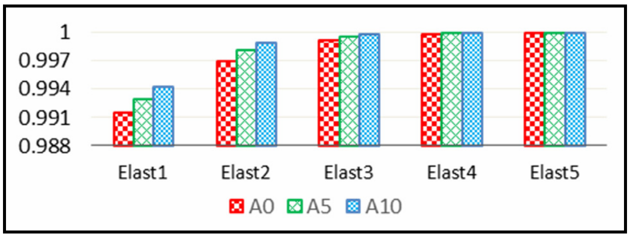

Fig. 12. Healthy probability in ecenario 3

6. Conclusion

Demand side management is one of the important factors that can have significant impacts on system reliability. Demand response in different load sectors due to difference sensitiveness to price change can have a different effect on reliability indices. Therefore partnership of these sectors in demand side management is different and it is necessary to consider in power system reliability calculation.

This paper by applying demand side management based on load sectors elasticity and maximum benefit of customers to the IEEE-RTS illustrates load response in residential, large users, commercial and industrial loads, respectively, have the highest effects on reliability improvement criteria such as healthy, marginal and risk probability and reduction of expenses related to ENS. Agricultural, official, and governmental loads have had almost no effects, and application of demand response is not recommended in these groups. Application of the fuzzy method increases health state probability value and served energy in this state as compared to deterministic methods, and provides a better vision of the system's well-being conditions for better operation.

The results show to make use of demand side response, each sector had better be examined separately. It is better system decision-making and planning is performed based on different loads' behavior in different sectors. Use of demand response is more reasonable and economical in some sectors, and recognition of their behavior can provide the system designer and operator with a better vision. For instance, in intelligent networks, instead of using a wide range of equipment for measurement and data exchange with a very high number of residential customers, the same results can be obtained by lower arrangements and expenses in other sectors such as the large user loads sector considering the low number of customers.

With full recognition of different sectors' behavior, demand response can apply to a mixture of loads, like large users, industrial, and commercial loads, with greater effects.

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Muhammad Naseh Hassanzadeh received the B.Sc. degree from Electrical and Computer Engineering Department at Tabriz University, Tabriz, Iran, in 1996 and the M.Sc. degree from Electrical Engineering Department at Sharif University of Technology, Tehran, Iran, in 1999, both in electrical engineering. He is presently pursuing the Ph.D. degree at Islamic Azad University, Science and Research Branch, Tehran, Iran.

Mahmud Fotuhi-Firuzabad received the B.S. degree from the Sharif University of Technology, Tehran, Iran, in 1986, the M.S. degree from Tehran University, Tehran, in 1989, and the M.S. and Ph.D. degrees from the University of Saskatchewan, Saskatoon, SK, Canada, in 1993 and 1997, respectively, all in electrical engineering. Currently, he is a Professor of the Department of Electrical Engineering, and president of Sharif University of Technology.

Amir Safdarian received the B.Sc. degree from Tehran University, Tehran, Iran, in 2008, and the M.Sc. and Ph.D. degrees from Sharif University of Technology, Tehran, in 2010 and 2014, respectively, where he is currently an Assistant Professor. He was the recipient of the 2013 IEEE Power System Operation Transactions Prize Paper Award and 2016 IEEE Iran Section Best Ph.D. Dissertation Award and on the list of outstanding reviewers of IEEE Transactions on Sustainable Energy for 2016. His research interests include distribution system operation and planning, smart grid issues, and power system reliability and resilience.