An Approach to Assess the Responsive Residential Demand to Financial Incentives

Qinran Hu, Xin Fang, Fangxing Li
Dept. of EECS
The University of Tennessee
Knoxville, USA
{qhu2, fli6, xfang2}@utk.edu

Xiaojing Xu, Chien-fei Chen
CURENT
The University of Tennessee
Knoxville, USA
{xxu20, cchen26}@utk.edu

Haolu Hu
Pudong Electric Power Company
State Grid Cooperation of China
Shanghai, China
hlhu1987@gmail.com

***Abstract*—Due to the development of intelligent energy management system with automatic control, the large population of residential appliances have the opportunity to be effectively utilized by load serving entities (LSEs) to reduce their operating costs and increase total profit. In practice, LSEs are promoting various demand response (DR) programs to stimulate the flexibility of industrial and commercial demand. However, in the residential sector, due to customers' versatile electricity consumption patterns, fully utilizing the responsive residential demand through DR programs such as incentive based demand response (I-DR) is difficult. Specifically, in I-DR, the most crucial issue for LSEs is how to estimate the residents' potential responses to certain financial incentives. Therefore, this paper presents an approach which integrates three data sets (1. the residential energy consumption survey by the U.S. energy information administration; 2. the American time use survey by the U.S. Department of Labor; and 3. the survey of customers' reactions to financial incentives in DR program by the center for ultra-wide-area resilient electric energy transmission networks) to assess responsive residential demand in a stochastic model. This proposed approach can be easily customized for any given times, locations, financial incentives, and residents' portfolios. Also, it will help LSEs get the valuable insights on regulating the residential demand by adjusting the financial incentives to customers and improving the mechanism existing demand response programs.**

***Index Terms*—Incentive based demand response (I-DR), load serving entity (LSE), stochastic modelling, residential demand, financial incentive, demand response, behavioral analysis.**

I. Introduction

In recent years, the electrical power industry has undergone a modernization, moving from traditional power systems towards smart grids. Efficient, flexible, and controllable energy consumption becomes one of the fundamental goals in smart grid initiatives. According to the forecast from U.S. Census Bureau, the American population will swell to 336 million by 2020, and 400 million by 2043. Due to the rapid growth of the population, residential energy consumption will increase. The data from the energy review by U.S. Energy Information Administration (EIA) [1], the residential electricity use in the U.S. in 2013 is 1,391,090 million kWh, which is the largest share (38%) of the total electricity consumption. Ref [2] shows that the development and investment on demand side management have been increasing, especially, for residential sector. Moreover, in the past few years, the availability of technologies, including advanced metering infrastructures (AMI), GPU computing [3-4], communication, renewables [5-6], energy storage [7-8], etc., creates the opportunities for academia and industry to explore the possibility of utilizing the flexibility of residential demand [9-11]. In practice, load serving entities (LSEs) have been deploying various demand response (DR) programs as potential resources to balance supply and demand, reduce peak-hour loads, and enhance the generation efficiency [12] for large industrial and commercial demand. Similarly, as for the residential demand, customers are expected to change their electricity usage patterns in response to the financial incentives offered by LSEs [13-14].

Incentive based DR (I-DR) attempts to induce the demand flexibility in retail customers (such as small/medium size commercial, industrial, and residential customers) to realize the accurate residential demand reduction on a voluntary basis [15]. However, in practice, methods such as peak time rebate (PTR) and critical peak pricing (CPP) are still prevalent ways to realize the demand side management. I-DR is different from them in terms of the mechanism. In PTR, the rebate rates during critical periods are pre-determined and fixed whereas the incentive rates vary in I-DR. In CPP, mandatory high prices are utilized to motivate residents to adjust their electricity consumption whereas the residents are voluntary to participate in I-DR. Despite the advantages of I-DR, the application of I-DR is still difficult for LSEs, due to customers' versatile electricity consumption patterns. In order to assess the responsive residential demand to financial incentives, a stochastic model has been proposed in this paper. With the proposed approach, LSEs will be able to know the characteristics of residential responsive demand under I-DR program based on the residents' portfolio and to generate the probability distribution of the possible residential demand reduction for any given time, location, and amount of incentive.

The rest of this paper is organized as follows: Section II illustrates the structure of electricity market and procedure for LSEs to perform I-DR. Section III presents the details of residential responsive demand model formulation. Section IV discusses the simulation results and numerical analyses to clearly justify the validity of proposed approach. Finally, Section V summaries and concludes this paper.

II. ELECTRICITY MARKET AND I-DR

A. *Electricity Market Structure*

Fig. 1 illustrates the multi-layer electricity market structure: generation companies provide their offers including the available generation quantities and prices to the corresponding independent system operator (ISO)/regional transmission organization (RTO), in the meantime, LSEs provide their demand bids to the ISO/RTO, and then the ISO/RTO clears the market with the objective of maximizing social welfare. In the U.S., most ISOs/RTOs implement the two-settlement system [16]: day-ahead (DA) market and real-time (RT) market. The energy cleared in real-time market is around 2%-8% [17], which represents a considerable with respect to the possible demand response amount. Here, LSEs are able to adjust the demand bids and perform strategic bidding in electricity market to maximize their profit by offering proper financial incentives to the customers who have enrolled I-DR program.

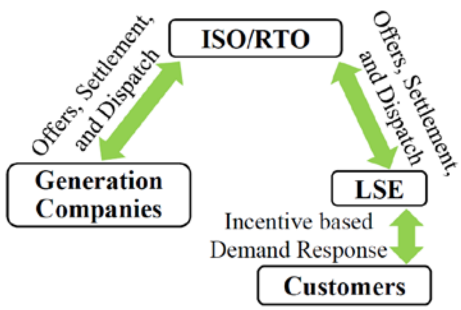

Fig. 1. Electricity market structure

B. *Procedure of I- DR*

The flowchart of the procedure for LSE to perform I-DR is as shown in Fig. 2. First, the LSE obtains location marginal prices (**L**MPs) information from ISO/RTO's DA market [18]. Then, the LSE broadcasts the incentive price for the hours when performing I-DR to stimulate customers reducing their demands can help increase their profit (i.e., the hours when locational marginal price exceeds the electricity flat retail rate). After gathering all the information of potential demand reduction, the LSE mimics ISO's economic dispatch (ED) to identify the optimal demand reduction. Finally, the LSE performs strategic market bidding with this revised demand to achieve maximum profit.

In the above procedure, the LSE has to broadcast and update the incentive prices multiple times through communicating with customers and iteratively obtain the optimal value of incentive price. While in practice, due to the huge data processing and communication with numerous customers, the times of information exchange between LSEs and customers are limited. In order to reduce the iterations between LSEs and customers and to speed up the updating process of incentive prices, LSEs should be able to determine a rough range of the incentive price before broadcasting it; hence, I-DR can serve as an online implementation for LSEs in the actual practice.

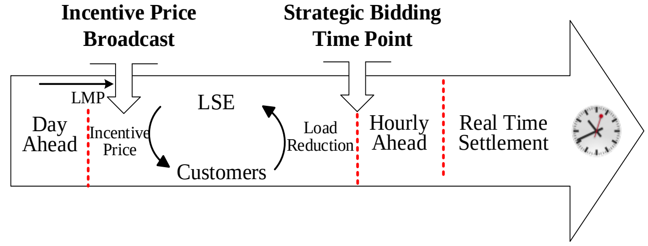

Fig. 2. Flowchart of the LSE's strategic bidding

To determine the initial optimal incentive price, the LSE should be able to assess the amount of residential responsive demand that can be reduced with different incentive prices, and then perform strategic bidding for each incentive price, and finally obtain an optimal amount. The details about the proposed stochastic model will be discussed in the next section.

III. RESIDENTIAL RESPONSIVE DEMAND MODELLING

A. *Model Overview*

As previously discussed, the uncertainty of customers' demand reduction is typically modeled as follows in I-DR based strategic bidding: 1) the LSE offers an incentive price to customers; 2) the customers provide their ranges of corresponding demand reduction to the LSE; 3) the LSE calculates the expected net revenue through bidding this revised demand in electricity market; and 4) by repeating steps 1)-3) with different incentive prices, the optimal incentive value, which brings the LSE the maximum net revenue, can be found. However, there are two issues for this process: 1) it is rarely feasible to keep frequently updating customers' demand reduction data; and 2) interaction with numerous customers makes it too time-consuming to serve as an online implementation. Therefore, a stochastic model of demand reduction is proposed in this paper.

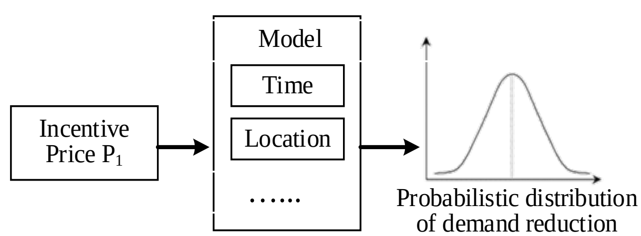

Fig. 3. Schematic diagram of the proposed model

Different from the traditional method, with the consideration about the characteristics of residential demand for a given time, location and customers' portfolios, the proposed model is able to assess the probability distribution of residential demand response to certain incentive price. As the schematic shown in Fig. 3, instead of iteratively updating information between LSE and customers, the proposed model directly generates the results, and this avoids the time-consuming procedure of communicating and makes the online implementation of I-DR feasible for LSEs.

B. Residential Responsive Demand Model Formulation

The proposed model is established based on adequate data analysis of three data sets: 1) the Residential Energy Consumption Survey [19] (RECS) by the U.S. Energy Information Administration (EIA), 2) the American Time Use Survey [20] (ATUS) by the U.S. Department of Labor (USDL), and 3) the Survey of Customers' Reactions to Financial Incentives (SCRFI) in DR by the Center for Ultra-wide-area Resilient Electric Energy Transmission Networks (CURENT) [21].

- RECS collected data from 12,083 households in housing units statistically selected to represent the 113.6 million housing units that are occupied. Specially trained interviewers collect energy characteristics on the housing unit, usage patterns, and household demographics. This information is combined with data from energy suppliers to these homes to estimate energy costs and usage for heating, cooling, appliances and other end uses that are critical to energy demand and efficiency.
- ATUS provides nationally representative estimates of how, where, and with whom Americans spend their time, and is the only federal survey providing data on the full range of nonmarket activities. Moreover, ATUS data files have been used by researchers to study a broad range of issues; the data files include information collected from over 148,000 interviews conducted from 2003 to 2013.
- SCRFI collected self-reported data from 711 U.S. residents across 48 states in 2013. This study estimates the adopting rates of major DR behaviors as a function of the demanded financial incentives. Specifically, this survey was conducted by CURENT through Amazon's Mechanical Turk (MTurk). MTurk has been received great popularity among social scientists as a useful research tool to collect data [23]. The SCRFI was published on MTurk as a "hit." The respondents read the instructions and voluntarily completed the survey. It needs to be noted that another sample of 826 residents has just been collected, and that CURENT is continuously improving the question designs in SCRFI and aiming to gather more representative responses across the U.S.

By creatively integrating RECS, ATUS and SCRFI, the proposed method can be formulated. The procedure of the model formulation is summarized as follows:

Step 1) Based on the given location to be studied, the residents will be categorized into several groups (G_1, $G_2 \ldots\ldots G_N$) based on the demographic information. For each group of residents, step 2) to 5) will be performed.

Step 2) For group G_i, the types and ratings of the appliances customers owned can be obtained by analyzing RECS. Here, the proposed model considers the I-DR over appliances including electrical water heaters (EWH) and air conditioner (ACs), since EWH and ACs account for the dominating part (over 53%) of residential demand. Therefore, for residents of G_i, the average ratings their of ACs and EWHs can be obtained as $R_{ac,i}$ and $R_{EWH,i}$.

Step 3) For group G_i, ATUS can provide information about the activities which the residents are doing at a given location and at a given time of a day. The proposed model considers only AC and EWH-related activities such as working (out/at home), taking shower, sleeping, etc. Therefore, at time t, the probability of the residents in G_i doing activities $a_j \in \{a_1, a_2, \ldots\ldots, a_m\}$ can be expressed as $P_{activity,i}(a_j,t)$.

Step 4) To study customers' reactions to financial incentives, SCRFI helps estimate the distribution of group G_i in terms of the willingness to respond to a certain incentive price $r_k \in \{r_1, r_2, \ldots\ldots, r_p\}$ in I-DR. Then, based on the residents' responsiveness to different incentive prices, their spectrum of responsiveness can be modeled. The responsiveness for AC and EWH of the residents in G_i are expressed as $P_{resAC,i}(r_k,a_j,t)$ and $P_{resEWH,i}(r_k,a_j,t)$ respectively.

Step 5) With the integration of the appliance and activity information, the possible amount of the residential demand reduction can be obtained. The potential reducible demand for group G_i at time t with given financial incentives r_k, can be formulated as below.

$$D_{RED}(G_i, r_k, t) = \sum_{j=1}^{m} R_{AC,i} \cdot P_{activity,i}(a_i,t) \cdot P_{resAC,i}(r_k, a_i, t)$$
$$+ \sum_{j=1}^{m} R_{EWH,i} \cdot P_{activity,i}(a_i,t) \cdot P_{resEWH,i}(r_k, a_i, t)$$

Step 6) By repeating step 2) to 5), the residents' responsiveness distribution and the potential reducible demand of all the groups (G_1 to G_N) are known. Then, it is easy to obtain the probabilistic distribution of the residential responsive demand reduction.

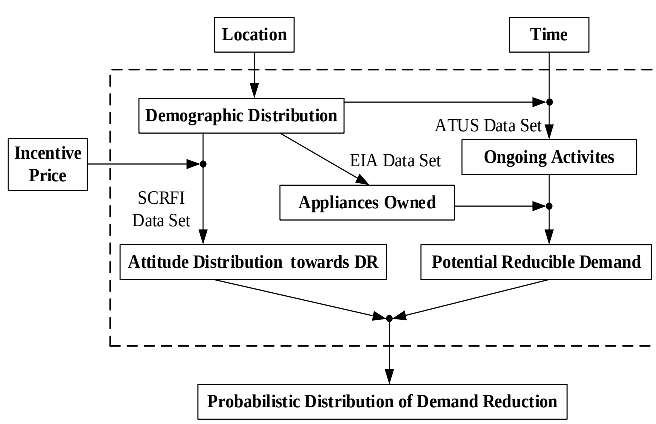

Fig. 4. Schematic diagram of the information flow for the proposed model

The schematic diagram of the information flow for the residential demand reduction model is as shown in Fig. 4, where the inputs of the model are the incentive prices, the I-DR's location and time length, and the output is the corresponding probabilistic distribution of residential demand reduction in I-DR with a given incentive price in a given location at a given time.

In summary, the above proposed stochastic model evaluates the characteristics of residential demand reduction under I-DR programs based on the local residents' portfolios and provides the probability distribution of demand reduction for given times, locations, and coupon prices.

IV. CASE STUDIES

In this section, the proposed method has been tested to demonstrate the model features. However, since this work is early work in this area, there is no practical results public available for comparison. In order to verify the validity and effectiveness of the proposed model, various case studies in Northeast, Midwest, South and West regions of U.S. have been performed for comparison to check whether the results comply with common knowledge. The simulation has been performed in Matlab on a desktop with Intel Xeon 3.2GHz CPU, 8 GB RAM, and Window 8.

A. Fixed Time

The model has been applied to simulating the probability distribution of reduced power ratio (RPR) in residential aspect with various incentive prices for the whole U.S. at 12pm in a summer day. Fig.5 shows the probability distribution results, which indicate that the higher the financial incentive is, the more likely customers are willing to reduce their load. Meanwhile, due to customers' different responses to financial incentives in DR, with the increasing of the financial incentive, the probabilistic distribution of demand reduction becomes broader.

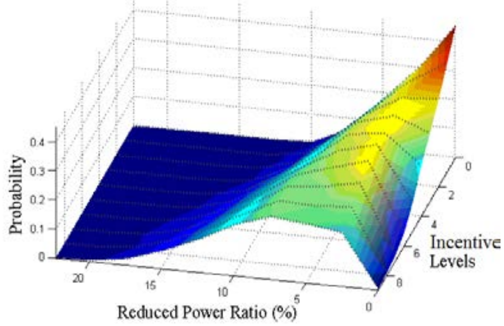

Fig. 5. Probability distribution of RPR under different incentive prices

Fig. 6 is the customers' responses towards different incentive prices in the Northeast, Midwest, South and West regions of U.S. respectively. The results show that the residential demand in the South at summer time responds more significantly to I-DR than that of the other three regions. This phenomena is reasonable, because 1) SCRFI shows that residents in the South are more sensitive to financial incentives and 2) RECS reflects that more space cooling appliances are operating in South region at summer time, which increases the total capacity of the potential reducible demand.

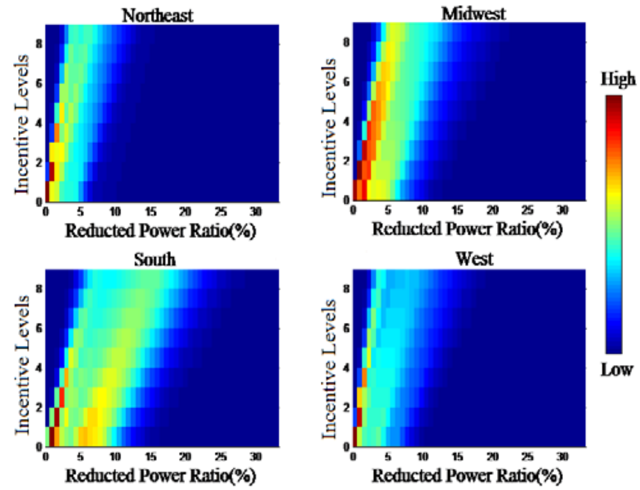

Fig. 6. Probability distribution of RPR with different incentive prices in the Northeast, Midwest, South and West regions of U.S

B. Fixed Incentive Price

The characteristics of residential demand of the whole U.S. with a given incentive price in a random summer day for 24 hours is illustrated in Fig. 7. The result shows the residential demand is most probable to be reduced by I-DR from 7AM-7PM. The possible reasons are 1) the possible reducible demand is high when most of the residents are awake (by ATUS), and also 2) SCRFI shows that residents are more likely to turn off home appliances when they are not at home (i.e., are at work place).

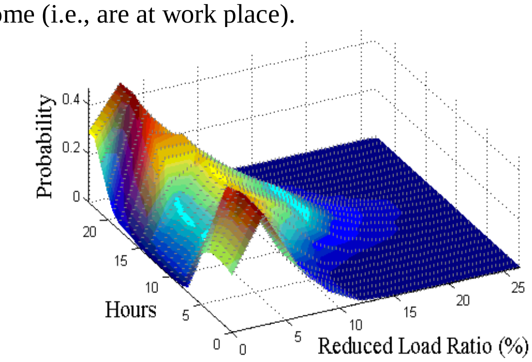

Fig. 7. Probability distribution of 24-hour RPR

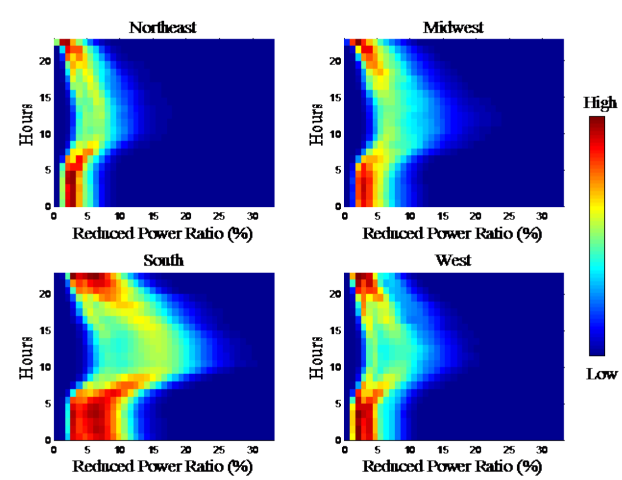

Fig. 8. Probability distribution of 24-hour RPR in different areas

Furthermore, the residential responsive demand varies with different resident portfolios. For example, the probability distribution of RPR for 24 hours is significantly different in the Northeast, Midwest, South, and West regions of U.S., as shown in Fig. 8. The possible reason is, as aforementioned, more space cooling appliances are operating in summer in South region, which can be reduced by I-DR.

Therefore, the simulation results of the preliminary study regarding residential demand modeling comply with common knowledge, and these facts help verify the validity and effectiveness of the proposed approach.

V. CONCLUSTION

This paper presents a stochastic model based on the residents' portfolios to assess responsive residential demand in response to certain given times, locations, and financial incentives. By implementing the proposed model, LSEs will be able to solve the two aforementioned issues with typical procedures of performing I-DR: 1) it is rarely feasible to keep frequently updating customers' demand reduction data; and 2) interaction with numerous customers makes it too time-consuming to serve as an online implementation.

Instead of iteratively communicating and updating information between LSE and customers, the proposed approach creatively integrates three data sets (RECS from EIA, ATUS from USDL, SCRFI from CURENT) to directly generate the probability distribution of demand reduction for specific times, locations, and coupon prices. Therefore, it avoids the time-consuming procedure of communicating and makes the online implementation of I-DR feasible for LSEs. Moreover, various case studies of Northeast, Midwest, South and West regions of U.S. with fixed time or fixed incentive prices have been conducted to verify the validity and effectiveness of the proposed model.

Also, if this approach can be widely used in the future, it will provide great potentials for LSEs including:

1) LSEs will be able to quicky estimate the residents' response to certain financial incentives and then perform accurate the residential demand control with optimized financial incentives.
2) With the capability of accurately controlling residential demand by financial incentives, LSEs will be able to perform strategic bidding in the market in real-time to maximize their profit.
3) This stochastic model allows LSEs to perform economic analysis before actual executing I-DR in certain areas. In this way, LSEs can have an assessment of whether it is worthy to invest on replacing devices in certain areas to make I-DR feasible in advance.
4) Also, the proposed approach will help LSEs get insights on how to improve the existing demand response programs.

ACKNOWLEDGEMENT

The authors would like to acknowledge that this work made use of share facilities of the CURENT research center supported by the US NSF/DOE Engineering Research Center Program under NSF Award Number EEC-1041877 and the CURENT Industry Partnership Program.

REFERENCE

[1] U.S. EIA, "Monthly Energy Review," Dec. 2014, pp. 109.
[2] U.S. EIA, "Annual Energy Review 2011," Sept. 2012, pp. 262-267.
[3] X. Li and F. Li, "GPU-based Power Flow Analysis with Chebyshev Preconditioner and Conjugate Gradient Method," *Electric Power Systems Research*, vol. 116, pp. 87-93, Nov. 2014.
[4] X. Li, F. Li, and J. Clark, "Exploration of Multifrontal Method with GPU in Power Flow Computation," *IEEE PES General Meeting*, Vancouver, BC, Canada, 2013.
[5] Y. Xu, Q. Hu, and F. Li, "Probabilistic model of payment cost minimization considering wind power and its uncertainty," *IEEE Trans. on Sustainable Energy*, vol.4, no.3, pp. 716-724, 2013.
[6] C. Huang, F. Li, T. Ding, and Zhiqiang Jin, "Second-order Cone Programming-based Optimal Control Strategy for Wind Energy Conversion Systems over Complete Operating Regions," *IEEE Trans. on Sustainable Energy*, vol. 6, no.1, pp. 263-271, Jan. 2015.
[7] J. Xiao, L. Bai, C. Wang, et al. "Method and software for planning and designing of microgrid," *Proceedings of CSEE*, vol. 32, no. 25, pp. 149-157.
[8] J. Xiao, L. Bai, Z. Lu, and K. Wang, "Method, implementation and application of energy storage system designing," *Int. Trans. Elect. Energy Syst.*, vol. 24, pp. 378–394, 2014.
[9] Q. Hu and F. Li, "Hardware design of smart home energy management system with dynamic price response," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1878-1887, Dec. 2013.
[10] Q. Hu, J. Chan, F. Li and D. Chen, "A comprehensive user interactive simulation tool for smart home application," *Power Engineering Conference(AUPEC), 2014 Australasian Universities*, Sept. 2014.
[11] Q. Hu, F. Li and C. Chen, "A smart home test bed for undergraduate education to bridge the curriculum gap from traditional power systems to modernized smart grids," *IEEE Trans. Edu.*, vol. 58, no. 1, pp. 32-38, Feb. 2015.
[12] R. Herranz, A. M. S. Roque, J. Villar, and F. A. Campos, "Optimal Demand-Side Bidding Strategies in Electricity Spot Markets," *IEEE Trans. Power System*, vol. 27, no. 3, pp. 1204-1203, Aug. 2012.
[13] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An Algorithm for Intelligent Home Energy Management and Demand Response Analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166-2173, Dec. 2012.
[14] C. Goldman et al., Customer Strategies for Responding to Day-Ahead Market Hourly Electricity Pricing. Berkeley, CA: Lawrence Berkeley National Laboratory, 2005.
[15] H. Zhong, L. Xie, and Q. Xia, "Coupon Incentive-Based Demand Response: Theory and Case Study," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1266-1276, May 2013.
[16] A. L. Ott, "Experience with PJM market operation, system design, and implementation," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 528-534, May 2003.
[17] Report on Market Issues and Performance. CAISO Department of Market Analysis, 2010. [Online]. Available: http://www.caiso.com.
[18] H. Yuan, F. Li and Y. Wei, "LMP Step Pattern Detection based on Real-Time Data," *IEEE PES General Meeting*, Vancouver, BC, Canada, 2013.
[19] Residential Energy Consumption Survey, U.S. EIA. [Online]. Available: http://www.eia.gov/consumption/residential/.
[20] American Time Use Survey, U.S. Depart of Labor. [Online]. Available: http://www.bls.gov/tus/.
[21] Center for Ultra-wide-area Resilient Electric Energy Transmission Networks. [Online]. Available: http://curent.utk.edu/.
[22] J. Xiao, L. Bai, F. Li, H. Liang, C. Wang. "Sizing of energy storage and diesel generators in an isolated microgrid using discrete Fourier transform (DFT)," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 907-916, Jul. 2014.
[23] M. Buhrmester, T. Kwang, & S. D. Gosling, "Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data?" *Perspectives on Psychological Science*, vol. 6, no. 1, pp. 3-5, 2011.