Energy 47 (2012) 230–236

Contents lists available at SciVerse ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Residential demand response behavior analysis based on Monte Carlo simulation: The case of Yinchuan in China

Yongxiu He [a,*], Bing Wang [a], Jianhui Wang [b,c], Wei Xiong [a], Tian Xia [a,d]

[a] School of Economics and Management, North China Electric Power University, Zhu Xin Zhuang, Bei Nong Road No. 2, Changping District, Beijing 102206, China
[b] Decision and Information Sciences Division, Argonne National Laboratory, 9700 S. Cass Avenue, Argonne, IL, USA
[c] School of Economics and Management, Shanghai University of Electric Power, Ping Yang Road No. 2103, Yangpu District, Shanghai, China
[d] Gansu Electric Power Corporation, Xi Jin East Road No. 628, Lanzhou, Gansu Province, China

ARTICLE INFO

Article history:
Received 24 January 2012
Received in revised form
29 August 2012
Accepted 30 August 2012
Available online 15 October 2012

Keywords:
Smart grid
Monte Carlo simulation
Residential demand response
TOU rates

ABSTRACT

Demand response to time-varying pricing of electricity is critical to a smart grid's efficient management of electrical resources. This paper presents a new approach to quantify residential demand responsiveness to (time-of-use) TOU rates, which does not entail an econometric estimation of TOU demand equations. Based on one of the four smart grid pilots in China, our approach uses the survey data collected in 2011 from 236 residents in Yinchuan to implement a Monte Carlo simulation to obtain the minimum, expected and maximum demand responsiveness to four TOU rate designs. We find that residents do not respond to TOU pricing when the TOU rate design only causes a 10% increase in their existing electricity bills under non-TOU rates. However, their estimated peak demand responsiveness is 8.41% (21.26%) when the peak-time price increases by 20% (40%). Based on these findings, we conclude that suitably designed TOU rates are useful to the efficient operation of a smart grid.
© 2012 Elsevier Ltd. All rights reserved.

1. Introduction

A smart grid is a network that can intelligently integrate the actions of all users connected to it [1]. The key benefits of smart grids are that they are more reliable, resilient, economical, efficient, environmental friendly, and safer as compared to traditional electricity networks. It has significance in the achievement of targets for promoting competition, increasing the safety of electricity systems, and combating climate change [2].

(Demand response) DR is very important to the construction of the smart grid. The U.S. (Department of Energy) DOE submitted a report to the U.S. Congress in February 2006 on DR in the electricity market [3], pointing out the importance of DR and its role in the power system. DR is useful for managing demand during a system emergency, resulting in benefits that can be estimated through various approaches [4–7]. With the development of the smart grid, the number of types of DR programs is increasing [8]. The NYISO (New York Independent System Operator) in America currently operates three kinds of DR programs: reliability-based DR programs, an economic DR program, and ancillary services [9]. Horowitz and Woo [10] explored three voluntary service options (real-time pricing, (time-of-use) TOU pricing, and curtailable/interruptible service) in order to encourage residential customers to alter their electricity usage in response to changes in the electricity price. In Australia, (dynamic peak pricing) DPP was implemented to reduce peak electricity demand [11]. Faria and Vale [12] presented a DR simulator called DemSi to study DR actions and obtain load reduction under real-time pricing and the value of the price elasticity of demand. Hartway et al. [13] refuted the common belief and demonstrated that offering a TOU option can be profitable to a utility. Parks and Weitzel [14] used the data from an experiment to measure the consumer welfare effects of time-differentiated electricity prices.

Residential loads often contribute significantly to seasonal and daily peak demand. In Europe, the long-standing programs involving large industries have been increasingly complemented by programs aimed at residential customer groups [15]. Torriti [16] found that TOU tariffs bring about higher average electricity consumption and lower payments by residential consumers. Many studies analyzed the response of consumers from the econometrics perspective [17–19]. Allcott [17] found that households are significantly (i.e., statistically) price elastic. Caves and Christensen [18] indicated that price elasticities vary substantially with prices and that peak and off-peak loads are partially substitutes. Caves et al. [19] tested the hypothesis that the elasticities of substitution are identical across TOU rates and created a model for predicting residential responses to TOU rates.

* Corresponding author. Tel.: +86 010 51963733; fax: +86 010 80796904.
E-mail addresses: heyongxiu@ncepu.edu.cn, yongxiuhe@126.com (Y. He).

0360-5442/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.energy.2012.08.046

The magnitude of residential response depends on several factors. Some experiments showed a statistically significant average participant response to (critical peak pricing) CPP: participants saved up to 13% of energy but did not respond more to higher CPP rates [20,21]. Moore et al. [22] indicated that an incentive payment based on the option value alone is likely insufficient to attract customer participation. Mountain and Lawson [23] found that peak reductions in the summer are marginally larger than those in the winter. Herter [24] indicated that large customers responded significantly more in kW reduction, whereas small customers saved more in percentage reduction. Faruqui and Segici [25] observed that the magnitude of price increase, the presence of central air conditioning, and the availability of enabling technologies can influence the response. Faruqui and Malko [26] indicated that residential responses vary with several conditioning variables such as level of total (daily) electricity use, composition of appliance portfolio, and duration of pricing periods. Vassileva et al. [27] sent a questionnaire to 2000 Swedish households and showed clear differences in the response rates from different types of residences, different income areas of the city, and in the methods respondents preferred most for receiving information and feedback.

Although experimental methods are used in most of the studies on the response of residential consumers to prices, Aigner [28] pointed out the uncertainty in using experimental results. Due to the lack of data, we cannot perform an econometric analysis of residential DR in China. Therefore, this paper presents an alternative method to analyze residential DR based on both the survey results and Monte Carlo simulation, which needs less information and thus can solve the problem of lacking statistical samples. The results of this paper can provide recommendations for the implementation of DR programs in different areas. Our findings demonstrate how residential consumption responds to time-varying pricing, thereby aiding the formulation of a rational electricity pricing policy.

2. Survey

To determine residential DR in the context of the smart grid, a survey was conducted in Yinchuan, one of the four smart grid construction pilot cities of State Grid Corporation. Of the 250 questionnaires that were distributed, 236 valid responses were received. The survey respondents included residents of different ages, educational backgrounds, household incomes, and household structures. The basic information pertaining to the respondents is shown in Table 1.

We also surveyed the appliances portfolio, including bulbs, televisions, refrigerators, washing machines, electric fans, electric cookers and so on, in every household. Then, according to the average load of each appliance, the total load of home appliances in each household can be calculated. On the basis of the survey results, the minimum value of the total load of home appliances is about 3 kW, while the maximum is about 23 kW. Considering the distribution of the total load of household appliances, we divide the residents into four categories. For category 1, the household appliances are for the basic necessities of living. The upper limit of the total demand is about 10 kW. For the other three categories, the number of household appliances increases and the total demand is also higher. All the categories are shown in Table 2.

Residential DR behaviors describe the customers' responses to prices and are reflected in a series of adjustments in power consumption. The assumption is that residents will make various responses when the electric bill increases by a certain level. Five scenarios are assumed in the investigation, in which the level of the increases in the electricity bill varies, in order to analyze how responsive the residents in Yinchuan are to the electricity prices. The scenarios are shown in Table 3.

Table 1
The basic information describing the Yinchuan survey respondents.

Contents	Items	Survey results		
		Count	Proportion (%)	Cumulative percentage (%)
Age	20–24 years old	43	18.22	18.22
	25–30 years old	58	24.58	42.80
	31–36 years old	62	26.27	69.07
	37–45 years old	46	19.49	88.56
	46 years old and above	27	11.44	100
Education Background	Master and above	7	3.07	3.07
	Undergraduate	103	45.18	48.25
	Junior college	57	25.00	73.25
	Senior high school or technical secondary school	46	20.17	93.42
	Junior high school and below	15	6.58	100
Occupation	Civil servants	27	11.64	11.64
	Public institution staff members	24	10.34	21.98
	State-owned enterprise staff and workers	77	33.19	55.17
	Private company staff and workers	23	9.91	65.08
	Self-employed individuals	18	7.76	72.84
	Managers of private companies	44	18.97	91.81
	Others	19	8.19	100
Average annual income	Under 20 thousand RMB	20	8.55	8.55
	20–50 thousand RMB	54	23.08	31.63
	50–100 thousand RMB	87	37.18	68.81
	100–150 thousand RMB	48	20.51	89.32
	150–20 thousand RMB	17	7.26	96.58
	200–300 thousand RMB	3	1.28	97.86
	300 thousand RMB and above	5	2.14	100
Time when somebody is at home	Throughout the day	53	25.48	25.48
	Evening (after work)	99	47.60	73.08
	Noon and night	56	26.92	100
Residential square footage	Less than 60 square meters	19	8.08	8.08
	60–90 square meters	90	38.30	46.38
	90–144 square meters	106	45.11	91.49
	More than 144 square meters	20	8.51	100
House type	High-rise apartment (more than 8 floors)	47	20.43	20.43
	Regular apartment (2–8 floors)	171	74.35	94.78
	Bungalow	12	5.22	100

Table 2
Categories of respondents based on total demand of house appliances.

Categories	Total demand of home appliances	Features
Category 1	10 kW and below	The home appliances are for the basic necessities of living.
Category 2	11–13 kW	Several more appliances to improve quality of life besides the basic appliances.
Category 3	14–17 kW	The home appliances are similar to the second category but the electrical demand of appliances is larger than the second.
Category 4	18 kW and above	The household electrification is of high degree and there are many appliances of high electric demand.

Table 3
Classification of residents' preferences and responses to prices.

No.	Response preferences
1	Make consumption adjustments when the electricity costs rise by 5%.
2	Make consumption adjustments when the electricity costs rise by 10%.
3	Make consumption adjustments when the electricity costs rise by 15%.
4	Make consumption adjustments when the electricity costs rise by 20%.
5	Do not make power consumption adjustments no matter how much electricity costs rise.

According to the survey in Yinchuan, when the electricity cost rises by 10% or below, residents will not make a response (i.e., change their consumption behaviors); however, when the electricity cost rises by 10% and more, some residents will start to make adjustments in their power usage. The main reason for a low response is that the household electricity cost is only a small proportion of household total income, and thus a small increase in electricity cost will not stimulate residents to make adjustments in their consumption of power.

Currently, depending on the time of power consumption, Ningxia Power Grid Corporation, which is the electricity supplier for the city of Yinchuan, divides the 24 h in one day into three periods: the peak time (8:00–12:00, 18:00–22:00), the normal time (7:00–8:00, 12:00–18:00) and the off-peak time (22:00–7:00). According to the survey, we have obtained the electricity consumption information in each period for every category of residents, and the average proportion of electricity consumption in each period can be derived, as shown in Table 4.

3. Simulation

3.1. Monte Carlo simulation

The Monte Carlo simulation method associates the problem of uncertainty with a probabilistic model, which is based on the estimated statistics produced by a large number of random tests as the approximated solution to the original problem. The Monte Carlo simulation method can solve many problems where it is normally difficult to determine the distribution patterns of variable parameters [29]. On the basis of the historical statistical distribution or a certain kind of probability distribution, a random variable parameter model is obtained. The cumulative probability can then be generated by using a computer program, which repeatedly simulates the random variable and produces the possible values of all random variables based on the computer simulation model. After thousands of sampling simulations without repeated statistics, the algorithm can achieve as much accuracy as possible for simulating all of the possible values, calculate the results of the statistical simulation, and determine the Eigenvalue of the random variable.

This paper analyzes the changes in residential electricity consumption and the responsiveness of electricity consumption based on the TOU price policy according to the patterns of residential power consumption and use of household electric appliances. Because of the lack of sufficient statistical data for China, an econometric analysis may not be appropriate for this purpose. Hence, the Monte Carlo simulation method discussed above can be used to cope with less information and produce some meaningful results at the same time. As every resident has his or her own attitude and response to price signals, this paper estimates the maximum, the most likely, and the minimum values of the responsiveness of residential electricity consumption based on the survey results. Thus, the distribution of residential response can be established. Therefore, according to the probability theory, a triangular distribution can be used to approximate the actual distribution of residential electricity consumption responsiveness. The probability distribution of the triangular distribution is shown in Fig. 1.

Table 4
Proportion of residential electricity consumption in each period.

Total consumption of home appliances	Proportion of peak time	Proportion of normal time	Proportion of off-peak time
Category 1	65.53%	10.14%	24.33%
Category 2	71.70%	5.97%	22.34%
Category 3	68.97%	8.86%	22.18%
Category 4	71.01%	9.03%	19.96%

The triangular distribution function is shown as follows:

$$F(x) = \begin{cases} 0, x \le a \\ \dfrac{(x-a)^2}{(c-a)(b-a)}, \ a \le x \le c \\ 1 - \dfrac{(x-b)^2}{(b-c)(b-a)}, \ c \le x \le b \\ 1, x \ge b \end{cases} \tag{1}$$

where a represents the minimum value, b represents the maximum value and c represents the most likely value.

This study undertakes the Monte Carlo simulation, according to the characteristics of the triangular distribution, through simulating changes in residential electricity consumption. Random numbers that follow a uniform distribution can be produced at first, and then they can be converted to the triangular distribution. These random numbers of uniform distribution are assumed as x and then, the random numbers u, which obey the triangular distribution, are produced by using equation (2).

$$u = \begin{cases} a + \sqrt{x(b-a)(c-a)} & 0 \le x < \dfrac{c-a}{b-a} \\ b - \sqrt{(1-x)(b-a)(b-c)} & \dfrac{c-a}{b-a} \le x \le 1 \end{cases} \tag{2}$$

The accuracy of Monte Carlo simulation is proportional to $1/N$ (N represents the total number of samples). Therefore, a large amount of computation is required to achieve higher levels of

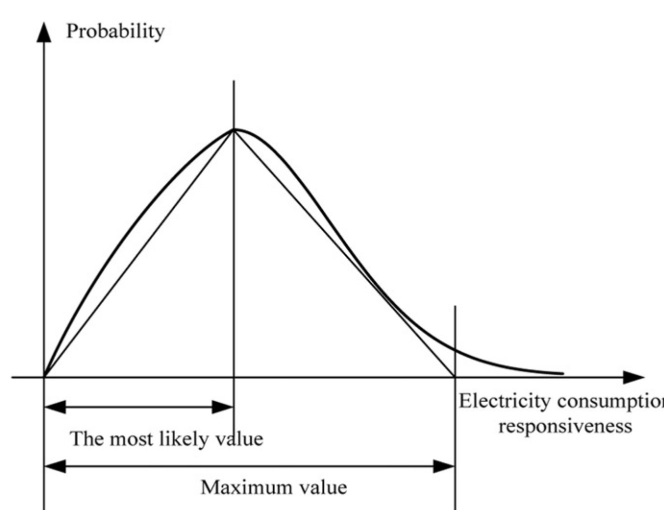

Fig. 1. The probability distribution of residential electricity consumption responsiveness.

accuracy. This study entailed running the simulation 2000 times, which could truly reflect the response of residents under the TOU rates.

3.2. Simulation method

As mentioned previously, the TOU rates divide the 24 h in a day into three sections: the peak time T_1, the normal time T_2, and the off-peak time T_3. The corresponding electricity prices during the three sections are represented by P_1, P_2, and P_3. This paper assumes that P represents the residential electricity price before the implementation of TOU rates, and that the daily electricity consumption of residents is represented by Q, such that the electricity consumption at the peak time, the normal time, and the off-peak time is represented by Q_1, Q_2, and Q_3 respectively. Suppose that C represents the daily cost of electricity; then C can be calculated by equation (3).

$$C = PQ \tag{3}$$

Assume that the electricity price at the normal time is equal to the original residential electricity price, and α, β represent the rate of price increase at peak time and the rate of price decrease at off-peak time, respectively; then the electricity prices in the three periods can be calculated by equation (4).

$$\begin{cases} P_1 = P(1+\alpha) \\ P_2 = P \\ P_3 = P(1-\beta) \end{cases} \tag{4}$$

It is assumed that residential power consumption behaviors remain the same as they were originally at the beginning of the implementation of TOU rates; that is, the electricity consumption at each time is equal to that before the implementation of TOU rates. C' represents the daily cost of electricity at this time and can be calculated by equation (5).

$$C' = P_1Q_1 + P_2Q_2 + P_3Q_3 \tag{5}$$

Therefore, the cost difference ΔC between the two different price strategies can be expressed as follows:

$$\Delta C = C' - C = (\alpha Q_1 - \beta Q_3)P \tag{6}$$

After the implementation of TOU rates, the average household power price $\overline{P}$ can be expressed as follows:

$$\overline{P} = \frac{P_1Q_1 + P_2Q_2 + P_3Q_3}{Q_1 + Q_2 + Q_3} = P\left(1 + \frac{\alpha Q_1 - \beta Q_3}{Q_1 + Q_2 + Q_3}\right) \tag{7}$$

The survey results indicate that the household responds to the TOU rates if

$$C' > SC \tag{8}$$

where S = scalar, which may be 1.1, 1.2, 1.3, or 1.4.

After a period of time after the implementation of the TOU price policy, some residents will adjust their consumption behaviors accordingly. This adjustment takes two main forms: single-time response and multi-time response. Single-time response refers to the behavior where users decide how much power they will consume based on the level of the electricity price at that time. They respond to higher prices simply by reducing their (overall) electricity consumption. A multi-time response refers to the behavior where users respond by transferring the consumption from the high-price periods to lower-price periods, in addition to reducing their (overall) electricity consumption.

This paper assumes that all residents make rational decisions. Normally, the residents will save electricity by reducing their power consumption during the peak time and the normal time, by transferring part of the power consumption to the off-peak time. Suppose that ΔQ_1 represents the change in residential electricity consumption at the peak time, ΔQ_2 represents the change in residential electricity consumption at the normal time, and ΔQ_3 represents the change in residential electricity consumption at the off-peak time, such that:

$$\begin{cases} \Delta Q_1 = \Delta Q_1' + \Delta Q_{12} + \Delta Q_{13} \\ \Delta Q_2 = \Delta Q_2' + \Delta Q_{23} \\ \Delta Q_3 = \Delta Q_3' \end{cases} \tag{9}$$

where $\Delta Q_1'$ represents the single-time response value at the peak time; $\Delta Q_2'$ represents the single-time response value at the normal time; $\Delta Q_3'$ represents the single-time response value at the off-peak time; ΔQ_{12} represents the consumption transferred from the peak time to the normal time; ΔQ_{13} represents the consumption transferred from the peak time to the off-peak time; and ΔQ_{23} represents the consumption transferred from the normal time to the off-peak time. Here, the residential response can be measured by the net flow of electricity.

In order to assess the response behaviors of residents, this paper introduces a relative measurement indicator, which is electricity consumption responsiveness, λ_j (j = 1, 2, 3), calculated as follows:

$$\lambda_j = \Delta Q_j / Q_j \tag{10}$$

Simulating the DR based on the survey results entails the following steps:

Step 1: Assume the minimum, the most likely, and the maximum values of residential electricity consumption responsiveness for each category of residents.
Step 2: Input the original residential electricity prices and the new TOU rates.
Step 3: Use equation (3) to compute the electricity bill for a household in the survey prior to TOU.
Step 4: Use equation (5) to compute the electricity bill for the same household in the survey after TOU.
Step 5: Test whether equation (8) holds. If “yes,” go to Step 6; otherwise, repeat Steps 3 and 4 for the next household.
Step 6: Use the triangular distribution function to generate numbers randomly based on the assumptions for residential electricity consumption responsiveness in Step 1.
Step 7: Compute the household’s consumption change by TOU period based on the responsiveness.

Table 5
Changes in residential electricity costs without behavioral changes.

Items	Fixed price	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Electricity price change ratio	0	10%	20%	30%	40%
Average power price (Yuan/kWh)	0.4486	0.4706	0.4925	0.5145	0.5365
Monthly electricity costs increase value	0	4.89%	9.78%	14.68%	19.57%

Table 6
Maximum electricity consumption responsiveness of four categories of residents in Yinchuan.

Response period	Category 1	Category 2	Category 3	Category 4
Peak responsiveness	42.40%	70.36%	67.03%	73.33%
Normal time responsiveness	32.88%	11.57%	64.42%	75.84%
Off-peak responsiveness	12.96%	27.03%	18.35%	11.95%

Table 7
The most likely electricity consumption responsiveness of the four categories of residents in Yinchuan.

Electricity price change ratio	Category 1	Category 2	Category 3	Category 4
Scenario 1	0	0	0	0
Scenario 2	Peak responsiveness: 17% Off-peak responsiveness: 10%	Peak responsiveness: 13% Off-peak responsiveness: 10%	Peak responsiveness: 5% Off-peak responsiveness: 0	Peak responsiveness: 0 Off-peak responsiveness: 0
Scenario 3	Peak responsiveness: 17% Off-peak responsiveness: 12%	Peak responsiveness: 13% Off-peak responsiveness: 10%	Peak responsiveness: 5% Off-peak responsiveness: 1%	Peak responsiveness: 4% Off-peak responsiveness: 0
Scenario 4	Peak responsiveness: 22% Off-peak responsiveness: 12%	Peak responsiveness: 17% Off-peak responsiveness: 13%	Peak responsiveness: 5% Off-peak responsiveness: 5%	Peak responsiveness: 4% Off-peak responsiveness: 0

Step 8: Repeat Steps 6 and 7 for a total of 2000 times for the same household.
Step 9: Store the results form Step 8.
Step 10: Go to Step 3.

4. Results

We then analyze residential response behaviors at different levels of price change ratios at the peak times and the off-peak times, assuming that the price change ratios at the peak time and the off-peak time are equal, which means $\alpha = \beta$ in equation (4). In this paper, we use four scenarios to simulate residential responsiveness under different electricity price change ratios.

If the residents maintain their existing power consumption behaviors under different TOU rates, their monthly electricity bills will be changed according to equation (6), and the results are shown in Table 5. When the price change ratio is 20%—that is, $\alpha = \beta = 20\%$—the residential monthly average electricity cost increases by 9.78%, close to 10%, and some of the residents will make power usage adjustments.

From the four categories of residents classified by total power usage, some typical residents are used as representatives for analysis. According to the historical household electricity consumption of the typical residents, the minimum, the maximum, and the most likely values of electricity consumption responsiveness for each category of residents can be obtained.

Clearly, the minimum value of residential electricity consumption responsiveness is zero, which means the responsive behaviors do not occur. Working on the premise that residential daily life will not be affected, the maximum power consumption change in each period for every category of residents has been investigated. The

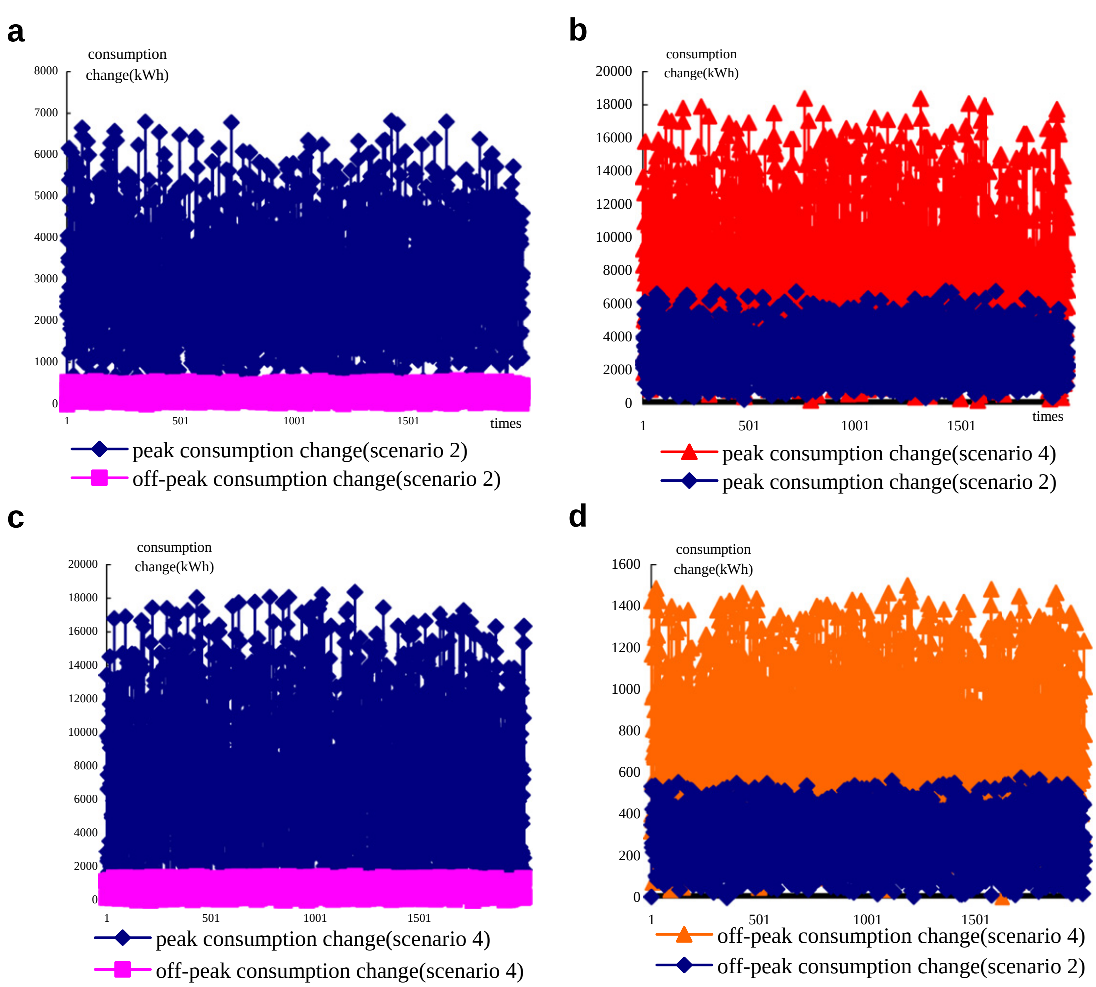

Fig. 2. The simulation results of residential electricity consumption change.

Table 8
Simulation of residential electricity consumption responsiveness in Yinchuan.

Electricity price change ratio	Peak responsiveness	Normal responsiveness	Off-peak responsiveness
Scenario 2 (20%)	8.41%	0	2.69%
Scenario 4 (40%)	21.26%	0	7.10%

maximum responsiveness of each category of residents is calculated, as shown in Table 6.

As can be seen, there is a noticeable difference when a user identifies the stimulus based on the consumer's preference. When the monthly electricity cost increase is below a certain threshold, residents will not take actions or the responsiveness will be very small. However, when the monthly electricity cost increase is above this threshold, residents will take response actions, and their responsiveness has a relationship with the degree of increase. The most likely value of residential electricity consumption responsiveness will increase with the increase in price difference between the peak time and the off-peak time. Of the four scenarios of electricity price change ratios, residents do not take response actions for price changes occurring at normal power consumption time. Based on the survey results, the most likely responsiveness can be calculated, as shown in Table 7.

The Monte Carlo simulation was conducted on the basis of the above analysis, and the changes in the total electricity consumption levels and the residents' responsiveness to each period at different levels of price change ratios can be obtained from the simulation. Scenario 2 (where the price change ratio is 20%) and Scenario 4 (where the price change ratio is 40%) are taken as examples for the analysis of residential responses at peak and off-peak times, and the results are shown in Fig. 2 and Table 8.

Based on the research of Faruqui and Segici [25], TOU rates induce a drop in peak demand that ranges between 3% and 6%. Comparing the responsiveness results from the Monte Carlo simulation in this paper, it is clear that the percentage drop in this paper is higher. This is because Yinchuan is located in the western area of China where the economic development is poor compared with the other more developed regions in China. Increasing the electricity bill will stimulate residents to change their power consumption behaviors more easily. Therefore, their response is a little higher.

According to the Monte Carlo simulation, the peak responsiveness is significantly higher than the off-peak responsiveness at a certain level of price change ratio. Table 8 shows that the peak responsiveness is about three times the value of off-peak responsiveness. The main reason is that at peak time, the high electricity price prompts residents to consider their household electricity cost. They will accordingly reduce the use of electric appliances and shift the use of some household appliances to normal and off-peak times. However, the off-peak time is always at night with low power consumption and low adjustment capability. It is observed that the higher the ratio of electricity price change, the higher the responsiveness of residents. Table 8 also shows that when the price change ratio is 40%, residential peak or off-peak responsiveness is about 2.5 times the value of the responsiveness when the price change ratio is 20%. This result shows that the price incentive on residential power consumption behaviors increases with the rise in electricity price change ratio.

5. Conclusion

Based on the questionnaires and extensive interviews with the residents in Yinchuan, combined with the use of the Monte Carlo simulation method, we simulated the electricity consumption responsiveness of the residents in Yinchuan, China. We believe the results are of great significance to the implementation of DR programs and the design of electricity-related interactive mechanisms in the context of the smart grid.

The degree of residential demand responsiveness is attributed to the level of household energy usage and the change ratio of TOU rates. Residents will begin to adjust their consumption behaviors when their monthly electricity costs rise by 10%. In other words, in a business-as-usual case, residents mainly take energy-saving measures or shift some power usage of electric appliances to the off-peak time. Under the TOU price policy, residential demand responsiveness at the peak time is higher than it is at the off-peak time for a specific price adjustment range. The degree of the effectiveness of DR is bounded by the adjustment in the range of prices in each period accordingly. The larger the peak-time price adjustment, the higher the responsiveness of residents. When the electricity price change ratio of TOU rates is 20%, the peak residential responsiveness is 8.41%, and the low responsiveness is 2.69%. If the equivalent proportion of price increases is 40%, the responsiveness values are about 2.5 times larger.

Residential power consumption is influenced by both internal and external factors. The price level is an important factor in the response. At the same time, household incomes, residential square footage, and other factors will be important as well. Therefore, the division of the price levels by peak/low periods should be considered alongside local environmental conditions, weather conditions, local economic development and household characteristics.

Residents are the most important players in the DR programs for a smart grid. Although individual power consumption rates are small, the overall power consumption is tremendous. During the construction of a smart grid, the actual situation and the fact that the economic development gap between eastern and western regions in China will remain must be taken into account. Reasonable price policies should be developed for the stability of operation of the power system, depending on the load characteristics of different regions.

In the context of the smart grid, electricity DR programs are being implemented in various countries. For other types of energy, several DR programs are gradually being introduced, such as TOU rates and seasonal tariffs of natural gas in order to avoid the peak times of the usage of natural gas. Moreover, the Monte Carlo simulation method can be applied to a variety of DR programs to simulate the users' behavior in order to make references to the formulation of energy price policy.

Acknowledgments

The work described in this paper was supported by the National Natural Science Foundation of China (Grant No. 71273089) and Beijing Natural Science Foundation of China (Grant No. 9122022). Argonne National Laboratory's work was supported under U.S. Department of Energy contract DE-AC02-06CH11357.

References

[1] Pearson ILG. Smart grid cyber security for Europe. Energy Policy 2011;39(8):5211–8.
[2] Clastres C. Smart grids: another step towards competition, energy security and climate change objectives. Energy Policy 2011;39(8):5399–408.
[3] U.S. Department of Energy. Benefits of demand response in electricity markets and recommendations for achieving them: a report to the United State congress pursuant to section 1252 of the Energy Policy Act of 2005. Available at: http://energy.gov/sites/prod/files/oeprod/DocumentsandMedia/DOE_Benefits_of_Demand_Response_in_Electricity_Markets_and_Recommendations_for_Achieving_Them_Report_to_Congress.pdf; Feb. 2006.
[4] Woo CK, Kollman E, Orans R, Price S, Horii B. Now that California has AMI, what can the state do with it? Energy Policy 2008;36(4):1366–74.
[5] Cappers P, Goldman C, Kathan D. Demand response in U.S. electricity markets: empirical evidence. Energy 2010;35(4):1526–35.

[6] Aalami HA, Moghaddam MP, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market program. Applied Energy 2010;87(1):243–50.
[7] Sezgena O, Goldman CA, Krishnarao P. Option value of electricity demand response. Energy 2007;32(2):108–19.
[8] Strbac G. Demand side management: benefits and challenges. Energy Policy 2008;36(12):4419–26.
[9] Walawalkar R, Fernands S, Thakur N, Chevva KR. Evolution and current status of demand response (DR) in electricity markets: insights from PJM and NYISO. Energy 2010;35(4):1553–60.
[10] Horowitz I, Woo CK. Designing Pareto-superior demand-response rate options. Energy 2006;31(6–7):1040–51.
[11] Strengers Y. Air-conditioning Australian households: the impact of dynamic peak pricing. Energy Policy 2010;38(11):7312–22.
[12] Faria P, Vale Z. Demand response in electrical energy supply: an optimal real time pricing approach. Energy 2011;36(8):5374–84.
[13] Hartway R, Price S, Woo CK. Smart meter, customer choice and profitable time-of-use rate option. Energy 1999;24(10):895–903.
[14] Parks RW, Weitzel D. Measuring the consumer welfare effects of time-differentiated electricity prices. Journal of Econometrics 1984;26(1):35–64.
[15] Torriti J, Hassan MG, Leach M. Demand response experience in Europe: policies, programmes and implementation. Energy 2010;35(4):1575–83.
[16] Torriti J. Price-based demand side management: assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy. Energy 2012;44(1):576–83.
[17] Allcott H. Rethinking real-time electricity pricing. Resource and Energy Economics 2011;33(4):820–42.
[18] Caves DW, Christensen L. Econometric analysis of residential time-of-use rates electricity pricing experiments. Journal of Econometrics 1980;14(3):287–306.
[19] Caves DW, Christensen L, Herriges JA. Consistency of residential customer response in time-of-use electricity experiments. Journal of Econometrics 1984;26(1):179–203.
[20] Herter K, Wayland S. Residential response to critical pricing of electricity: California evidence. Energy 2010;35(4):1561–7.
[21] Herter K, McAuliffe P, Rosenfeld A. An exploratory analysis of California residential customer response to critical peak pricing of electricity. Energy 2007;32(1):25–34.
[22] Moore J, Woo CK, Horii B, Price S, Olson A. Estimating the option value of a non-firm electricity tariff. Energy 2010;35(4):1609–14.
[23] Mountain DC, Lawson EL. Some initial evidence of Canadian responsiveness to time-of-use electricity rates: detailed daily and monthly analysis. Resource and Energy Economics 1995;17(2):189–212.
[24] Herter K. Residential implementation of critical-peak pricing of electricity. Energy Policy 2007;35(4):2121–30.
[25] Faruqui A, Segici S. Household response to dynamic pricing of electricity: a survey of 15 experiments. Journal of Regulatory Economics 2010;38(2):193–225.
[26] Faruqui A, Malko JR. The residential demand for electricity by time-of-use: a survey of twelve experiments with peak load pricing. Energy 1983;8(10):781–96.
[27] Vassileva I, Wallin F, Dahlquist E. Understanding energy consumption behavior for future demand response strategy development. Energy 2012;46(1):94–100.
[28] Aigner DJ. The residential electricity time-of-use pricing experiments: what have we learned? Chicago: University of Chicago Press; 1985. p. 11–48.
[29] Zangiabadi M, Feuillet R, Lesani H, Hadj-Said N, Kvaløy JT. Assessing the performance and benefits of customer distributed generation developers under uncertainties. Energy 2011;36(3):1703–12.