The Effect of Time-Based Demand Response Program on LDC and Reliability of Power System

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Abstract: *In recent years, the Demand Response (DR) programs have been developed to improve power system operation. If DR programs are implemented successfully, the system operator will meet its goal of reducing the peak load, and the customers will achieve economic benefits. Response of the customers to the DR programs affects the daily load curve. Therefore, the Load Duration Curve (LDC) changes due to the responsiveness of the customers over a year. These changes in LDC can improve the reliability indices of the system. So far, the effects of DR are often investigated over the daily time horizon. In this paper, we comprehensively investigate the effect of several TOU programs on the yearly LDC using an analytical DR model. Simulations are performed on the IEEE 24-bus reliability test system (RTS). In our analysis, the effects of implementing the DR programs on the annual peak, annual energy, load factor, customer's bill and expected energy not supplied (EENS) as a reliability index, are investigated. According to the results, even the relatively low participation of the customers in DR programs can have considerable effects on the LDC and reliability of the system.*

Keywords: Demand Response, EENS, Load Duration Curve (LDC), Reliability.

1. Introduction

While, the electricity system infrastructure is highly capital intensive, Demand side response is a much cheaper resource available that can seriously affect the operation of restructured power systems. Therefore, in recent years, Demand Response (DR) programs have been developed for utilization in power system operation. These programs provide enough motivations for customers to participate in power market operation. This response is utilized for keeping the balance between supply and demand in normal situations and when contingency occurs in the power system. A main objective of DR programs is to reduce peak demand [1]. This objective results in [2-10]:

- ✓ Alleviation of the necessity for installation of new capacities in generation, transmission and distribution facilities.
- ✓ Mitigation the widespread shortages and blackouts in the system by providing a wider margin to the maximum capacity for operation of the system.
- ✓ Improving the reliability of the system by reducing the outages.
- ✓ Reduction in the price of electricity.
- ✓ Improvement the Load factor.

In cases that a DR program is successfully implemented, the system operator will meet its goal of reducing the peak load and the customers will achieve economic benefits [11]. Customers normally respond to high electricity prices by reducing their electricity usage or shifting part of their peak demand to off-peak periods. As a result, DR affects the daily load curve and therefore the Load Duration Curve (LDC) will change due to the responsiveness behavior of customers over a year.

LDC provides the percentage of time for different demand levels during a year. Most of the production cost and reliability models used in power systems, utilize LDC as a basic tool for economic analysis of electric power systems. However, it should be mentioned that LDC does not provide a detailed representation of load dynamics [12-14]. The expected change in LDC, after implementation of DR programs, is shown in Figure 1.

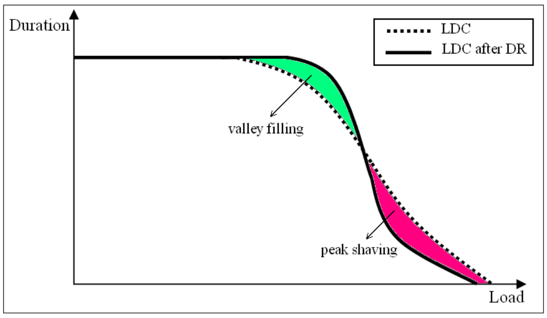

Fig. 1 LDC before and after implementation of DR

The upper and lower changes in Figure 1 correspond to valley filling and peak shaving, respectively. The horizontal shift of LDC on load axis corresponds to the peak reduction due to DR. The upper and lower painted areas of the curve express the change in energy usage. These changes in LDC also improve the reliability indices such as EENS.

Most researches, so far, have investigated the effects of DR programs on the operation of power systems. Shayesteh, et al. implemented a day ahead program which uses demand response as a source of spinning reserve [15]. They showed that the spinning reserve

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provision by DR can seriously reduce the total cost of reserve and improve the reliability indices. In [18], Azami investigated the effects of emergency demand response on improvement of system reliability. Goel, et al. considered the load shift to be stochastic together with its elasticity and evaluated its effect on nodal price and reliability of deregulated power systems [17]. They showed that the load shift can efficiently reduce the volatility of nodal price volatility and improve the reliability of the system. In [18], Zhong used the historical data of prices and consumption quantities of TOU measures to analyze consumers' ehaviors. hua-Liang proposed a method for quantifying the effects of participation of the demand in the electricity markets [7]. In his approach, the load shifting behavior of consumers is considered in market-clearing mechanism. It is shown that, increasing the level of demand shifting in the market can result in the reduction of market-clearing prices. In [19], optimization of time-of-use program is studied. Simulation results indicate that the load profile changes and the peak load in response to TOU pricing is reduced. Aalami, et al. have developed responsive model for the load. Then, to select the most effective DR program, they have used an Analytical Hierarchy Process (AHP) [10]. The same authors developed an economic model for two DR programs. The method is evaluated by using the load curve of the peak day of the Iranian power system grid in 2007. Then, the results of simulation studies for different scenarios are analyzed by using strategy success indices [6]. In the last two references, the characteristics of the load profile such as peak, energy consumption, load factor and the distance between peak and valley, are compared before and after implementation of DR.

In all of the above cited references, including those investigating reliability indices, the effects of DR are investigated over the daily time horizon. In [20], Osareh has presented an approach which utilizes the eigenvector method (EVM) and a load duration curve model for analyzing the impacts of demand side management on electricity demand. In this work, they have used estimated values instead of using accurate models.

In this paper, we have comprehensively investigated the effect of several TOU programs on yearly LDC using an analytical model of DR. Using this model, the effect of DR implementation on the reliability index is evaluated. The 24 bus IEEE Reliability Test System (RTS) has been used for implementing the simulations. In our analysis, the effects on annual peak, annual energy, load factor, customer's bill and EENS as a reliability index after DR is investigated.

The remainder of this paper is organized as follows: in Section 2, the model used for DR and also the developed method for calculation of reliability index is described. Section 3 explains our case study. Simulation results and discussion are presented in Section 4. Finally, conclusions of the study are given in Section 5.

2. Model Description

2.1 Demand Response Model

Participation of customers in DR programs changes the load profile. However, the evaluation of these changes requires modeling of the total load including responsive loads. In [21], using elasticity of price and customer benefit function, an economic model has been developed which represents the change in customer's demand versus changing the electricity price. This model is represented as:

$$d(h) = d_0(h) + \sum_{k=1}^{24} E(h,k) \times \frac{d_0(h)}{\rho_0(k)} \times [\rho(k) - \rho_0(k)] \tag{1}$$

$h = 1,2,\ldots,24$

$d_0(h)$: Initial demand value in hour h (MW).
$d(h)$: Demand value in hour h after DR (MW).
$E(h,k)$: Elasticity of the demand between h,k-th hours
$\rho_0(h)$: Initial electricity price in hour h (\$/MWh).
$\rho(h)$: Electricity price in hour h (\$/MWh).

According to this model, the customers change their consumption over 24 hours of a day, to gain the maximum benefit. The extended model of (1) has been widely used for investigating the effects of DR [6, 10, 15, 16]. Various DR programs have been implemented in different power markets. The FERC has classified DR programs into two main groups namely, "time based" and "incentive based" programs. In this paper, we have focused on Time of Use (TOU) as a time based program. Peak shavings, valley filling and smoothing the load curve, are normally considered as the most important goals for implementation of TOU pricing [18]. In spite of the need for multiple tariffs electricity meters in this approach (TOU programs), it will be cheaper than the infrastructure requirements of other DR programs.

2.2 Reliability Model

In our analysis, the reliability is considered only in Hierarchical Level II (HLII). This level refers to the composite generation and transmission system and its ability to deliver energy to load points [22].

Various indices are used to evaluate the reliability of power systems. However, one of the most common index, which has been used in this paper, refers to the Expected Energy Not Supplied (EENS). To calculate the EENS, we have used Monte Carlo simulation. In this approach, the EENS is determined based on the calculation of the maximum suppliable load at each state of the system (same as [23]). The problem of finding the maximum suppliable load is equivalent to minimizing the load which is not supplied. This linear optimization problem may be defined as followings:

$$Min \quad \sum_{j=1}^{NJ} P_{LCj} \tag{2}$$

Such that:

$$K.P_{Line} = A.P_G - B.(P_L - P_{LC}) \tag{3}$$

$$P_{Line,mn} = \frac{\theta_m - \theta_n}{x_{mn}} \quad \forall \text{ all lines} \tag{4}$$

$$\left|P_{Line,l}\right| \le P_{Line,l}^{Max} \quad \forall \text{ all lines} \tag{5}$$

$$0 \le P_{Gi} \le P_{Gi}^{Max} \quad \forall \text{ all units} \tag{6}$$

$$0 \le P_{LCj} \le P_{Lj} \quad \forall \text{ all loads} \tag{7}$$

PL_j: Peak load at bus *j* (MW).
PL_{Cj}: Load curtailment at bus *j* (MW).
PG_i: Power generation of unit *i* (MW).
$P_{Line,l}$: The power flow through line *l* (MW).
P_G: Power generation vector.
P_L: Load vector.
P_{LC}: Load curtailment vector.
P_{Line}: Real power flow vector.
A: Bus-unit incidence matrix.
B: Bus-load incidence matrix.
K: Bus-branch incidence matrix.
NJ: Total number of buses.

The constraints for this problem are namely; DC power flow equations, limits for generation and the power flow of network lines. Maximum suppliable load for each bus is obtained by subtracting the unsupplied load (P_{LCj}), which is obtained solving this problem, from the load of that bus (P_{Lj}). The Energy Not Supplied (*ENS*) can be calculated by integrating of LDC as shown in Figure 2.

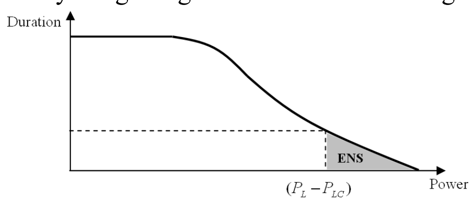


Fig. 2 Calculation of ENS using LDC

The probabilistic status of generating units and lines are considered by their forced outage rate (F.O.R). Solving the optimization problem (2-7) for many different statuses of the system (to cover all possible states), EENS is obtained as:

$$EENS = \frac{\sum_{s=1}^{NS} ENS_s}{NS} \quad \text{NS: Total number of samples} \tag{8}$$

3. Case Study

3.1 Main Assumptions

To investigate the DR effects on LDC and the reliability, simulations have been performed for the IEEE Reliability Test System. This system includes 32 generating units located at 10 buses, 33 transmission lines and 5 autotransformers. The peak load of the system is assumed to be 2850 MW and the total installed capacity of the system is considered to be 3405 MW. The data for the buses, the lines and the generators of the system and its load patterns for one year are taken the same as in [24]. Using the daily, weekly, and seasonal patterns of the load model, hourly loads for one year and thus LDC can be generated on a per unit basis. It is assumed that all buses have similar LDC pattern.

At the first, using (1), the daily load curve after DR is obtained for 365 days of the year and then the annual LDC is formed. Thus, the time horizon of this study is one year. Using the calculated LDC, the change in peak, the change in energy consumption after executing the DR are evaluated (The customer's bill is calculated using the daily load curve of 365 days). In addition, considering new LDC, EENS is determined (according to 2.2).

To analyze the effects of DR programs, various TOU programs are defined and simulated. All of these programs include three time intervals: valley period, middle period, and peak period. These programs are designed considering the load pattern shown in Figure 3. This figure shows the hourly load as a percentage of daily peak for a weekday in different seasons.

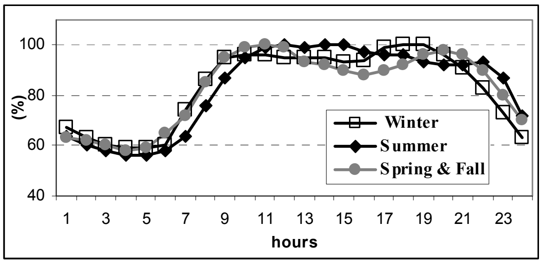


Fig. 3 Hourly load as a percentage of daily peak for a weekday

The price elasticity of the demand for various periods is considered the same as in [10]. The electricity price is assumed 100 $/MWh as flat rate tariff (i.e. before DR implementation), 50 $/MWh in valley period, 100 $/MWh in middle (off-peak) period, and 300 $/MWh in peak periods as TOU tariffs.

3.2 Selection of DR Programs

Three main parameters i.e. annual peak, annual energy consumption and annual bill of customers are chosen to evaluate the programs. Comparison of the values of these parameters before and after DR implementation shows that while the total possible states are eight states, the simulations end with only six distinct types of programs. Table I shows the characteristics of each of these programs (Two cases of 8 possible cases do not happen in numerous simulations).

TABLE I: Characteristics of The Defined DR Programs

Name	Annual Peak	Annual Energy	Annual bill
DR1	increased	increased	increased
DR2	increased	increased	decreased
DR3	increased	decreased	increased
DR4	decreased	increased	increased
DR5	decreased	increased	decreased
DR6	decreased	decreased	increased

To avoid unnecessary complexity one program is chosen as a representative of each program type. The time intervals of selected programs are shown in Table IV in the Appendix. It is assumed that %10 of customers would participate in DR programs.

3.3 Parameters for analyzing the effect of DR

According to the pervious works, several parameters such as the annual Load Factor, the average of daily Load Factor, the energy reduced because of peak shaving, the energy increased because of valley filling and EENS as the considered reliability index, are selected for analysis and comparison of the results of the DR programs. These parameters are added to three old parameters i.e. the annual peak, the annual energy consumption by DR participations and the total payment of DR participations in one year. Obviously, the energy consumption and the payment of those customers who do not participate in DR, does not change after implementation of DR. The annual Load Factor and the average of daily Load Factor are obtained as follow:

$$\text{Annual LF} = \text{Annual Load Factor} = \frac{\text{Energy consumption in a year}}{\text{Peak} \times 8760} \quad (9)$$

$$\text{LF}_{\text{avg}} = \text{Average of daily LF} = \frac{\sum_{d=1}^{365} \dfrac{\text{Energy consumption in a day}_d}{\text{Peak of day}_d \times 24}}{365} \quad (10)$$

4. Simulation Result

Initially, the assigned parameters for investigating the demand response impacts before implementation of DR (base case) are determined. The energy consumption by customers participating in DR programs in one year is $1.5343\times10^{6}\,MWh$ and the total payment of DR participations is $1.5343\times10^{8}\$$ in the year. The Annual Load Factor and The average of daily Load Factor are 61.45% and 83% respectively. The EENS is equal to 1765.8 MWh/year. Figure 4 shows the convergence curve of Monte Carlo simulation for the base case.

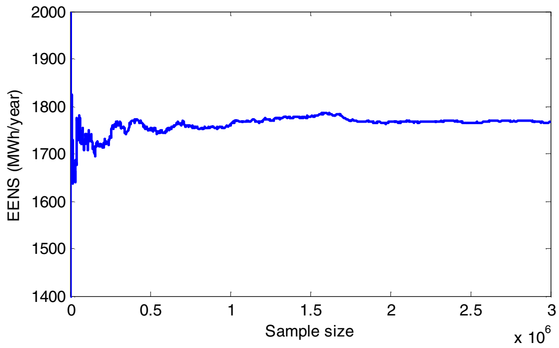


Fig. 4 The convergence curve of Monte Carlo simulation

4.1 Simulation results for DR1 and DR6

To investigate the effects of performing DR programs, results for DR1 and DR6 are explained in detail. Figure 5 shows the daily load curve of the peak day of year, before and after performing these two programs. As it can be observed, the peak value has increased after implementation of DR1 which is not a desirable result. This implies that incorrect design of DR programs may end with undesirable results.

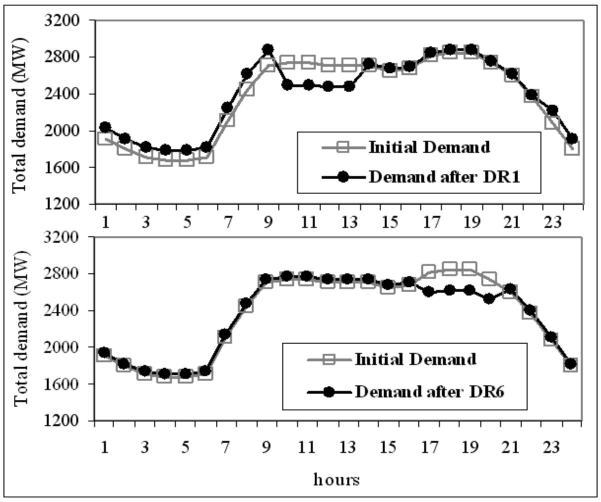


Fig. 5 Daily load curve of the peak day of the year

4.2 The effect of DR on Load Factor

The simulations for six different DR programs (according to Table IV) have been performed and characterizing parameters mentioned in section 3.3 have been calculated. Figure 6 shows the changes of the Load Factor as well as the changes of the peak for the DR programs. The annual load factor and the average of the load factor will often increase when the peak value decreases. It can be concluded that the DR programs which reduce the peak, also improve the load factor. However, the effect of the DR on the average of the load factor will be more than its effect on the peak value.

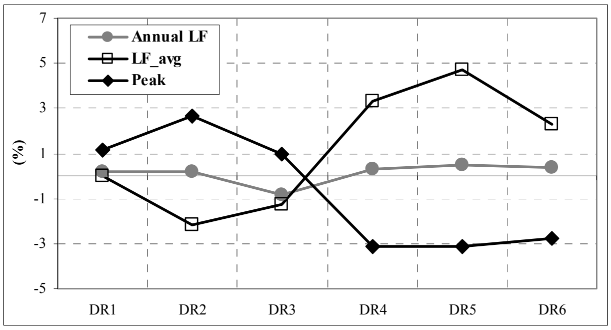
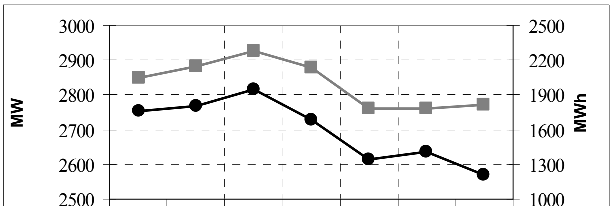


Fig. 6 The changes in Load Factor and in peak values due to DR

4.3 The effect of DR on peak, energy consumption and Reliability

As shown in Figure 2, increasing or decreasing the peak affect the EENS. Figure 7 shows the values of peak and EENS corresponding to the DR programs.



	D	DR1	DR2	DR3	DR4	DR5	DR6
Peak	2850	2882	2926	2877	2761	2761	2771
EENS	1765	1802	1944	1681	1347	1409	1208

Fig. 7 The value of peak and EENS corresponding to the DR programs

According to Figure 7, the curve of EENS correlates with that of the peak. Thus, it's concluded that the more the DR reduces the peak; the more the reliability will be improved.

The changes in peak, energy and EENS of the programs with respect to the base case are presented in Figure 8. As it can be observed, the reduction in the peak or the reduction in the energy of the load, results in the reduction of EENS. Comparison of the results (especially DR3 and DR4) shows that the effect of the peak on EENS reduction is more than that of the energy.

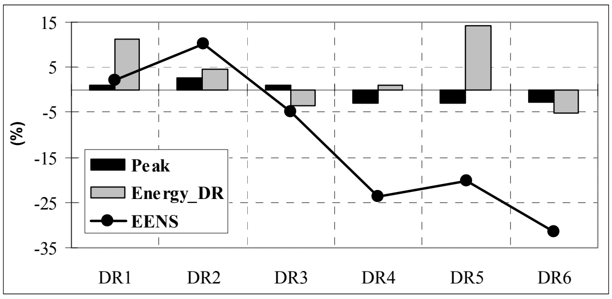


Fig. 8 The changes in peak, energy and EENS of six programs with respect to base case

Figure 9 shows the changes in customer bill and EENS sorted ascending with respect to customer's bill. It is expected that EENS decreases as the payment by the customers increases. However, it is observed that this is not true for the cases of DR4 and DR5. It can be said that decreasing the EENS, in these two programs, is mainly because of the reduction in peak (Figure 8). In addition, little participation of the customers in DR program can be considered as a main reason for these exceptions. However, as expected, the maximum payment in the bill corresponds to the minimum EENS and vice versa.

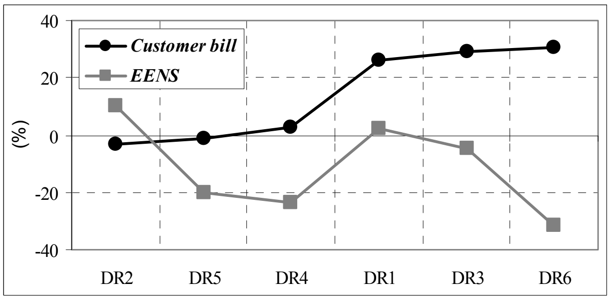


Fig. 9 The changes of customer bill & EENS (ascending sorted with respect to customer's bill)

4.3 Evaluation of the DR programs

Tables II and III, shows the complete results for all the DR programs. According to these Tables, the selected DR programs in this study are analyzed as follows. Because of the increment of peak, energy, customer's bill and EENS, the DR1 is the worst program, although this program has the maximum valley filling. The DR2 leads to the minimum bills for DR's participants. However, this program increases peak, energy and EENS and degrades the annual load factor. The DR3 increases peak and customer's bill and decreases energy consumption, EENS and annual load factor. This program is the only program that reduces the average of the load factor. Considering the reduction of the peak and EENS and low rise of the customers' cost, DR4 is a good program. Although DR5 has the most energy consumption, it is interesting that the peak and customers' bill experience a reduction owing to the implementation of this program. In addition, both load factor indices have their most values and energy of peak shaving has minimum its values in this program. The DR6 has the best improvement of the reliability (with 31.6% decrease in EENS) as well as the most cost for the customers. Furthermore, Minimum energy consumption occurs in DR6 and the energy of peak shaving takes its maximum values.

TABLE II: The Effects of The DR on Peak, Energy And Bill Payment

	Peak		**E_{DR}**		**CB_{DR}**	
Program	MW	change (%)	×1000 *MWh*	change (%)	$\times 10^8$\$	change (%)
Initial load	2850		1534		1.53	
DR1	2882	1.14	1708	11.35	1.93	25.9
DR2	2926	2.68	1602	4.45	1.49	-3.1
DR3	2877	0.96	1480	-3.49	1.98	29.1
DR4	2761	-3.12	1550	1.09	1.57	2.6
DR5	2761	-3.12	1751	14.20	1.52	-1.1
DR6	2771	-2.77	1453	-5.28	2.00	30.6

E_{DR}: Energy consumption by customers participating in DR programs in the year

CB_{DR}: Customers bill of customers participating in DR programs in the year

TABLE III: The Effects of The DR Programs on Peak Shaving, Valley Filling, Load Factor And EENS

Programs	Energy of peak shaving (MWh)	Energy of valley filling (MWh)	Annual LF (%)	LFavg (%)	EENS (MWh/ year)
Initial load			61.4	83.0	1765
DR1	68053	242237	61.4	83.2	1802
DR2	18847	87062	60.1	83.4	1943
DR3	78259	24779	60.6	82.3	1681
DR4	10325	27014	63.5	83.2	1347
DR5	6341	224249	64.3	83.4	1409
DR6	110696	29668	62.9	83.3	1208

LF_{avg}: The average of daily Load Factor

As it can be observed, from these results, even 10% participation of the customers in DR programs has considerable effects on LDC and reliability of the system. For example, the value of the annual peak of the system may decrease by 3.12%. In addition, Most of the DR programs improve the reliability index. On the other hand, the results for DR1 & DR2 show that inappropriate designs of DR programs can lead to undesired results.

5. Conclusion

The analysis of the DR impacts on the system operation is important for the policy-makers, regulators and operators of the power system. In this paper, the effects of the several TOU programs, on LDC, have been investigated comprehensively.

The main results of this work can be summarized as follows. The DR programs which reduce the peak, lead to the improvement of the load factor. The reduction in the peak or energy of the loads (due to DR implementation) results in the reduction of the EENS. The effect of the peak on the EENS reduction is more than that of the energy. The maximum payment for the bill corresponds to the minimum EENS and vice versa. Most of the DR programs improve the reliability index. Inappropriate designs of DR programs can lead to undesirable results. The results of simulations showed that even the relatively low participation of customers in DR (%10) can bring about considerable effects on LDC and reliability of the system. This will result in many benefits not only for the customers participating in DR programs but also for all the consumers in the system. This study can be helpful for analyzing the impacts of DR program in the tariff-based pricing system such as the Iranian power system.

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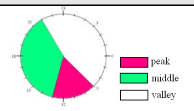
Appendix

TABLE IV: Assumed TOU Programs

Demand Response Programs		Hours of a day: Valley period	Middle period	Peak period
DR1		[23:24,1:9]	[14:22]	[10:13]
DR2	Critical month	[1:7,20:24]	[8:15]	[16:19]
	Other	[1:6]	[7:24]	[]
DR3	Winter	[]	[1:15,19:24]	[16:18]
	Other	[]	[1:9,14:24]	[10:13]
DR4	Critical month	[1:7,21:24]	[8:16]	[17:20]
	Other	[]	[1:24]	[]
DR5	Critical month	[1:7,21:24]	[8:16]	[17:20]
	Other	[1:10]	[11:24]	[]
DR6	Winter	[]	[1:16,21:24]	[17:20]
	Other	[]	[1:9,14:24]	[10:13]

Note1: The represented clock is scaled for 24 hours of a day.

Note2: According to the weekly load pattern, the final four weeks show the most consumption in the year. Therefore, December is considered as the critical month.