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Incentive based Residential Demand Aggregation

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To the Graduate Council:

I am submitting herewith a dissertation written by Qinran Hu entitled "Incentive based Residential Demand Aggregation." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Electrical Engineering.

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Incentive based Residential Demand Aggregation

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DEDICATION

This dissertation is dedicated to my beloved parents, Minqiang Hu and Shenbei Qin, whose love and encouragement make it possible for me to finish this work.

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Last but not least, this dissertation not only represents my work, but it is also a milestone representing more than five year of works at the University of Tennessee at Knoxville (UTK) and specifically within the Smart Home and Grid Laboratory. My experience at UTK has been nothing short of amazing.

ABSTRACT

From the beginning of the twenty-first century, the electrical power industry has moved from traditional power systems toward smart grids. However, with the increasing amount of renewable energy resources integrated into the grid, there is a significant challenge in power system operation due to the intermittency and variability of the renewables. Therefore, the utilization of flexible and controllable demand-side resources to maintain power system efficiency and stability has become a fundamental goal of smart grid initiatives.

Meanwhile, due to the development of communication and sensing technologies, intelligent demand-side management with automatic controls enables residential loads to participate in demand response programs. Therefore, the aggregate control of residential appliances is anticipated to be feasible technique in the near future, which will bring considerable benefits to both residential consumers and load-serving entities. Hence, this dissertation proposes a comprehensive optimal framework for incentive based residential demand aggregation. The contents of this dissertation include: 1) a hardware design of smart home energy management system, 2) a new model to assess the responsive residential demand to financial incentives, and 3) an online algorithm for scheduling residential appliances.

The proposed framework is expected to generate optimal control strategies over residential appliances enrolled in incentive based DR programs in real time. To residential consumers, this framework will 1) provide easy-to-use smart energy management solution, 2) distribute financial rewards by their quantified contribution in DR events, and 3)

maintain residents' comfort-level expectations based on their energy usage preferences. To LSEs, this framework can 1) aggregate residential demand to enhance system reliability, stability and efficiency, and 2) minimize the total reward costs for executing incentive based DR programs. Since this framework benefits both load serving entities and residents, it can stimulate the potential capability of residential appliances enrolled in incentive based DR programs. Eventually, with the growing number of DR participants, this framework has the potential to be one of the most vital parts in providing effective demand-side ancillary services for the entire power system.

Keywords: Power systems, demand response, residential demand aggregation, electricity market, incentive based demand response program, behavioral analysis.

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CHAPTER 1

INTRODUCTION AND GENERAL INFORMATION

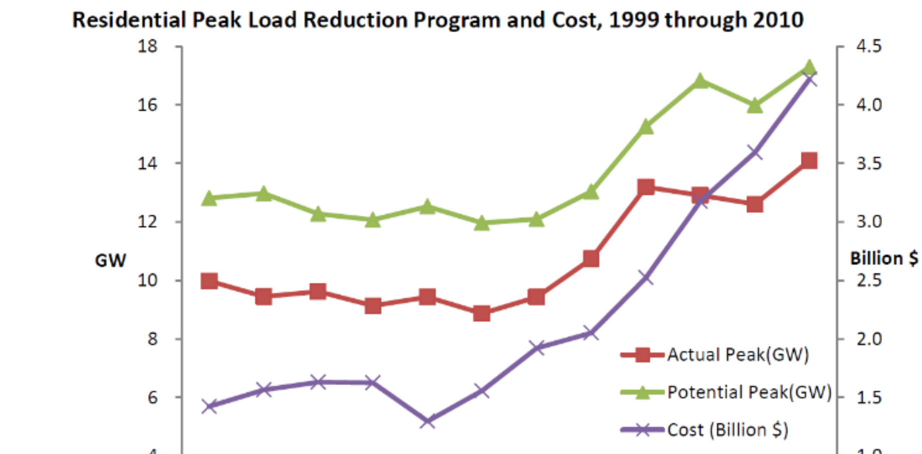
1.1 Demand Response

From the beginning of the twenty-first century, the electrical power industry has experienced significant transformation due to the integration of an increasing amount of distributed energy resources. The trend implies less conventional generators, suggesting that future power systems are inclined to have less generation reserve capability. Therefore, not surprisingly, the demand-side resources, which are under-utilized, have the potential to improve the reserve capacity and system efficiency for future smart grids.

Demand response (DR) refers to "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [1, 2]. DR, by promoting the interaction and responsiveness of the customers, determines short-term impacts on the electricity markets, leading to economic benefits for both electricity consumers and load serving entities (LSEs) [3, 4]. Moreover, by improving the power system reliability and, in the long term, lowering peak demand, DR reduces overall plant and capital cost investments and postpones the need for network upgrades [5, 6].

1.1.1 Residential Demand Response

According to the energy review of 2014 by the U.S. Energy Information Administration (EIA), the residential electricity use in the U.S. in 2013 is 1,391,090 million kWh, which is the largest share (38%) of total electricity consumption [7]. Figure 1 is re-generated from [8] and [9] to show the increasing development and investment on demand side management, in particular, peak load reduction.



	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Actual Peak(GW)	9.98	9.45	9.62	9.14	9.43	8.87	9.43	10.73	13.19	12.91	12.61	14.09
Potential Peak(GW)	12.81	12.97	12.27	12.07	12.53	11.97	12.10	13.04	15.26	16.83	15.99	17.29
Cost (Billion $)	1.42	1.56	1.63	1.63	1.30	1.56	1.92	2.05	2.52	3.18	3.59	4.22

Figure 1. Residential Peak Load Reduction Program and Cost

According to figure 1, both residential actual peak load reduction and potential peak load reduction in the U.S. have a general growing trend since 2004. The increasing demand-side participation in power systems has been creating new challenges and opportunities for electricity market participants [10, 11]. Meanwhile, with the development of communication and sensing technologies, the advanced platforms in which electricity consumers and suppliers to interact with each other become feasible. This creates opportunities for utilizing demand side resources enhance the power system reliability, stability and efficiency based on the cooperation among system operators, end consumers, and LSEs. For power system operators, various DR programs have been deployed as potential resources to balance supply and demand, reduce peak-hour loads, and enhance the generation efficiency [10]. For consumers, electricity consumption is expected to be responsive to the fluctuant pricing signals to reduce their electricity payments [1,11-15]. In a fully competitive electricity market, LSEs play a critical role to function as intermediaries between end consumers and wholesale market operators to connect them into an optimal operation framework [16].

1.1.2 Types of Demand Response Programs

Methods for engaging residential customers into DR include price-based DR programs via time-varying price mechanisms such as time-of-use pricing (TOU), critical peak pricing (CPP), real-time pricing (RTP), and peak load reduction credits, as well as incentive-based intelligent load control DR programs.

Time-of-Use Pricing (TOU)

TOU of electricity is set for a specific time period on an advance or forward basis, typically not changing more often than twice a year. Prices paid for energy consumed during these periods are pre-established and known to consumers in advance, allowing them to vary their usage in response to such prices and manage their energy costs by shifting usage to a lower cost period or reducing their consumption overall.

Critical Peak Pricing (CPP)

CPP of electricity is in effect except for certain peak days, when prices may reflect the costs of generating and/or purchasing electricity at the wholesale level.

Real-time pricing (RTP)

RTP of electricity may change as often as hourly (exceptionally more often). Price signal is provided to the consumers on an advanced or forward basis, reflecting the utilities' cost of generating and/or purchasing electricity at the wholesale level; and

Peak Load Reduction Credits

Peak load reduction credits are for consumers with large loads who enter into pre-established peak load reduction agreements that reduce a utility's planned capacity obligations.

1.1.3 Incentive based Residential Demand Response

I-DR was introduced in an attempt to induce flexibility in retail customers (such as small/medium size commercial, industrial, and residential customers) on a voluntary basis [31]. With an increasing amount of market products and research prototypes [17-23] of home energy management system appearing on the market, I-DR, which helps realize intelligent controls over residential appliances, will become easily feasible in the near future. The adoption of I-DR would bring benefits to both residents and LSEs including:

- Reduction of the total power generation and environmental impacts. Under the successful implementation of I-DR, the need of activating expensive-to-run power plants to meet peak demands is eliminated, and at the same time, while it enables energy providers to meet their pollution control obligations [1].

- Change of demand to follow available supply, especially in regions with high penetration of renewable energy sources, such as solar panels and wind turbines, to maximize the overall power system reliability [24].

- Reduction or even elimination of overloads in distribution system. The Distribution Management System (DMS) will monitor the distribution system, and takes near real-time decisions over residential appliances to enhance the reliability of distribution systems [25].

- Improvement on electricity market efficiency. Residents are expected to reduce their energy cost; meanwhile, the aggregated demand will give LSEs more flexibility in the electricity market bidding which may bring them more profits. [16][26-30]

At this point, an example is illustrated as follow to show how I-DR benefits LSEs while there is wind power integrated.

Figure 2 demonstrates the impact of I-DR and wind power uncertainty to both electricity supply curve and elastic demand curve. As shown in Figure 2, (D_1, π_1) is the intersection between the expected supply curve and the original demand curve, and (D_2, π_4) denotes the intersection between the expected supply curve and the new demand curve with financial incentives. Considering the wind power output, the locational marginal price (LMP) π_1 is greater than the flat rate price η at the system demand level D_1. If the wind power output is lower than forecasted, the LMP goes higher at π_3; however, if the wind generates more power than forecasted, the LMP becomes lower at π_2. Under demand level D_1, the expected net revenue for the LSE considering the wind uncertainty $(\eta-\pi_1)\cdot D_1$, is negative. When a financial incentive is provided, the elastic demand curve changes from $D_1(P)$ to $D_2(P)$. With the new demand curve, the corresponding LMP will be π_4 which is lower than the flat rate η. Consequently, as long as the net revenue $(\eta-\pi_4)\cdot D_2-r\cdot(D_1-D_2)$ is greater than $(\eta-\pi_1)\cdot D_1$, the LSE will have an incentive to offer the reward price r to customers in I-DR. Therefore, the I-DR program with proper reward prices can help LSEs increase their profits by mitigating the price volatility due to wind uncertainty in the wholesale market.

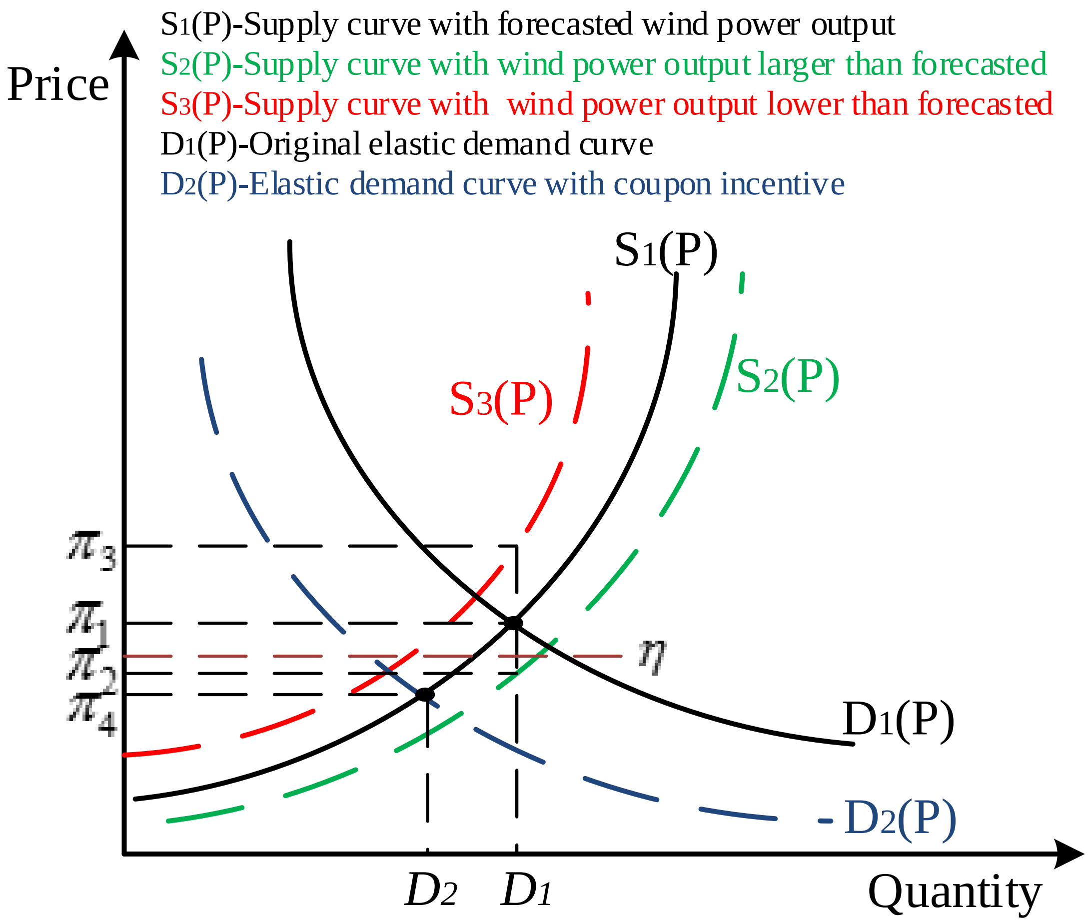


Figure 2. Impact of I-DR and Wind Power on Supply and Demand Curves

1.2 Electricity Market with Demand Response

With growing development in demand response, LSEs may participate in electricity market as strategic bidders by offering I-DR to customers. By aggregating the demand enrolled in I-DR, LSEs will be able to utilize the demand flexibility to increase their profit in the market [32].

1.2.1 Procedure of LSEs' Bidding

The three-layer electricity market structure is shown in Figure 3. The generation companies provide electricity offers including the available generation quantity and prices to the corresponding independent system operator (ISO); then, the LSEs provide demand bids to the ISO, and finally the ISO clears the market to maximize the social welfare. The illustration of LSEs' strategic bidding under this market structure will be discussed in this subsection. Most ISOs in the U.S. implement the two-settlement system [33]: day-ahead (DA) market and real-time (RT) market. The energy cleared in real-time markets is around 2%–8% [34] which is considerable with respect to the possible DR amount.

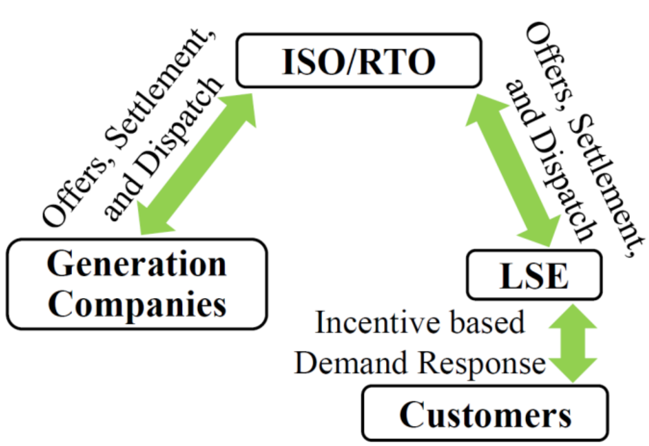


Figure 3. Structure of the Electricity Market

Figure 4 is the flowchart of LSEs' strategic bidding. First, the LSE obtains the locational marginal price (LMP) information from the ISO's DA market. Then, the LSE broadcasts the incentive price for the hours in which the LSE wants to perform I-DR to stimulate customers to reduce demand (i.e., the hours when LMP exceeds or is likely to exceed the electricity flat rate). After gathering all the information of potential demand reduction, the LSE mimics ISO's economic dispatch (ED) process to identify the optimal demand reduction. Finally, the LSE performs the bidding with the revised demand.

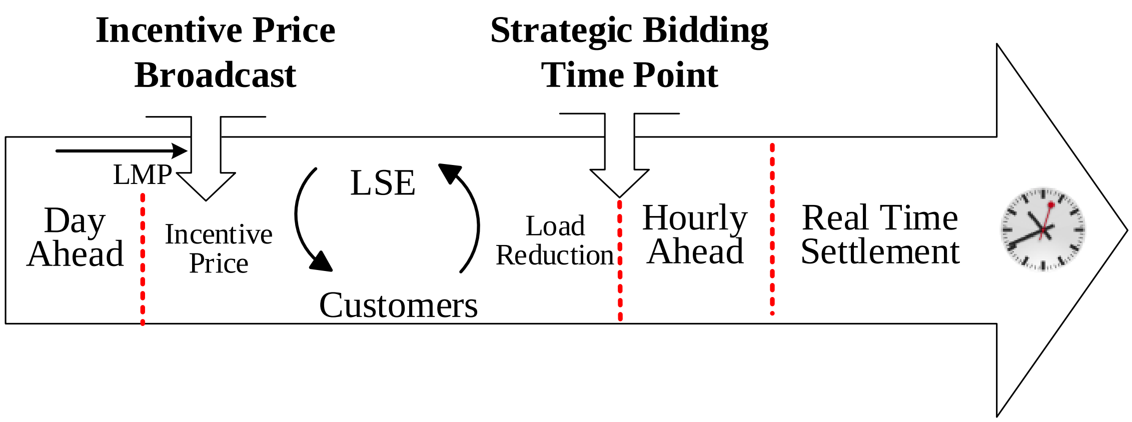


Figure 4. Flowchart of the Proposed Strategic Bidding

1.2.2 Net Revenue of LSEs

The LSE receives a gross revenue from each customer k ($k \in B_i$) at bus i ($i \in A$), as shown in k_4 to k_7 of LSE A in Figure 5. This revenue is calculated as the product of the retail price $\eta_{i,k}$ and electricity consumption $D_{i,k}$. Then, the payment (i.e., the product of spot price π_i and the electricity consumption $D_{i,k}$) is subtracted since the LSE purchases electricity from ISOs in the wholesale market at volatile nodal prices. Finally, the financial incentives that the LSE pays to customers should be subtracted as well, which is the product of incentive price $r_{i,k}$ and the deviation between the actual electricity demand and the baseline electricity consumption. Therefore, the LSE's net revenue, represented by R_n, should be expressed as (1-1):

$$R_n = \sum_{i \in A} \sum_{k \in B_i} [(\eta_{i,k} - \pi_i) \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})] \tag{1-1}$$

The LMP π_i in (1-1) is obtained from ISO's ED [31].

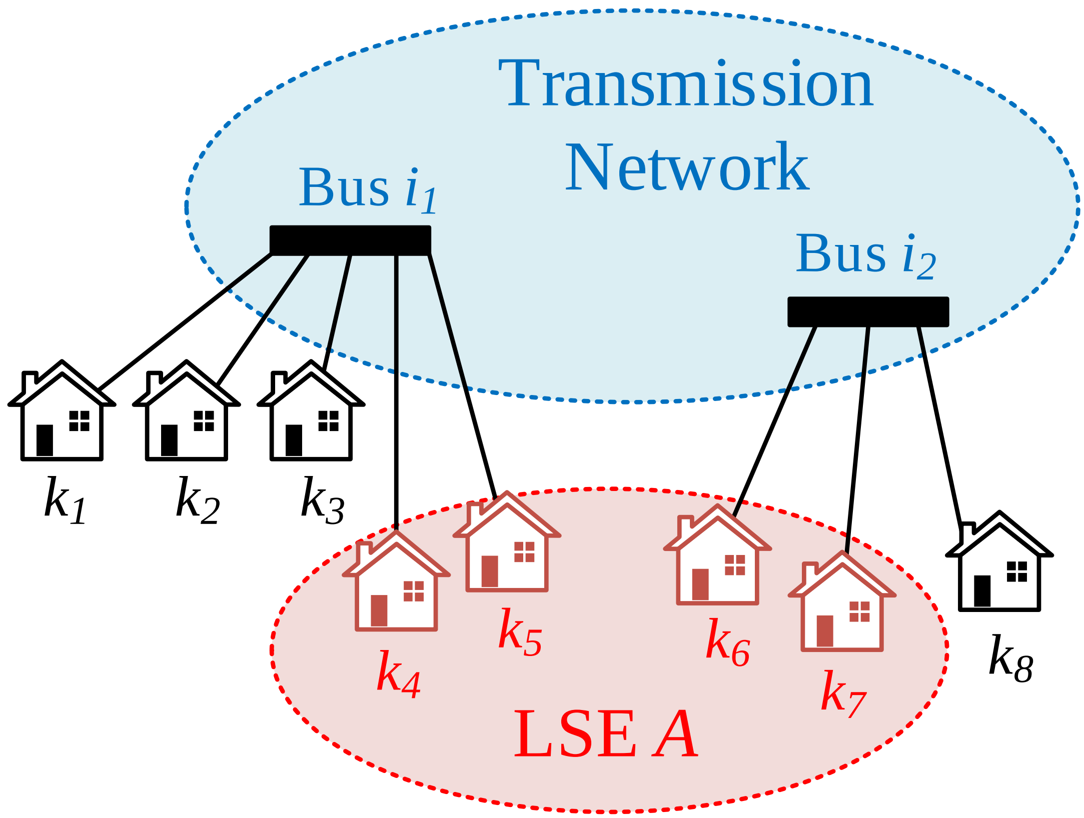


Figure 5. The Illustrative Figure of an LSE and Its Customers

Hence, it is clear that aggregating the demands with different incentive prices gives LSEs opportunities to increase their profits by strategic bidding in the market.

1.3 Residents in Demand Response

Most of the existing demand response programs target large industrial or commercial users. There are several reasons for this. First, demand side management is rarely invoked to cope with a large correlated demand spike due to weather or a supply shortfall due to faults, e.g., during a few of the hottest days in summer. Second, the lack of ubiquitous two-way communication in the current infrastructure prevents the participation of a large number of diverse users with heterogeneous and time-varying consumption requirements.

Here, I-DR attempts to induce the demand flexibility in residential demand to realize the accurate residential demand control on a voluntary basis. However, as aforementioned, the application of I-DR is difficult for LSEs, due to residents' versatile electricity consumption patterns and easy-to-use smart energy management system.

1.3.1 Smart Home Energy Management System

Smart home energy management system (SHEMS) is the residential extension of building automation. It is automation of the home, housework or household activity. SHEMS may include centralized control of an electrical water heater (EWH), air conditioner (AC), lighting, electrical vehicle (EV), and other appliances, to provide improved convenience, comfort, and energy efficiency. The popularity of home automation has been increasing greatly in recent years due to much higher affordability and simplicity through smartphone and tablet connectivity. The concept of the "Internet of Things" has been tied in closely with the popularization of home automation. Most importantly, SHEMS is the vital enabling technology of realizing the intelligent incentive based demand aggregation.

Currently, two issues are preventing SHEMS from being widely used:

1) Most of SHEMS designs request complex settings and controls from the users;

2) Existing SHEMS designs are hardly able to intelligently schedule the appliances considering residents' comfort levels.

1.3.2 Residents' Behavior towards Financial Incentives

If the model of residents' behavior toward financial incentives can be established can be established, it should help the algorithm of aggregating residential demands greatly. Promoting I-DR in the residential sector heavily relies on understanding residents' reactions to financial incentives and developing effective marketing strategies based on residents' characteristics.

In order to study customers' versatile behavior, the following questions should be answered: 1) how large do financial rewards need to be to induce major heating-cooling (HC)-related DR behaviors? 2) Do the residents prefer having utility companies adjust HC settings for them or would they rather do it themselves? 3) How do the answers to these questions vary across residents with different values, needs, and habits?

1.4 Contributions of This Work

This work proposes a comprehensive optimal framework for aggregating residential demands, and incorporates residential demand aggregation with current power system operation (depicted in Figure 6).

Specifically, the contributions of this work can be summarized into three aspects.

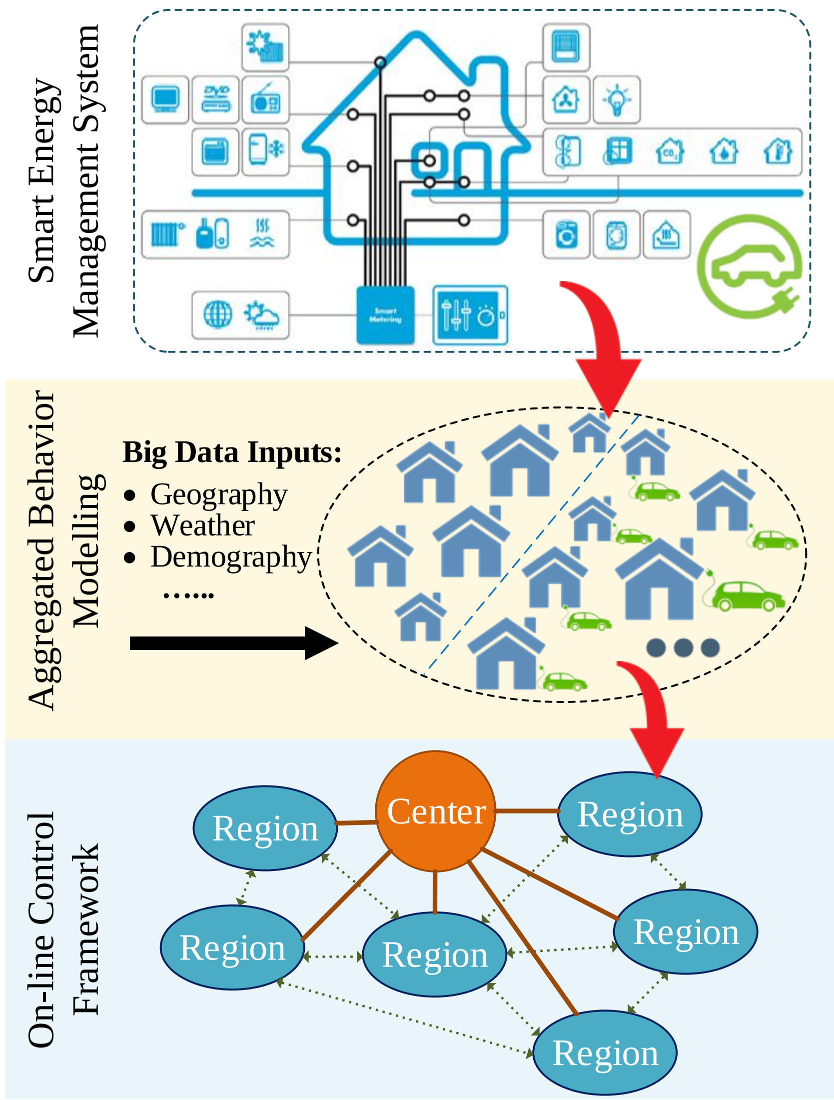


Figure 6. Overall Design of the Proposed Concept

- This work provides enabling technology for incentive based residential demand aggregation, i.e., the hardware design of a SHEMS. With the proposed design, residents can achieve a responsive control strategy over residential loads including EWHs, AC units, EVs, dishwashers, washing machines, and dryers. Also, they may interact with LSEs to facilitate I-DR. Further, SHEMS is designed with sensors to detect residents' activities and then apply a machine learning algorithm to intelligently help residents reduce total electricity payment without complex settings.

- This work solves the issues of residents' versatile energy usage behavior towards I-DR by establishing a stochastic model based on the residents' portfolios to assess responsive residential demand in response to certain given times, locations, and financial incentives. Also, the proposed model avoids the time-consuming procedure of communicating and makes the online implementation of I-DR feasible for LSEs.

- This work proposes an optimal online method for scheduling the residential appliances in I-DR. This method not only allocates demand reduction requests (DRRs) among residential appliances quickly and efficiently without affecting residents' comforts, but also intelligently reward residents for their participation.

In sum, the comprehensive framework for incentive based demand aggregation benefits both LSEs and residents, and it may stimulate the potential capability of residential appliances enrolled in I-DR programs. Eventually, with the growing number of DR participants, this framework has the potential to be one of the most vital parts in improving power system operating stability, reliability and efficiency.

1.5 Organizations of the Dissertation

The literature review is given in Chapter 2.

Chapter 3 presents a hardware design of SHEMS with the applications of communication, sensing technology, and machine learning algorithm. With the proposed design, customers can easily achieve price-responsive control strategy for residential home appliances such as EWHs, ACs, EVs, dishwashers, washing machines, and dryers. Also, residents may interact with LSEs to facilitate the load management at supply side. Further, the proposed SHEMS is designed with sensors to detect residents' activities and then a machine learning algorithm to intelligently help residents reduce total payment on electricity with very little involvements from the residents themselves. In addition, simulation and experiment results are presented based on an actual SHEMS prototype to verify the hardware design.

Chapter 4 presents a model 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 programs by the Center for Ultra-Wide-Area Resilient Electric Energy Transmission to assess responsive residential demand in a stochastic model. In practice, LSEs are promoting various 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 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. Here, this proposed model can be easily customized for any given times, locations, financial incentives, and residents' portfolios. Also, it will help LSEs get valuable insights on regulating residential demands by adjusting financial incentives to customers and improving the mechanism of existing demand response programs.

Chapter 5 introduces a mechanism for aggregating residential demands. Different from the common incentive based demand control, to residents, this method minimizes the impact of DR events to their pre-determined comfort settings; To LSEs, this method helps minimize the total financial reward costs of performing DRRs. Also, the innovative reward system may stimulate the potential capability of loads enrolled in DR programs which can further improve the performance of the proposed method. In addition, the proposed method has been verified with several simulation studies.

In Chapter 6, the conclusion regarding the whole work is given and the future work is also discussed.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the review of past and on-going research findings relevant to the design of SHEMS, residents' behavior in I-DR, and the mechanism of aggregating residential demand.

2.1 Smart Home Energy Management System

The relevant literature includes a broad range of previous works related to SHEMS on hardware prototypes, design simulations, and visions of future commercial products. Many of these works such as [35-38] point out that SHEMS will be an important and necessary component in smart grids.

As for hardware prototypes, a wireless, controllable power outlet architecture is introduced in [18] for developing home automation networks. Also, a prototype of an intelligent metering, trading, and billing system is presented with implementation in demand side load management in [19]. As for the design simulations, an agent-based smart home architecture is proposed in [20], in which the prediction of inhabitant activity and related automated control is considered. Based on the architecture in [20], further analyses of the prediction algorithms and the automated control of an agent-based smart home are discussed in [21].

The residential energy consumption scheduling considering electricity prices are discussed in [22, 23]. In [22], residential distributed energy resources are collectively considered to give a coordinated scheduling. In [23], a dynamic price responsive algorithm which leads to significant reduction in users' payment is discussed. Also, some works related to home energy management are documented in [39-42].

On the one hand, literature on previous hardware prototypes rarely considers the implementation and design of machine learning to achieve the responsive load management for DR programs. On the other hand, many simulation studies rarely give a SHEMS hardware design although they individual articles do appear from the "software" side, which delves into such topics as machine learning algorithms, dynamic price responsive mechanisms, and other challenges in practical applications.

2.2 Residents' Behavior in DR Programs

Many studies and industry practices have segmented customers or created customer profiles based on their electricity usage data and demographic information such as age, gender, house size, income, and education level, but very few attempts have been made to bring social-psychological variable into the light, despite the growing realization that those variables could be quite insightful in customer segmentation.

As examples of the very few attempts, Pedersen from BC hydro added "general attitudes" as a segmentation criterion besides self-reported household electricity usage habits [43]. The measure of general attitudes was composed of ten items, which ranged from self-perceived knowledge, eagerness to save energy and consumer confidence that saving energy benefits the environment and national security. The study clustered all customers into six categories, such as "turned-out and carefree," "stumbling proponents," "cost-consciousness practitioners," and "devoted conservationists," and analyzed how those segments differed in their habits, attitudes, and demographics. Sütterlin and his colleagues took this analysis one step further by bringing in more solid psychological concepts into the clustering algorithm such as awareness of consequences, ascription of responsibility, personal norms, response efficacy, self-efficacy, and perceived loss of comfort; they also measured energy saving actions in broader domains including food and mobility, as well as citizenship behaviors such as support for energy-efficiency policies [44]. This study also yielded six categories but with different connotations as can be seen in the following "idealists," "selfless," "thrifty," "materialistic," and "convenience-oriented," and "problem-aware well-being oriented."

Despite the wide scopes and careful analyses, the above-mentioned studies neglected the need to focus on the key behaviors in DR programs and to clearly postulate a relationship between social-psychological variables and successful customer programs. In fact, only one related peer-reviewed article was found, which segmented customers along the continuum from "reluctants" to "committeds" on environmental attitudes and behaviors (EAB), and further examined the effectiveness of feedback vs. financial incentives as impetuses to promote energy saving as a function of EAB segments [45]. Results showed that the higher up a segment was on EAB, the more likely the households preferred feedback; the lower down a segment was on EAB, the more likely the households preferred financial rewards.

2.3 The Framework of Aggregating Residential Demand

Various algorithms and techniques for optimally scheduling residential demand in DR programs have been discussed. [46] and [47] proposed models to control the aggregated demand from a population of ACs, through adjusting the temperature set points. [48] proposed a method to characterize the availability of residential appliances to provide reserve services with considering residents' energy consumption patterns and comfort preferences.

However, first, previous literature rarely considers the practical issues in realizing residential demand aggregation such as how to generate optimal schedules for a large number of appliances in real time; Second, existing literature seldom considers how to coordinate residents' energy usage preferences and their comfort levels in DR programs; Third, few articles present the advanced financial incentives distribution system to the participants of DR programs. This issue is essential, because it may affect the residents' participation levels directly.

CHAPTER 3

SMART HOME ENERGY MANAGEMENT SYSTEM

This chapter presents a smart home energy management system (SHEMS) hardware design integrated with the machine learning algorithm. This work collectively considers both interests from the electricity supplier side and the customer side. Particularly, the hardware design of a SHEMS system with communication, sensing technology, and machine learning is expected to provide an easy-to-use energy management solution for the residents who enrolled in I-DR programs.. Also, this chapter presents the experimental and simulation results based on a SHEMS prototype to verify the design of the proposed hardware system. Most importantly, this hardware design of SHEMS will be enabling technology of realizing the intelligent incentive based demand aggregation.

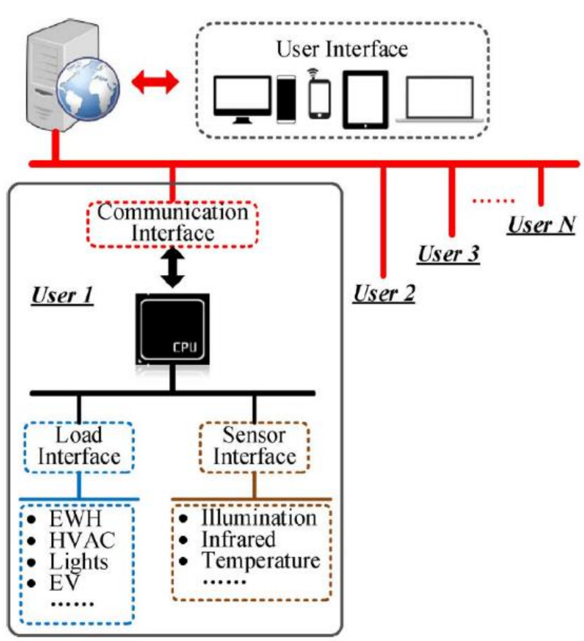


Figure 7. The Schematic Diagram of SHEMS

3.1 Nomenclature

F_i	Signals from sensors.
C	User's activity.
$X_T(t)$	Temperature in EWH at time t, ℃.
$X_a(t)$	Ambient temperature at time t, ℃.
a	Thermal resistance of tank walls, W/ ℃.
$A(t)$	Rate of energy extraction when water is in demand at time t.
$q(t)$	Status of the hot water demand at time t, ON/OFF
P_{EWH}	Power rating of the heating element, W.
P_{EV}	Power rating of EV charging station, W.
P_H	Power rating of dishwasher, washing machine, or dryer, W.
$m(t)$	Thermostat binary state at time t, ON/OFF.
$RTP(t)$	Real time price at time t, $/MWh.
$S_{EV}(t)$	Status of charging station, ON/OFF.
TF_{EV}	The time EV needs to get fully charged (hour).
R_{EV}	Desired percentage of battery being charged.
T_{start}	The time when EV is connected to the charging station.
T_{end}	The time when the user needs to drive EV.
T_{hstart}	The time when dishwasher, washing machine, or dryer starts to work.

T_{huse} Time duration for dishwasher, washing machine, and dryer to complete the work once started.

T_{hready} The time when dishwasher, washing machine, and dryer is ready to use.

T_{hend} The time when user needs to pick up things from dishwasher, washing machine or dryer.

3.2 Functional Requirement Analysis

In this section, the functions of the proposed SHEMS will be discussed.

From the customers' viewpoints, the essential goal of SHEMS is to reduce their total electricity payment while satisfying their needs as well. Specifically, the optimal strategy provided by SHEMS is to modify and adjust the control settings of each load in accordance to the financial incentives offered by LSEs, the preferred comfort level, the environmental temperature, and so on. As shown in Figure 8, the primary function of the proposed SHEMS includes:

- To collect useful information and other messages such as the financial incentives, residents' comfort preference, residents' activities at home, status of home appliances;
- To generate the optimal strategies by analyzing the collected data;
- To modify or adjust the settings of appliances based on the generated strategy by the control algorithms; and
- To send the feedback and other relevant data back to LSEs.

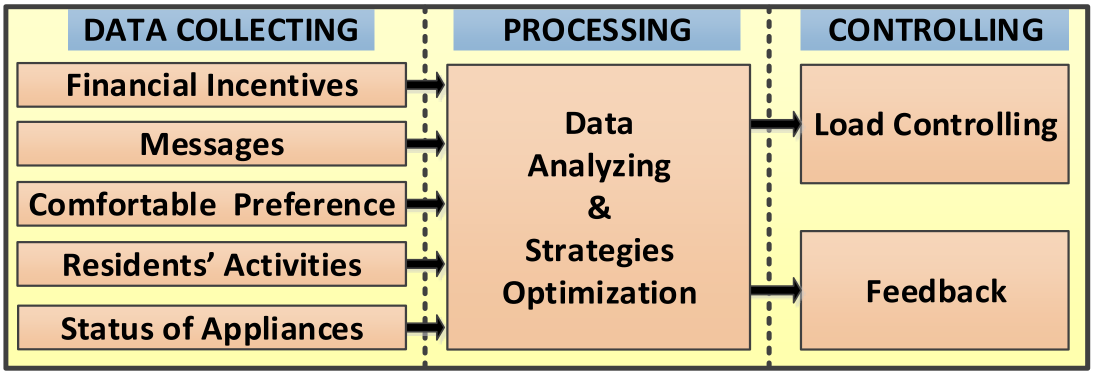


Figure 8 Expected Major Functions of the Proposed SHEMS

Moreover, the detailed requirement analyses about data collection, processing and control are discussed as blow.

3.2.1 Data Collection

1) Financial Incentives: It is necessary for reading the financial incentive signals from LSE. Therefore, an Ethernet module should be included in the proposed SHEMS design.

2) Messages: This function is designed to respond to extreme scenarios. For example, the supplier may send an important message to its customers such as scheduled outages, weather alerts, and so on. Meanwhile, the customers should be able to report issues related to electricity usage, which include meter-reading, billing, and payment. Note, since extreme scenarios always come with other

accidents, the 4G network should be considered in the design, at least as the premium service for backup purpose when a wired Internet connection is unavailable.

3) Comfort Preference: In order to obtain the residents' preference, a touch screen user interface is included for each customer to manually change the home energy management settings. Also, with the Ethernet module already mentioned in 1), it is feasible for remote changes to the settings.

4) Residents' Activities: Motion and flow sensors need to be installed to collect useful data for detecting residents' home activities. By applying machine learning algorithms in the processing part, the activities related to energy consumption can be predicted. For instance, the temperature settings of EWH and AC units may be changed to a lower setting if little residents' motion is detected. As such, SHEMS is able to further optimize the energy consumption of residential appliances.

5) Status of Home Appliances: Interfaces need to be developed to obtain the status of residential appliances, such as EWH, AC, EV, dishwasher, washing machine, and dryer. Temperature and illumination sensors are also needed and perhaps deployed in a number of, if not all, rooms to monitor the environmental parameters.

Figure 9 below summarizes this part.

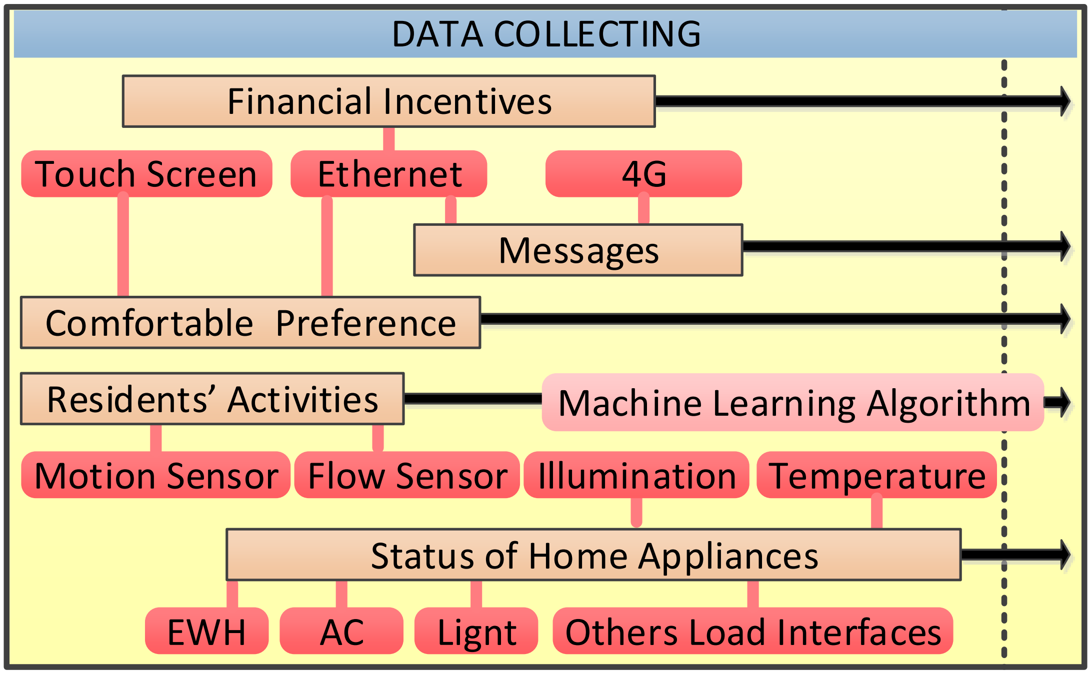


Figure 9 Summary of the Data Collection

3.2.2 Processing

The design will optimize the control strategies of home appliances by analyzing the collected data on the processor which works as the brain of SHEMS. The tasks for the processor to perform are as following:

1) Receiving Data: Ethernet, 4G module, and touch screen can have wired connection with the processor. However, as for the sensors and load interfaces, they are designed with a wireless connection with the processor.

2) Host of User Interface: The processor is also the user interface (UI) host. In addition, the processor may host a customized webpage on which remote control is implemented.

3) Event Analysis: The processor reminds the customer about the messages from LSEs through a specific user interface. This information may affect the scheduling of residential appliance, and the proposed design should have the capability of analyzing these events and providing the information such as whether the room temperature can still meets residents' comfort preferences. For example, if there is a scheduled one-hour locational outage, the SHEMS will pre-heat the EWH and/or pre-cool the room to reduce the residents' uncomfortableness. Further, SHEMS should alarm the residents about whether their comfort levels will be significantly impacted under any inclement event.

4) Residents' Activity Prediction: Machine learning and pattern recognition algorithms will be implemented to analyze and predict residents' activities based on data collected by motion and flow sensors. The prediction can provide important information for the processor to generate the optimal strategies at a later time. Here, pattern recognition helps the identification of activities, and machine learning trains the system to have a better understanding and prediction of the residents' living habits. That is, the longer the system is in use, the more accurate the predictions will be.

5) Load Optimal Strategies: Since all the useful information including incentive prices, customers' needs, special events, and residents' activities can be obtained, the

processor will offer the optimal strategy for each load based on the models of different loads.

Figure 10 summarizes the processing part. The collected data of residents' activities or motions combined with other information will be used for machine learning and pattern recognition algorithms to induce behavior changes and to further optimize all the loads.

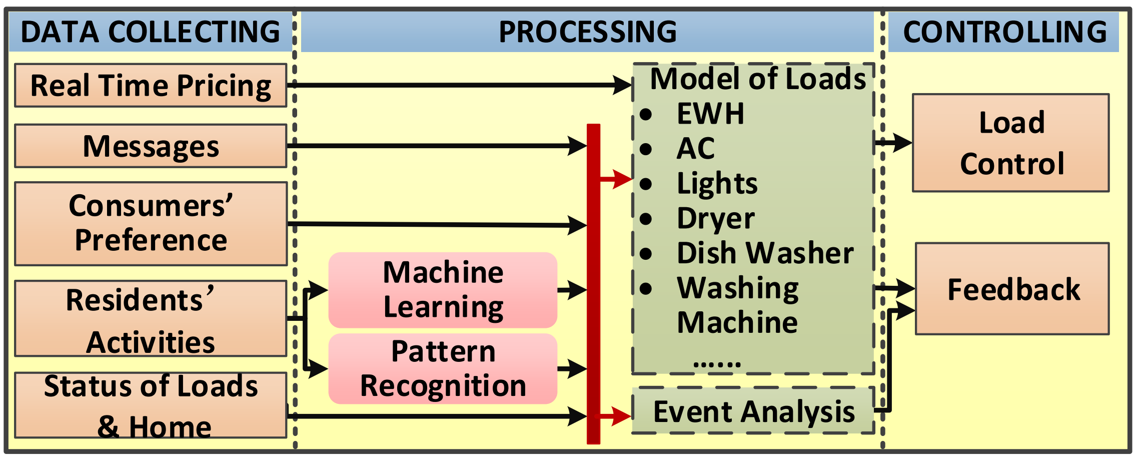


Figure 10 Summary of the Processing Part

3.2.3 Control

The functions for the control part are load control and information feedback.

For load control, it has been mentioned in the data collection part that the proposed design has load interfaces to obtain the real-time status of the home loads. Meanwhile, in the proposed design the load interfaces are also expected to modify the appliances' settings according to the results calculated from the processing part.

For feedback, the status of appliances and important event information will be shown to the customer through a touch screen user interface and a Web page for remote control.

3.3 Proposed Hardware Designs

According to the functional requirement, the objective of SHEMS is to enable minimization of the customer's total electricity payment cost meanwhile satisfying the customer's needs in comfort levels such as the indoor temperature, the hot water temperature, and the indoor illumination. SHEMS will identify optimal load control strategy responsive to the incentive signals from LSEs, the customer's needs, as well as extreme scenarios. Further, the administrators (e.g. residential load aggregator) have the capability to monitor and analyze the real-time status of a specific area.

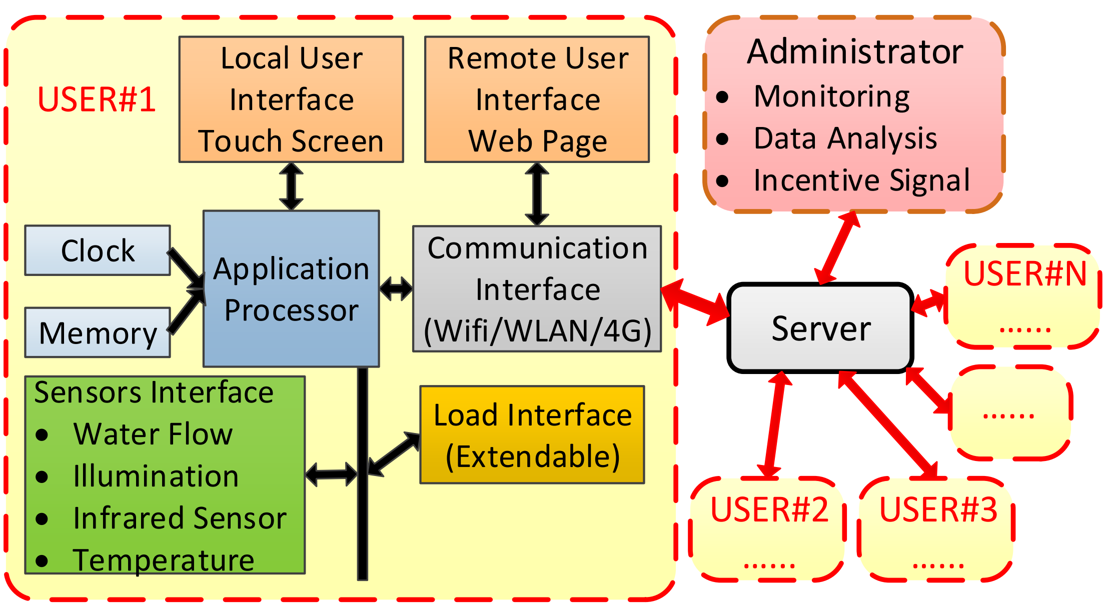


Figure 11. Brief Hardware Design of SHEMS

Figure 11 shows a brief hardware design of a typical SHEMS. From the hardware design perspective, the SHEMS shall have five main components:

1) Application Processor: This is the brain of SHEMS to solve issues in three aspects. First, the processor communicates with other parts to obtain necessary information and coordinates the works among those parts. Second, the processor is in charge of realizing various algorithms, which include machine learning, pattern recognition, and customized tasks for different types of loads based on their own individual characteristics and models. Third, the processor serves as the Web page host, from which the customer is able to perform remote operations, for instance, via a wireless smart phone. Meanwhile, the processor also drives the local touch screen UI. The design here is to use embedded system because of its strength in computational capability and portability.

2) Communication Interface: According to the requirement analysis, the communication methods in the proposed SHEMS may vary. Several different hardware modules related to communication are needed. First, Ethernet ports are the essential for reading incentive signals, communicating messages with suppliers, and ensuring the remote control to function. Second, the deployment of 4G module is to ensure the communication still available under some extreme scenarios like power blackout or catastrophic weather. Third, as for sensors, Zigbee and Wi-Fi are two popular options. The advantage of Zigbee is low energy consumption, but Wi-Fi is so widely used nowadays such that it can be easily implemented almost

everywhere. Moreover, most houses today are already Wi-Fi covered, therefore, it helps reduce the initial installation cost if Wi-Fi is adopted as the communication method between the sensors and the processor, as well as between the load interfaces and the processor.

3) User Interface: Since ordinary customers are not familiar with the operation of electricity markets or power systems, it is very necessary to have a friendly and easy-to-use UI to change settings at the customer's side. The touch screen, which is driven by the processor, provides a local UI to the customer. Meanwhile, the remote UI is the Web page hosted by the processor. It needs to be emphasized that in order to make this system easy to set, SHEMS is designed with machine learning algorithms to fit the customer's needs after several weeks of automated training with the data monitored. Hence, customers do not have to perform detailed settings or to change their preferences frequently.

4) Sensor Interface: SHEMS has various sensors to collect all the real-time information that the processor needs. This part should be extendable in case the system needs to measure new parameters due to the addition of a new appliance. For the present version of the proposed hardware design, it has temperature sensors to detect the temperature of rooms and the water in EWH, motion sensors to record residents' activities, flow sensors to monitor water usage, and illumination sensors to detect indoor brightness. The data collected from those sensors will be sent to processors via Wi-Fi.

5) Load Interface: This part is also extendable. A designated load Interface transfers the strategies generated by the processor to control signals, which loads can accept. For example, the load interface for EWH has a relay to turn it on and off; and the load interface for AC should work as a remoter to set its operating temperature and operating modes.

To facilitate user's operation on this system, the prototype is designed with three quick, built-in setting modes for users to realize the "Easy Setting" feature.

- Comfort mode: In this mode, the highest priority of SHEMS is to ensure the most comfort level for residents. That is, a resident will always have sufficient hot water and perfect room temperature, and the resident's comfort level will not be reduced by participating in the supplier's DR program.

- Smart mode: In this mode, SHEMS will make a tradeoff between the comfort level and the payment saved. Occasionally, the resident probably has to bear the water with a little lower temperature than normal, and also a little difference (e.g., +/- 3 ℃ or 5 ℉) in indoor temperature. SHEMS will take part in the load reduction program, if it does not affect the resident's comfort level much.

- Saving mode: In this mode, the highest priority of SHEMS is to save the total electricity payment. In peak hours, residents may have to bear the water with a lower temperature than normal, and also some difference (e.g., +/- 5 ℃ or 9 ℉) in indoor temperature. Under this mode, SHEMS will participate in the power supplier's load reduction program as much as possible.

The details of the schematic design of SHEMS for a typical end user are shown in Figure 12. It demonstrates how SHEMS processes the inputs, applies machine learning algorithm, calculates the optimal strategy, and uploads useful information to the server.

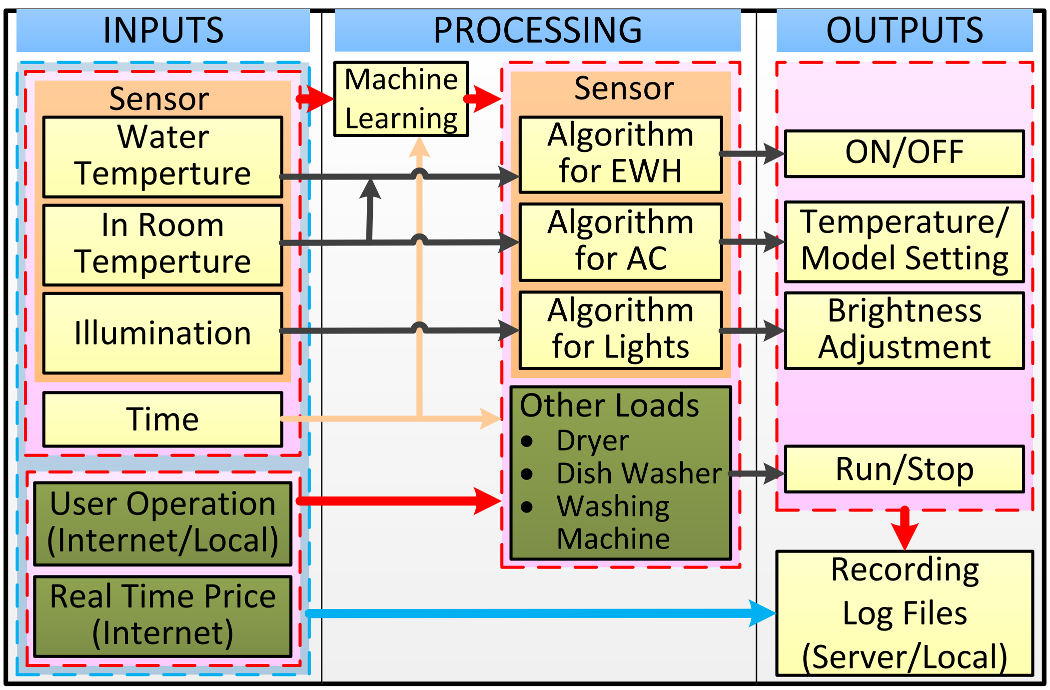


Figure 12. Schematic Design of SHEMS (User End)

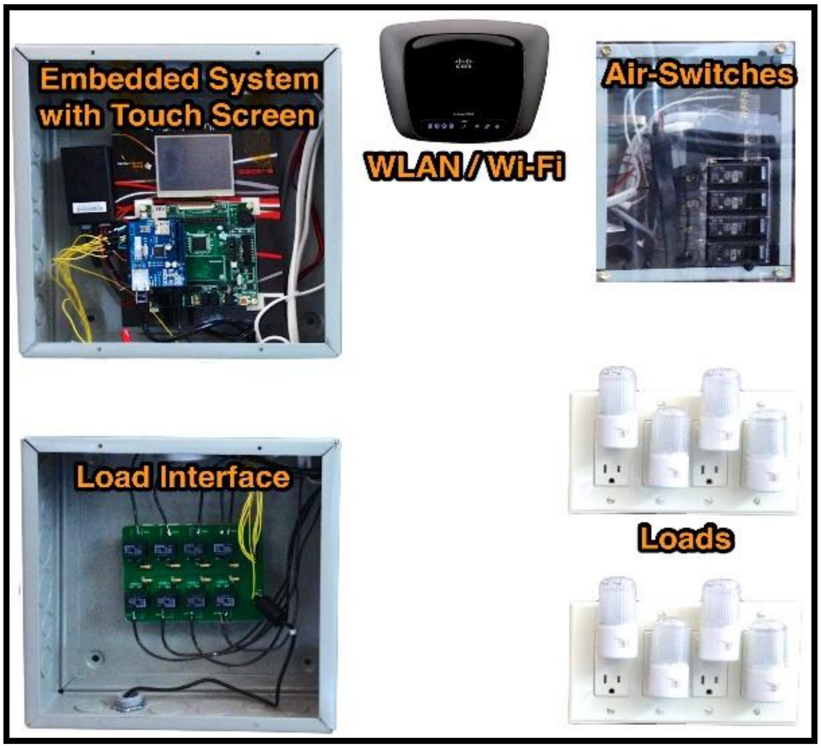


Figure 13. Model Platform of SHEMS

Based on the design described above, a model platform is established as shown in Figure 13. The model platform of SHEMS is based on Stellaris LM3S9D96 MCU, and it realizes the functions mentioned in Section 3.2. In addition, a set of protection system like air switches have been included for safety and reliability consideration of the proposed SHEMS.

This system is able to perform the following four tasks:

1) Reading incentive price signals;

2) Providing optimal control strategy with automatically adjusted loads including EWH, AC, EV, dishwasher, washing machine, and dryer;

3) Providing both local and on-line user interfaces; and

4) Uploading log files to the server. Therefore, users can make simple operations to remotely monitor the state of energy usage via the Internet.

3.4 Machine Learning Algorithm for SHEMS

A machine learning algorithm is implemented in the proposed SHEMS prototype design to analyze and predict residents' activities based on data collected by the sensors. However, machine learning for SHEMS is not like other machine learning applications such as the voice or handwriting recognition where users can help with updating the training set. Learning user's living habit is difficult, because SHEMS is not supposed to correct its own judgment by making frequent queries to users.

Here, Naive Bayes Classifier (NBC) and Hidden Markov Model (HMM) are implemented collectively to generate a practical solution. Specifically, NBC is used to learn and identify the on-going activities of the user, and HMM is employed to learn and predict user's living habits.

The data used to test the algorithm here is from a project called "Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors" which is done by a research group in MIT [49]. In that experiment, sensors are installed in a single-person apartment collecting data about residents' activity for two weeks. In this work, 9 activities related to the usage of home appliances are studied: going out, toileting, bathing, grooming, preparing breakfast, preparing lunch, preparing dinner, washing dishes, and doing laundry.

3.4.1 Naive Bayes Classifier

A naive Bayes classifier is a simple probabilistic classifier based on Bayes' theorem with strong (naive) independence assumptions. Abstractly, the probability model for a classifier is a conditional model [50] given by $p(C \mid F_1,...,F_n)$,$\mathrm{p}(\mathrm{C}|\mathrm{F}_1, ???, \mathrm{F}_\mathrm{n})$ which is over a dependent class variable C with a small number of outcomes or classes, conditional on several feature variables F_1 through F_n.

Using Bayes' theorem, it can be written as

$$\mathrm{p}(\mathrm{C}|\mathrm{F}_1, ???, \mathrm{F}_\mathrm{n}) = \frac{\mathrm{p}(\mathrm{C})\mathrm{p}(\mathrm{F}_1, ???, \mathrm{F}_\mathrm{n}|\mathrm{C})}{\mathrm{p}(\mathrm{F}_1, ???, \mathrm{F}_\mathrm{n})} \tag{3-1}$$

With sufficient data to train the system, the criterion of the classifier can be built.

3.4.2 Hidden Markov Model

An HMM is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. A HMM can be considered as the simplest dynamic Bayesian network [51]. Here, the discrete model should be used to apply HMM to this problem. The unobserved states are the user's on-going activities, and the observed states are the data collected by the sensors as well as the previous classification results generated by NBC.

Markov matrix (i.e., the matrix of transition probabilities) can be generated by the given training data set. Then, Markov matrix and NBC can update each other during the actual use of SHEMS to learn the residents' behavior.

Figure 14 is an example showing how this works. The diagram within the red, dashed rectangle shows the general architecture of an instantiated HMM. Also, $x(t)$ is the hidden state at time t, which stands for the present activity of the user, and $y(t)$ is the observation at time *t*, which stands for the data collected by the sensors.

Assume that at time t, NBC detects an on-going activity *A1* by the criterion of the classifier. However, $x(t)$ obtained by HMM is different from *A1*. As discussed before, SHEMS is not supposed to ask the user for any correction. Thus, $x(t)$ and *A1* demonstrates a probabilistic characteristic in HMM and NBC. Without losing generality, we may call them a and b for *A1* and $x(t)$, respectively. Therefore, we have three scenarios:

1) If the values of a and b are very close within a given threshold, SHEMS will record the event and wait for user's input for final judgment.

2) If b is much greater than a, SHEMS will record the correspondence between $x(t)$ and $y(t)$, and update the training set of NBC to update the criterion of the classifier.

3) If a is much greater than b, SHEMS will record the correspondence between *A1* and $y(t)$, and update the training set of HMM to eventually update the Markov matrix.

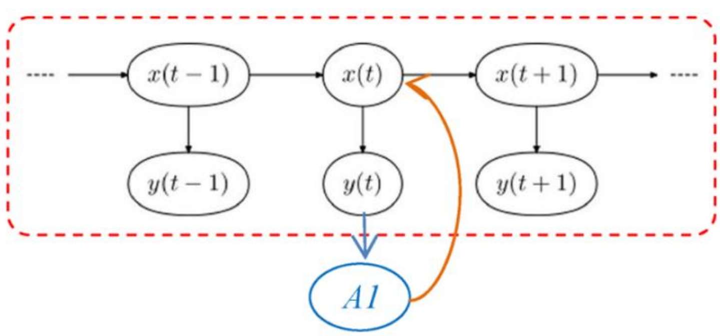


Figure 14. The Learning Process of SHEMS

3.4.3 Simulation Results

Applying the methodologies discussed previously, this work obtains some preliminary results shown in Table 1. Note that these results are based on the data of two weeks, and the training set is one week long for demonstrative purpose.

Table 1. Simulation Results of Machine Learning Algorithm

Activity Name	**Right Cases**	**Wrong Cases**	**Accuracy(%)**
Going out to work	11	1	91.67
Toileting	70	14	83.33
Bathing	13	5	72.22
Grooming	33	4	89.19
Preparing breakfast	9	5	64.29
Preparing lunch	13	4	76.47
Preparing dinner	6	2	75.00
Washing dishes	6	2	75.00
Doing laundry	19	0	100.00
Total	**180**	**37**	**82.95**

3.5 Appliance Models and Verification Results

Various appliances' models will be studied first in Subsections from 3.5.1 to 3.5.3. Then, test and verification studies about the effect of the proposed SHEMS system will be presented in this section.

Residential load is the largest share in electricity end use of year 2014, as shown in Figure 15. Residential load profiles are inherently difficult to model. Each household has different lifestyles and set of habits. There is also a wide variation in the load profiles of different appliances.

Figure 15. Electricity End Use of Year 2014, USA

As for residential electricity use, EWH and AC hold two largest shares totaling 53% of the total residential electricity consumption [52], or 20% of the total electricity consumption. Since EWHs and ACs have a great potential to be optimized by SHEMS, Subsections 3.5.1 and 3.5.2 will discuss the detailed models of EWH and AC with testing results. Nevertheless, the models of EV, dishwasher, washing machine and dryer are also briefly discussed since they have potentials in the future DR.

RTP signals are implemented in the simulation instead of incentive signals, because there are practical RTP data available. It needs to be noted that the purpose of the simulation here is to verify the proposed hardware design has the capability of generating optimal control strategies over the appliances. Hence, using RTPs or incentives signals will both have the same effect in testing the capability.

3.5.1 Electrical Water Heater

The general model of EWH has been discussed in [53-54]. The discrete state dynamics model is applied here, since the RTP signals may change as fast as every 5 minutes which is a discrete variable. The model can be described by:

$$\frac{dX_T}{dt} = -a\left(X_T(t) - X_a(t)\right) - A(t)q(t) + P_{EWH} \cdot m(t) \tag{3-2}$$

Table 2 shows the specifications of EWH used in the experiment. For testing and simulation purposes, Table 3 shows some useful information applied here. Also, a typical water usage curve as shown in Figure 16 is obtained from [55].

Table 2. Water Heater Characteristics

Water Heater Type	Electrical
Power Rating of Heating Element	4.5 kW
Tank Surface Area	2.8 m^2
Tank Volume	40 gal
Thermal Resistance of Tank Wall	0.04 W/(min ℃)

Table 3. Water Usage Information for Testing

Number of Residents	4
Resident Type	Townhouse
Daily Water Demand	1000 Liter
Low Temperature Setting	40 ℃
High Temperature Setting	80 ℃

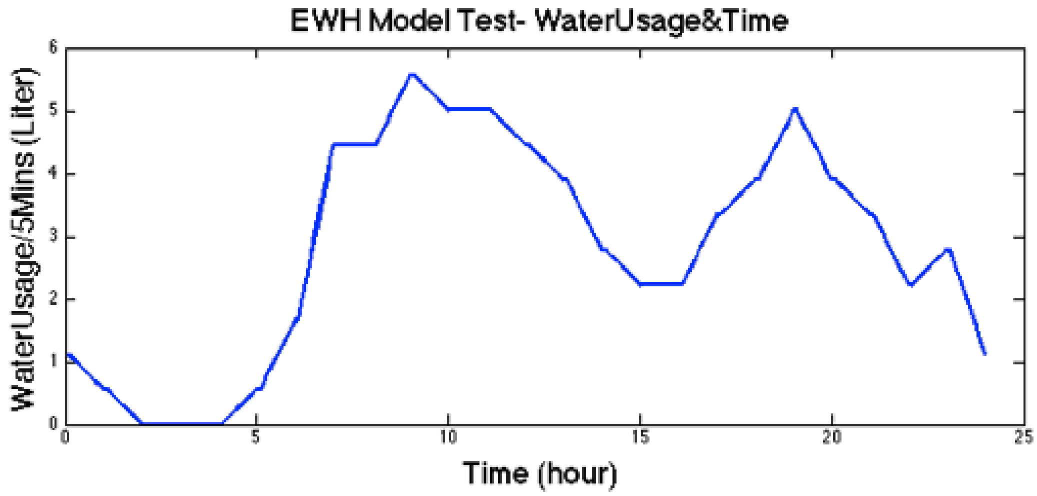


Figure 16. Typical Water Usage Curve for 24 hours

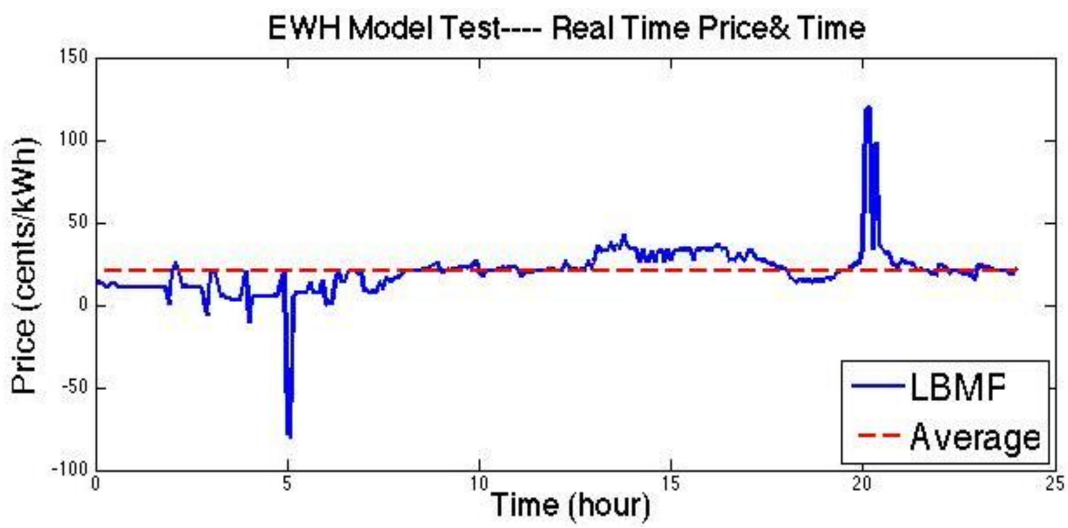


Figure 17. Real Time Price Curve for 24 hours

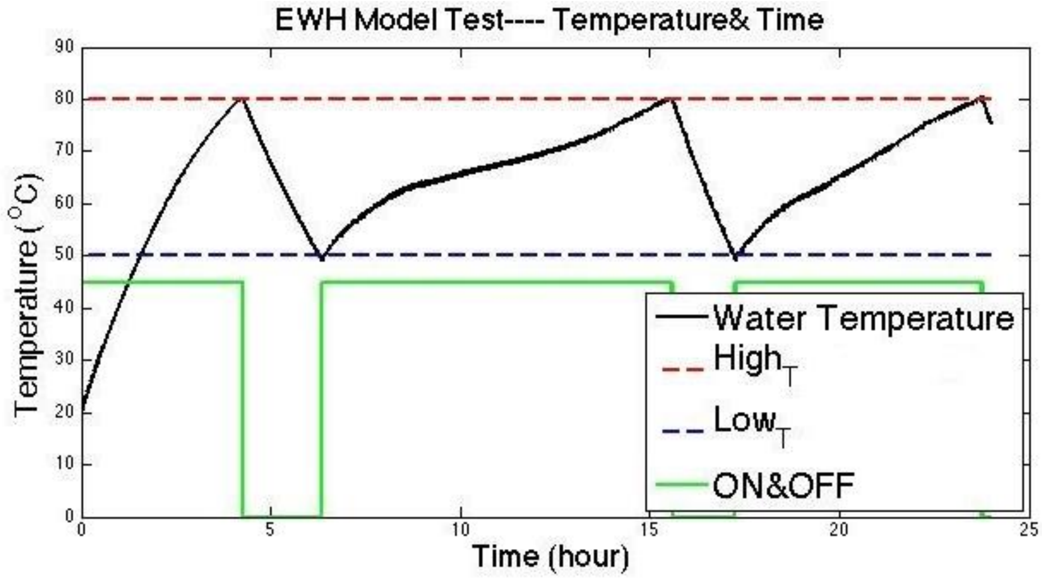


Figure 18. Typical EWH Strategy

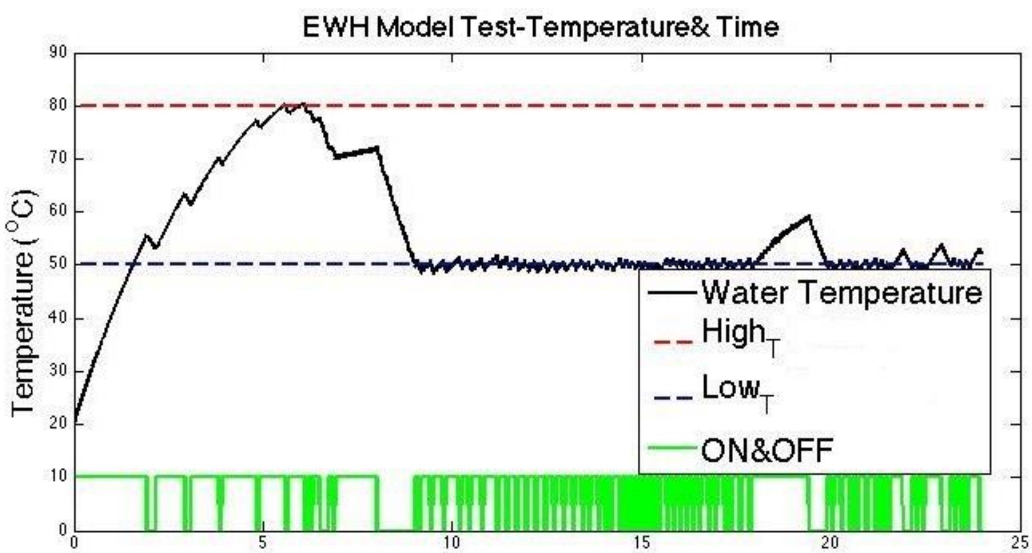


Figure 19. Optimized EWH Strategy

In this study, the LMPs on a randomly selected day from New York independent system operator (NYISO) is used as the real-time price, which is shown in Figure 17. The result without SHEMS is shown in Figure 18, and the results after applying an RTP-responsive algorithm to change the ON and OFF strategy of EWH is shown in Figure 19.

The optimized strategy used in the test can be further improved in future algorithm/software studies, while this work focuses on the hardware part. Nevertheless, the straightforward algorithm still works greatly. A brief description of the algorithm is presented next.

The principle of the algorithm is to turn EWH on for a while before the dropping temperature reaches the lower bound. Meanwhile, the algorithm also considers whether the EWH can provide comfortable hot water based on the predicted demand of water usage with a look-ahead consideration. For example, the algorithm will preheat the EWH to a higher temperature before the resident takes a shower. The mathematical description is an optimization model as following.

$$min \int_{0}^{120} RTP(t) \cdot m(t) \cdot P_{EWH} \tag{3-3}$$

s.t.: Eq. (3-2)

$$T_{low} \leq X_T(t) \leq T_{high} \tag{3-4}$$

Since $RTP(t)$ refreshes every 5 minutes, this model given by (3-2), (3-3) and (3-4) is discretized into a time interval of 5 minutes. The genetic algorithm (GA), an intelligent search algorithm using stochastic operations, is customized in this work to solve the model to find the global optimal scheduling for the EWH. With this approach, SHMES can reduce the total payment and energy consumption while meeting the customers' needs.

The result verifies that SHEMS helps reduce the thermostat ON time by 14%, while reducing the customer's electricity payment by 60% of the original payment on heating water.

The proposed SHEMS system has been programmed and tested to connect and disconnect a mock EWH load in accordance with Figure 20.

3.5.2 Air Conditioning

The American Society of Heating, Refrigeration and Air Conditioning Engineers, Inc. (ASHRAE) has compiled modeling procedures in its Fundamentals Handbook [56]. The Department of Energy (DOE) has produced the EnergyPlus program for computer simulation [57]. Also, the detailed model for simulating AC systems is given in [58, 59]. Accurate model for energy consumption needs to consider many factors including weather, season, thermal resistance of rooms, solar heating, cooling effect of the wind, and shading. Unlike EWH which has constant and relatively accurate parameters, those AC parameters are difficult to be precisely modeled with the possibility to change over the time due to other factors.

Therefore, the testing here is not based on any detailed model but relies on the actual measurement from the experiments performed at The University of Tennessee with the SHEMS prototype and a portable AC unit.

In this experiment, the SHEMS optimizes the AC based on three parameters: the mock RTP from the prices in a randomly selected day in NYISO used in the previous EWH test, the real-time temperature in the test room, and the temperature setting by the user. Table 4 shows the related parameters.

Table 4. AC Parameters in the Test

Room Area	800 sq ft
Room Type	Single room
AC Power Rate	3.5kW
Room Temperature Setting	73 °F (23 °C)

For comparison purpose, a parameter named "Comfort Level" is considered here. In market economics, a customer has to compromise between quality and price. The introduction of "Comfort Level" is based on similar idea for home energy management. Simply speaking, "Comfort Level" in this case means the difference between the actual indoor temperature and the temperature desired by the customer.

Table 5 shows the energy consumption and the total payment reduction of the cases under different comfort levels with SHEMS. The results are in percentage with respect to the case without SHEMS. As shown in Table 5, considerable reduction of energy consumption and payment is achieved. Further, if a customer can tolerate a higher temperature difference, more payment or credit to AC from the supplier can be achieved. This is sensible from the standpoint of market economics.

Table 5. AC Results with SHEMS

	Different Comfort Level		
	+/-0 ℃	+/-3 ℃ (5.8 ℉)	+/-5 ℃ (9 ℉)
Energy Consumption (% w.r.t the case w/o SHEMS)	91%	79%	72%
Payment (% w.r.t the case w/o SHEMS)	86%	73%	64%

3.5.3 Other Appliances

In order to fully exploit the potential of SHEMS and contribution to the power grid, low cost is an important characteristic of the prototype. Since considering bidirectional power flow will significantly increase the total cost of SHEMS design, the EV model in the proposed prototype is to charge a battery. That is, this design of SHEMS does not include the consideration for EV to send power back to grid.

Loads such as charging the battery for an EV are interruptible [23]. It is possible to charge the battery for 1 hour, then stop charging for another hour, and then finish the charging after that. In contrast, the loads like dishwasher, washing machine and dryer demonstrate similar features to EV, but differ from EV considerably because they are uninterruptible. That is, as soon as the corresponding appliance starts operation, its operation should continue till completion.

3.5.3.1 Electrical Vehicles

An EV should be fully charged, for example, at 8AM but the EV user does not care when or how the EV battery is charged. Therefore, SHEMS chooses the possible hours with the low electricity price to charge. Meanwhile, SHEMS must make sure EV to be fully charged before being used at 8AM.

As an interruptible load, the mathematical expression of the discrete model of EV can be expressed in Eqs. (3-5) and (3-6). Since the real-time price refreshes every 5 minutes, the time interval of discrete model is also set to 5 minutes. Here, $S_{EV}(t)$ is the optimal solution that needs to be generated by SHEMS.

$$min \sum_{t=T_{start}}^{T_{end}} P_{EV} \cdot RTP(t) \cdot S_{EV}(t) \tag{3-5}$$

$$\text{s.t.: } \frac{1}{12} \cdot \sum_{t=T_{start}}^{T_{end}} S_{EV}(t) = TF_{EV} R_{EV} \tag{3-6}$$

3.5.3.2 Dishwasher, Washing Machine and Dryer

As an uninterruptible load, the mathematical expression of the discrete model of dishwasher, washing machine and dryer can be all expressed in (3-7), (3-8) and (3-9), respectively. The time interval of discrete model is also set to 5 minutes. T_{hstart} is the optimal solution which needs to be generated by SHEMS.

$$min \sum_{t=T_{hstart}}^{T_{hstart}+T_{huse}} P_H \cdot RTP(t) \tag{3-7}$$

s.t.: $T_{hready} \leq T_{hstart} \leq T_{hend}$ (3-8)

$$T_{hready} \leq \left(T_{hstart} + T_{huse}\right) \leq T_{hend} \tag{3-9}$$

3.5.4 Effects of SHEMS in Load Shifting

Based on the previous analysis on EWH and AC, it is rational to conclude that SHEMS can make substantial contribution to reduce home energy consumption from not only EWH and AC, but also EV, dishwasher, washing machine, dryer, etc. To study the effect of SHEMS in a large-scale system, this subsection demonstrates a comparison on the load curves with and without SHEMS.

The simulation here is to give a quantified verification that SHEMS will play a critical role in load shifting. The total real-time load curve (including residential, commercial, industrial and other) is selected from NYISO again. The date of the data is the same as the date of the selected RTP.

The EWH and AC parameters are as the same as the previous Subsections 3.5.1 and 3.5.2. The EV parameters are chosen based on Nissan Leaf [60] for this simulation study:

- Charging power rate: approx. 6 kW;
- Battery volume: 24 kWh;

- Time of fully charging: 4 hour; and
- The percentage of EV battery to be charged is set as 100%.

The parameters of dishwasher, washing machine, and dryer are shown in Table 6.

Table 6. Parameters of Dishwasher, Washing Machine and Dryer

	Model	P_H ***(W)***	T_{huse} ***(min)***
Dishwasher	Danby	1000	30
Washing machine	Danby	400	45
Dryer	Whirlpool	3000	40

The reduction of energy consumption from individual appliance is scaled up to simulate the optimized residential load consumption. The results are shown in Figure 20, which illustrates that SHEMS can help with load shifting. In addition, it reduces the loads in peak hours by nearly 10 percent which is significant.

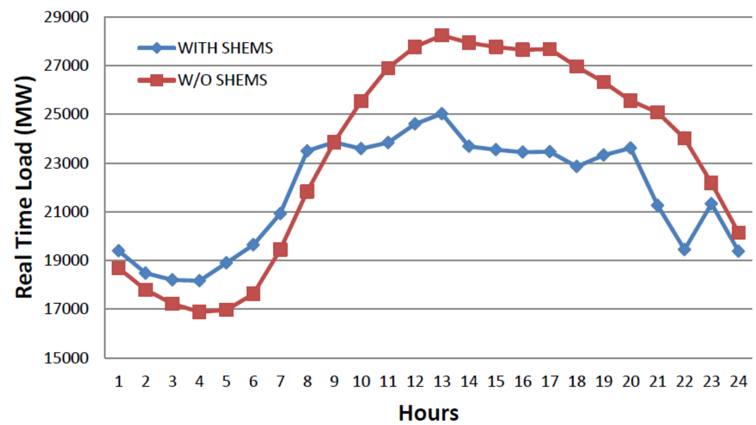


Figure 20. Load Curve Comparison with and without SHEMS

3.6 Comparative Analysis and Conclusion

3.6.1 Comparative Analysis

As mentioned in the Introduction, there are several companies working on products related to DR. However, those early products do not take full considerations of all aspects mentioned in this work. Most of these previous products focus on displaying and monitoring the status of home energy consumption. Some advanced ones may help analyze power usages of different appliances, then offer tips for conserving energy and reducing payment in electricity, which is represented by the “Indirect Feedback” [61, 62]. None of those previous works has reported any real intelligent control down to the appliance level, and users’ interaction is needed. However, the proposed design and the actual prototype carried out in our Smart Home lab implements automated, intelligent controls for smart home energy management to the appliance level.

As for the cost, the proposed design typically costs less than $200 with off-the-shelf retail prices for materials and components. The actual cost also depends on the number of appliances that the customers want to install load interfaces, as well as the number of rooms to be monitored. Here is the cost breakdown in a typical case. The main controller costs around $80 based on to the off-the-shelf retail price ($15 for a microcontroller, $20 for making PCB and accessories, $15 Wi-Fi module, and $30 for touch screen). Each load interface and room monitoring unit costs around $20 ($15 for Wi-Fi module and $5 for accessories).

With the assumption that a customer wants to control AC and EWH, and has 3 4 rooms to monitor, the total cost will be around $200 in this typical setting. In addition, this design is expandable and can be easily upgraded by updating programs running in the processor without any change of existing hardware.

Table 7 provides a high-level comparison of the proposed design and 4 SHEMS-like devices from commercial vendors. These 4 devices include eMonitor12 by Powerhouse, Home monition and Control by Verizon, Nucleus by GE, and Thermostat controller by NEST. The listed features are monitoring, remote control, real-time price responsive, machine learning, and easy setting. They are randomly named Vendor 1 to 4 without any particular order in Table 7. One of the vendor's cost is the annual service cost, while the device is sold separately. The cost of the system from Vendor 1 is relatively low, but with relatively simple functions. It does not have machine learning algorithm and cannot provide optimized schedule for home appliances. Vendor 4 provides a fancy user interface which is easy and efficient, but cannot control appliances other than AC.

Note, the cost of the developed prototype may not be directly comparable with the costs of the four vendors' products since the cost of the developed prototype does not include labor cost and the expected profit. However, on the other hand, the prototype cost is based on retail prices of various materials and components, which are usually higher than wholesale prices under mass production. Nevertheless, the cost information is listed in Table 7 for future references.

Table 7. Comparison of Existing SHEMS

Name	***Appliances***	***Monitor /Control***	***Response***	***Learn***	***Easy Setting***	***Cost ($)***
Proposed Design	Extendable	X	X	X	X	~200
Vendor 1	Vendor's own devices	X	X			199
Vendor 2	12 switches	X				1024
Vendor 3	Extendable	X				120/yr
Vendor 4	Thermostat	X		X	X	250

3.6.2 Conclusion

Chapter 3 presents a hardware design of a SHEMS with the application of communication, sensing technology, and machine learning algorithm. With the proposed design, customers can achieve responsive control strategy over residential loads including EWHs, AC units, EVs, dishwashers, washing machines, and dryers. They may interact with LSEs to facilitate the management at the supplier side. Further, SHEMS is designed with sensors to detect residents' activities and then apply machine learning algorithm to intelligently help the customers reduce total electricity payment without much of their involvement. In addition, the testing and simulation results shows the effectiveness of the hardware system of the SHEMS prototype. The expandable hardware design makes SHEMS fit to houses regardless of its size or number of appliances. The only modules to extend are the sensors and load interfaces.

Also, this design is the enabling technology for aggregating residential demands. If this design can be widely used in the future, the administrator-user structure will provide good potentials for electricity aggregators. Likely, utilities may not be interested or motivated to administrate all individual, millions of end energy consumers directly and simultaneously. Therefore, electricity aggregators can play as agents between customers and utilities. This business mode may facilitate the popularity of SHEMS or similar systems and create win-win results for all players.

CHAPTER 4

RESIDENTIAL RESPONSIVE DEMAND MODELING

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 [31]. However, in practice, methods such as PTR and 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 this chapter, in order to assess the responsive residential demand to financial incentives, a stochastic model has been proposed. With the proposed model, LSEs or residential load aggregators (RLAs) can obtain the characteristics of residential responsive demand under I-DR programs based on the residents' portfolio and generate the probability distribution of the possible residential demand reduction for any given time, location, and amount of incentive.

4.1 Model Overview

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: it is rarely feasible to keep frequently updating customers' demand reduction data; and interaction with numerous customers makes it too time-consuming to serve as an online implementation. Therefore, a stochastic model of demand reduction is proposed.

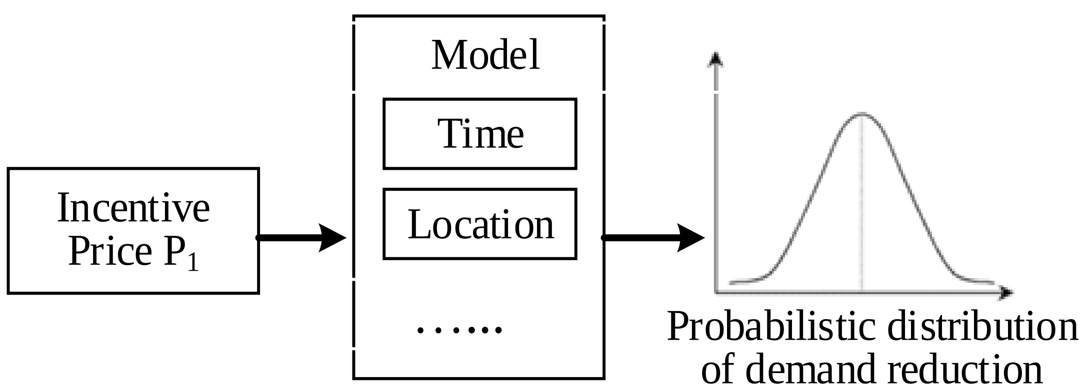


Figure 21. Schematic Diagram of the Proposed Model

Different from the traditional method, with the consideration of 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 shows in Figure 21, 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 or RLAs.

4.2 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 [63] (RECS) by the U.S. Energy Information Administration (EIA), 2) the American Time Use Survey [64] (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) [65].

- 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. In addition, 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 [66]. 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 EWHs and ACs, since EWHs 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 conducting activities $a_j \in \{a_1, a_2, ..., a_m\}$ 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 $r_k \in \{r_1, r_2, ..., r_p\}$ 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 by (4-1).

$$
\begin{aligned}
D_{RED}(G_i, r_k, t) &= \sum_{j=1}^{m} R_{AC,i} \cdot P_{activity,i}(a_i, t) \cdot P_{resAC,i}(r_k, a_i, t) \\
&+ \sum_{j=1}^{m} R_{EWH,i} \cdot P_{activity,i}(a_i, t) \cdot P_{resEWH,i}(r_k, a_i, t)
\end{aligned}
\tag{4-1}
$$

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.

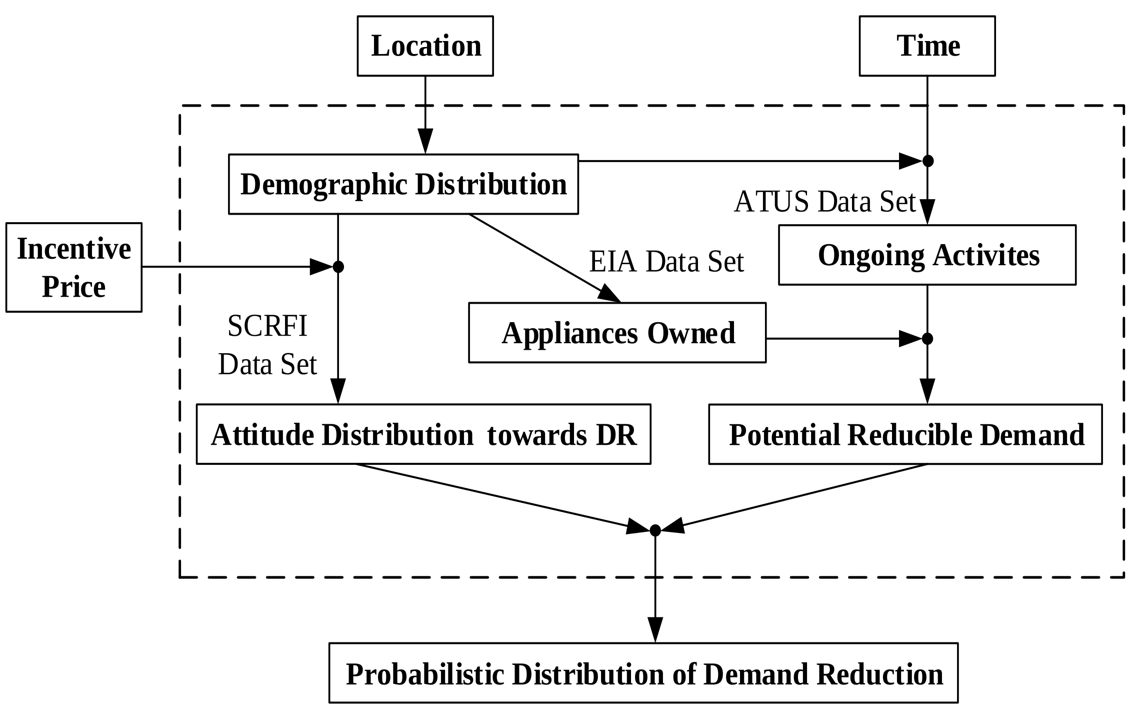


Figure 22. Schematic Diagram of the Information Flow for the Proposed Model

The schematic diagram of the information flow for the residential demand reduction model is shown in Figure 22, where the inputs of the model are the incentive prices, the I-DR's location and time length. The output is the corresponding probabilistic distribution of residential demand reduction in I-DR with a given incentive price at a given location in 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 incentive prices.

4.3 Case Studies

The proposed method has been tested to demonstrate the model features. However, since this is an early work in this area, there is no practical results publically 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.

4.3.1 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. Figure 23 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.

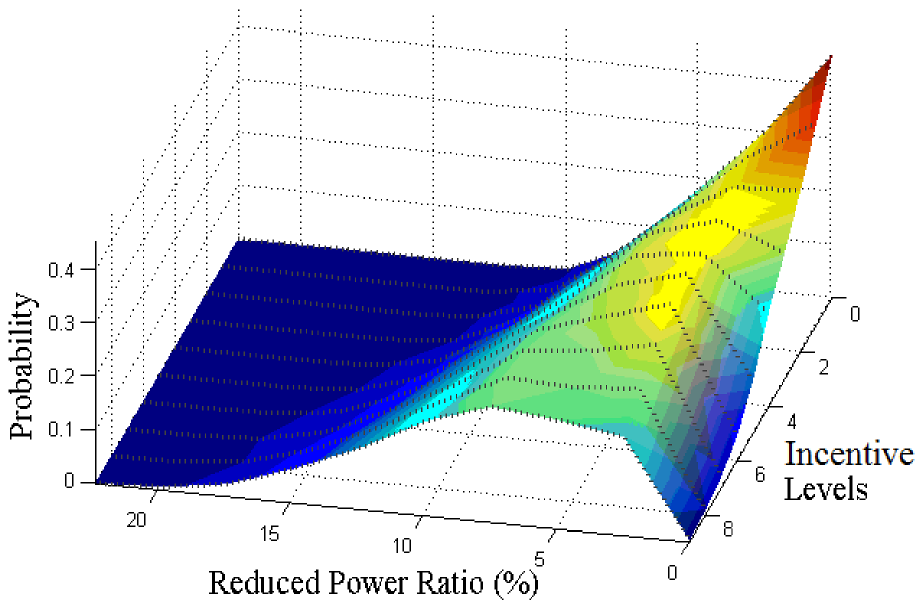


Figure 23. Probability Distribution of RPR under Different Incentive Prices

Figure 24 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 the South region at summer time, which increases the total capacity of the potential reducible demand.

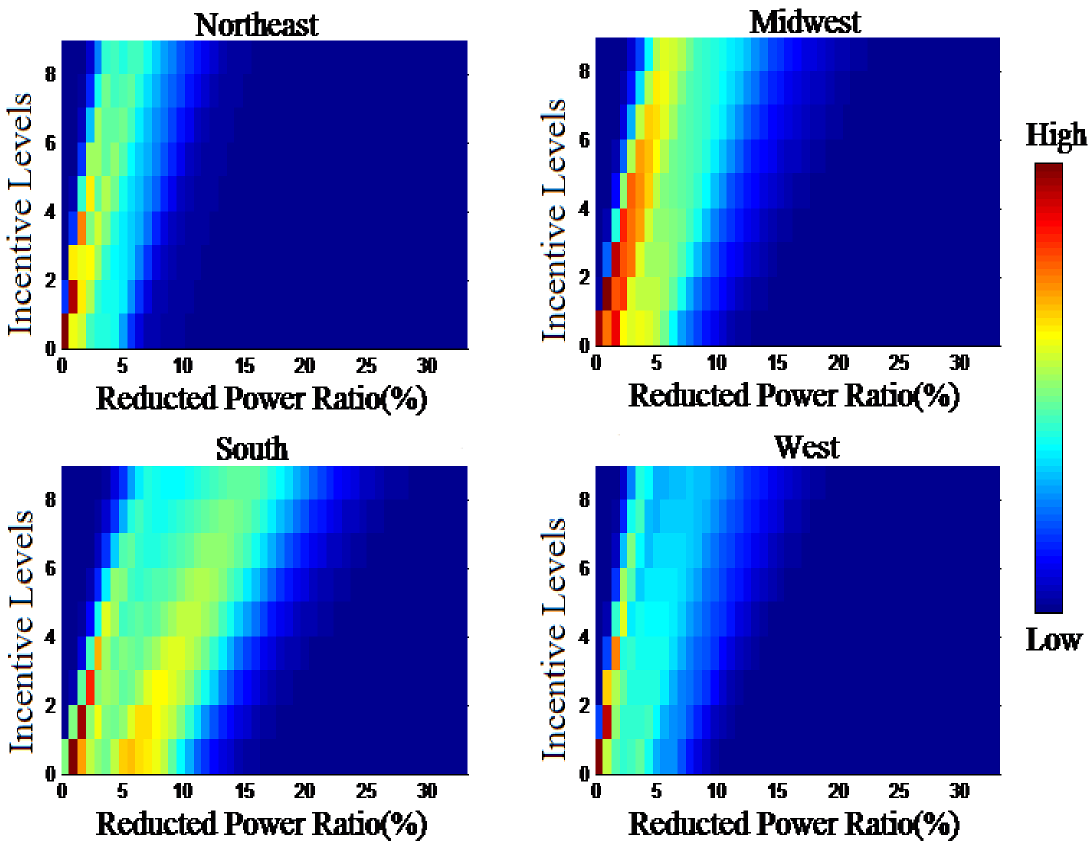


Figure 24. Probability Distribution of RPR with Different Incentive Prices in the Northeast, Midwest, South and West Regions of U.S.

4.3.2 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 are illustrated in Figure 25. The result shows that 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).

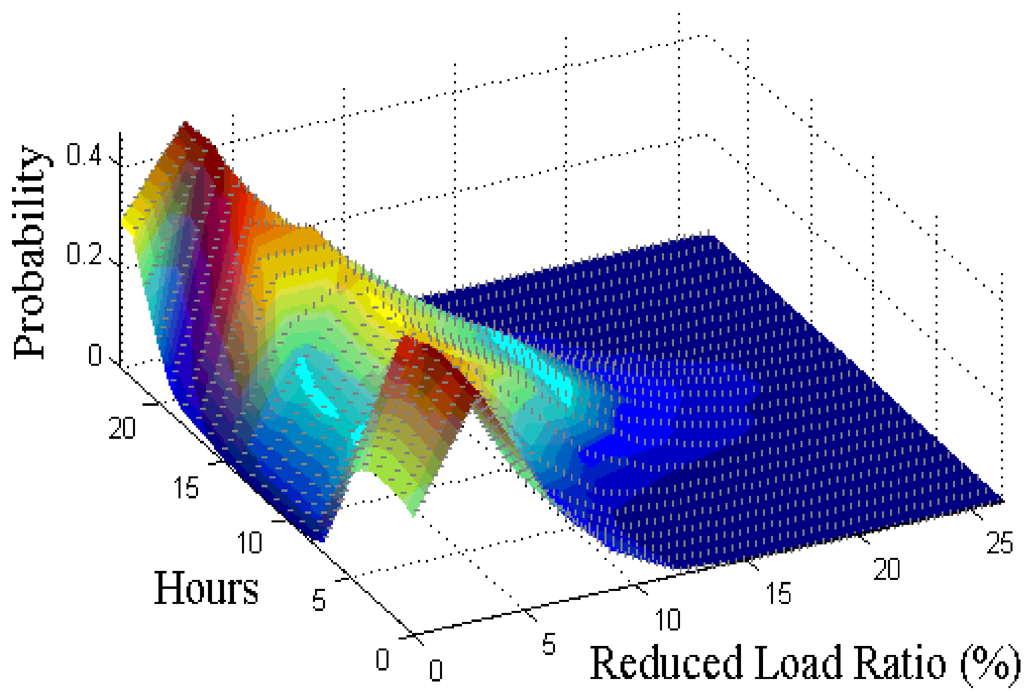


Figure 25. Probability Distribution of 24 Hour RPR

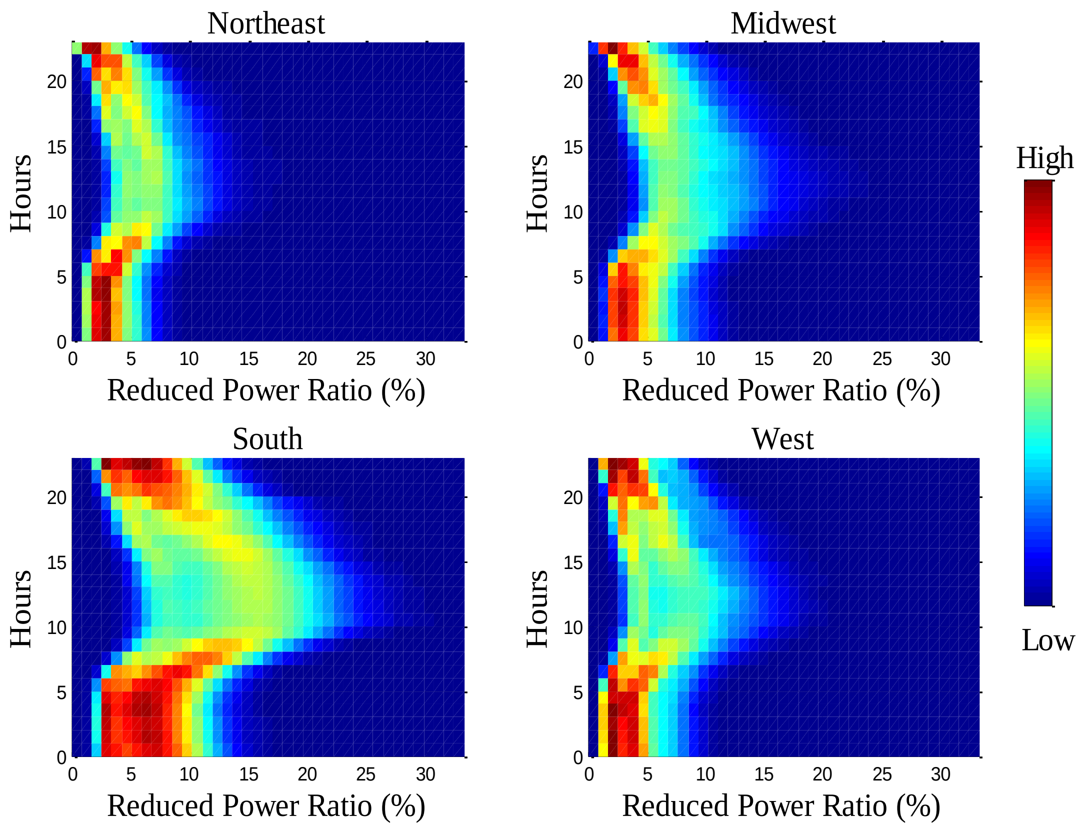


Figure 26. Probability Distribution of 24-hour RPR in different areas

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 Figure 26. The possible reason is, as aforementioned, more space cooling appliances are operating in summer in the 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 model.

4.4 Conclusion

Chapter 4 presents a stochastic model based on the residents' portfolios to assess responsive residential demand in response to specific 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) the 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 model 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 incentive 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 the 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.

If this model can be widely used in the future, it will provide great potentials for LSEs including:

- 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.

- 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.

- 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.

- Also, the proposed model will help LSEs get insights on how to improve the existing demand response programs.

CHAPTER 5

A FRAMEWORK FOR DEMAND AGGREGATION

This chapter proposes the optimal framework for incentive based residential demand aggregation for LSEs to provide effective demand-side ancillary service by strategically controlling residential appliances based on residents' unique energy usage preference and impartially rewarding the participants of DR program. In the proposed design, residential load aggregators (RLAs) serving as the agents, who receive demand response requests (DRRs) from load serving entities (LSEs) and real-time environmental parameters from every household as shown in Figure 27. Then, the RLAs generate the optimal operating strategy of appliances based on residents' preferences, and then send the optimized control strategies to the actual appliances.

For residents, this framework is expected to 1) distribute financial rewards according to their quantified contribution in DR events, and 2) maintain residents' level of in-home comfort based on their personal preferences. For LSE, this framework is expected to 1) realize the DRR by controlling residents' appliances, and 2) minimize the total reward costs for performing the DRR. Hence, this framework enables residents to become more active and to customize their energy usage preferences. This may stimulate the potential capability of demand-side resources from the residential aspect.

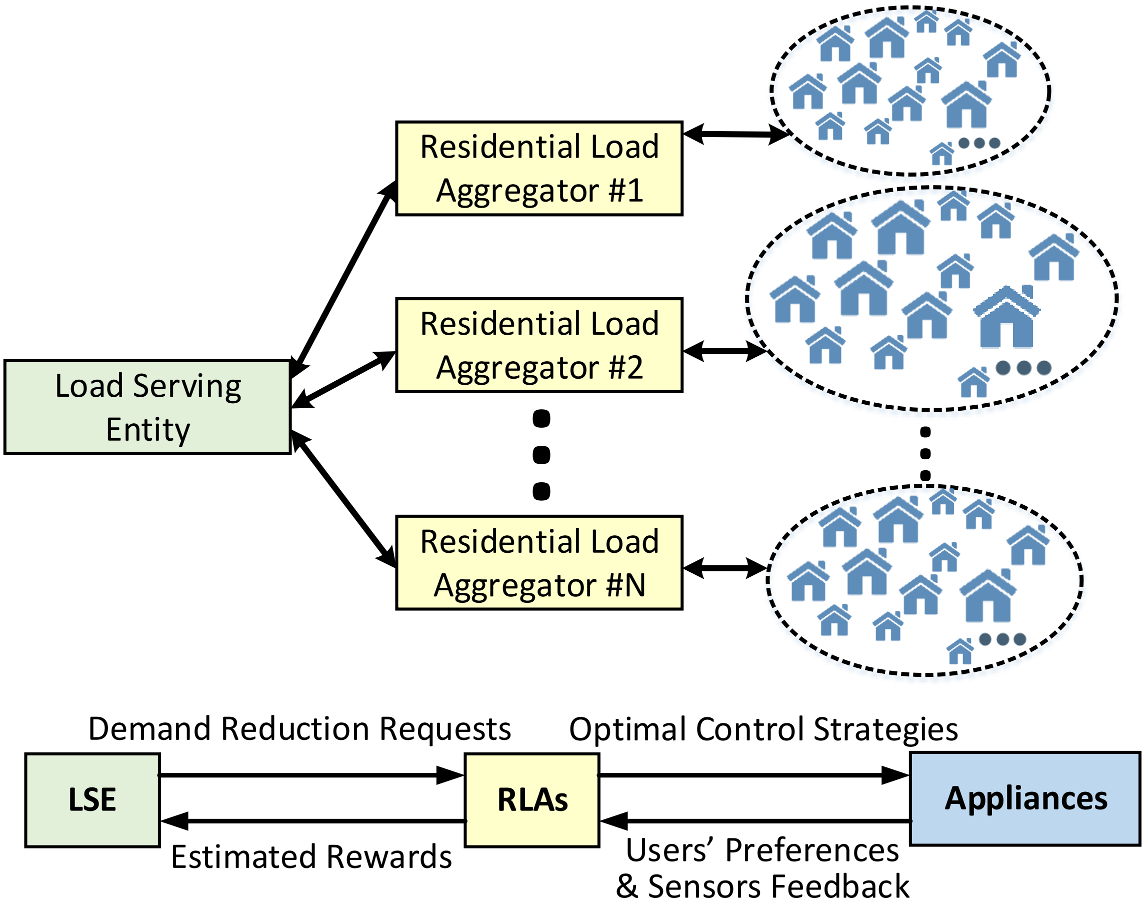


Figure 27. Schematic Information Flow Chart of the Optimal Framework

5.1 Nomenclature

n Number of households under one RLA.

R_1 Level 1 reward rate, cents/(kW·5min).

R_2 Level 2 reward rate, cents/(kW·5min).

R_3 Level 3 reward rate, cents/(kW·5min).

$T_{RM,i}$ Room temperature for resident i, °F.

$T0_{RM,i}$ Initial room temperature for resident i, °F.

$T_{L,i}$ Low room temperature threshold for resident i, °F.

$T_{H,i}$ High room temperature threshold for resident i, °F.

PA_i AC power rate of resident i, kW.

SA_i Operating status of the AC of resident i, ON/OFF.

AE_i Effect of the AC of resident i, °F/kW.

$LR_{RM,i}$ Room temperature loss rate of resident i.

$RWR_{A,i}$ AC reward rate for resident i, cents/(kW·5min).

$T_{T,i}$ EWH tank temperature of resident i, °F.

$T0_{T,i}$ EWH initial tank temperature of resident i, °F.

$T_{TL,i}$ Low tank temperature threshold of resident i, °F.

$T_{TH,i}$ High tank temperature threshold of resident i, °F.

PE_i EWH power rate of resident i, kW.

SA_i EWH operating status of resident i, ON/OFF.

E_i Effect of the EWH for resident i, °F/kW.

$LR_{T,i}$ Tank temperature loss rate for resident i.

$RWR_{E,i}$ EWH reward rate for resident *i*, cents/kW·5min.

Com_i if resident *i* compromises to the appliances operating beyond their comfort temperature ranges, YES/NO.

CV_i Comfort level violation for resident *i*.

TA_i Ambient temperature for resident *i*.

TDR Total demand secluded to reduce, kW.

D Amount of demand reduction required, kW.

δ Parameter associated with demand reduction accuracy relaxation.

RW_i Total financial rewards for resident *i*, $.

w Weight of comfort level violation.

μ_i, υ_i Auxiliary binary variables for converting the optimization problem.

5.2 Overview of the Optimal Framework

According to several pilot studies by utilities [67-72], air conditioners (ACs) and electrical water heaters (EWHs) are critical loads in DR programs, because they are predominant inertia loads and able to provide fast responses with minimal impact to residents in a short time period. Moreover, in the residential aspect, ACs and EWHs typically account for more than one half of the total peak demand [73]. Therefore, RLAs are expected to perform DRRs by controlling ACs and EWHs without affecting residents' normal life, while rewarding residents by quantifying the contributions they made under the proposed framework.

There are several assumptions for the proposed framework:

1) ACs and EWHs have bi-directional communication with RLAs; this fact also indicates that RLAs are able to obtain the real time room temperature from ACs, and the tank water temperature of EWHs;
2) The real-time ambient temperature is known to RLAs;
3) Residents provide comfort temperature ranges of both indoor air and hot water to RLAs; and
4) Residents decide whether they are willing to sacrifice, if RLAs have to adjust (lower) the comfort level of some residents.

Figure 28 is a schematic diagram of the information flow in the proposed optimal framework. In Figure 28, when the RLA receives a request from the LSE notifying that there is demand D_r that needs to be reduced, this RLA considers the residents' appliances profile, their energy usage preferences, real time ambient temperature, and real time indoor air temperature as well as water temperature of every household from ACs and EWHs. From this information, the RLA performs the optimization within a very short time. As a result, the framework achieves several tasks including:

1) generating and sending out optimal control instructions to residents' appliances;
2) providing the LSE with a cost-effective way of realizing the DRR with minimal reward costs;
3) recording the contributions that individual residents made for this DRR, and
4) distributing the financial rewards to the residents.

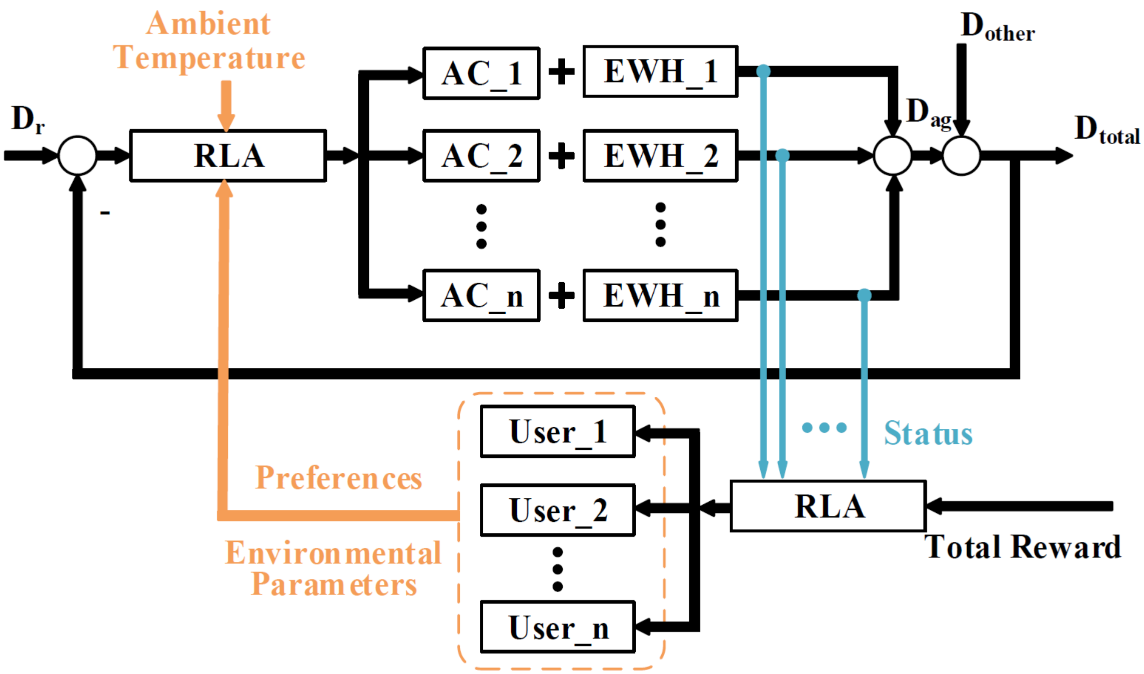


Figure 28. Schematic Diagram of the Information Flow

5.3 The Reward System

There are 55 utilities all over the U.S. offering incentive based demand response programs to their residential customers. However, few existing programs provide residents with an opportunity to customize their energy usage preferences. Moreover, most of the programs ignore to minimize the overall impact of DR events to residents' living comfort levels.

It needs be noted that an appealing reward system is one of the vital factors to make the optimal framework feasible and then attract sufficient demand-side resources to provide system ancillary services. Therefore, the rest of Section 5.3 introduces the innovative reward system which is implemented in the proposed optimal framework.

5.3.1 Multilevel Reward Rates

In this optimal framework, DR program participants will be rewarded strategically. In order to get rewards, participants have to provide their energy usage preferences including their personal comfort temperature setting ranges for EWH and AC units, and whether they are willing to compromise by turning off EWH and AC units even if either the room or water tank temperatures go beyond their comfort temperature ranges. With some large amounts of DRRs, whenever the RLA has to enforce some residents' comfort to work out a compromise, those residents will receive extra compensation, which means higher reward rate for participating in such DRRs. Moreover, if an emergency occurs, in order to maintain the stability of the power system, the LSE has to send a DRR with a tremendous amount to the RLA. Then, the RLA figures that executing such DRR will have to make the appliances of residents, who claim not to compromise, operate beyond their comfort temperature ranges. In this case, those participant residents will get the highest reward rate.

Generally, the differences among various reward rates are as shown in Table 8. Take AC units for example, the reward rates for resident *i* can be determined based on the flow chart as shown in Figure 29. Mathematically, the various reward rates can be expressed as (5-1). Since one of the objectives of the optimal framework is to minimize the total reward payment to perform certain DRR, naturally, the higher the reward level is, the less probability such situation happens. (The total reward payment minimization will be discussed in Section 5.4)

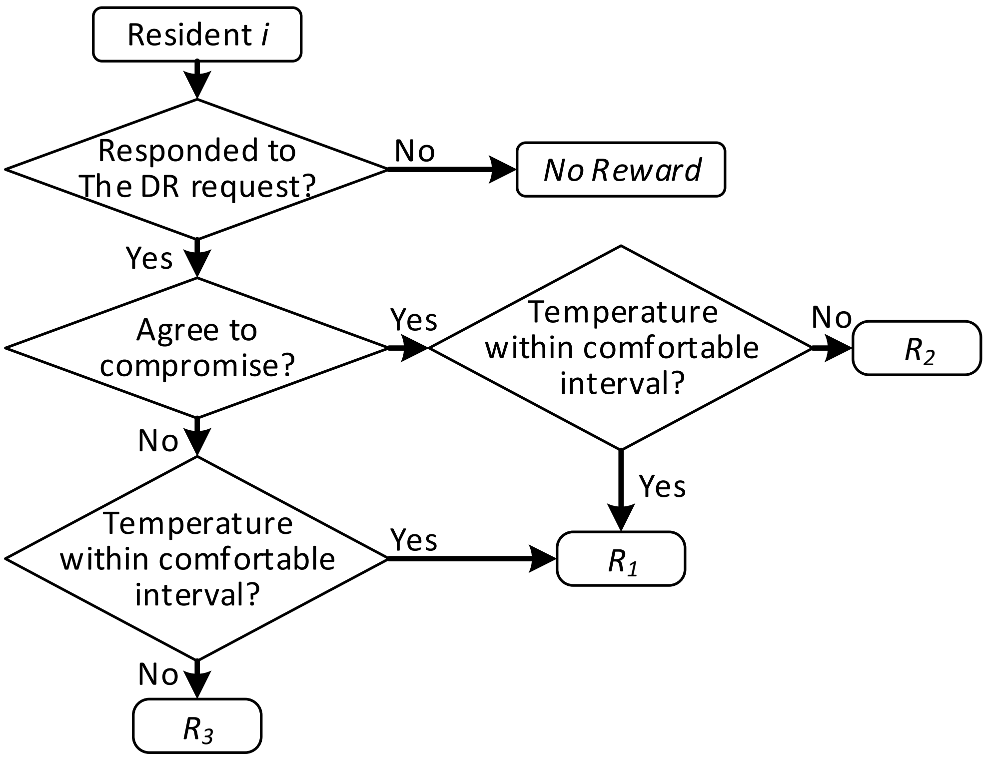


Figure 29. The Flow Chart of Determining the Reward Rate for Resident *i*

Table 8. Various Reward Rates

Resident Type	***Rate***	***Symbol***	***Probability***
Compromise	Common	R_1	Common
	Higher	R_2	Occasional
Not Compromise	Common	R_1	Common
	Highest	R_3	Emergency

$$RWR_{A,i} = \begin{cases} R_1 & ,if \quad T_{L,i} \le T_{RM,i} \le T_{H,i} \\ R_2 & ,if \quad T_{RM,i} \le T_{L,i}\ , Com_i = 1 \\ R_2 & ,if \quad T_{H,i} \le T_{RM,i}\ , Com_i = 1 \\ R_3 & ,if \quad T_{RM,i} \le T_{L,i}\ , Com_i = 0 \\ R_3 & ,if \quad T_{H,i} \le T_{RM,i}\ , Com_i = 0 \end{cases} \tag{5-1}$$

5.3.2 Comfort Level Violation

When allocating DRRs to appliances, the RLA always faces the issue of how to select the proper available appliances to turn off. Here, the proposed framework introduces the concept of "Comfort Level Violation" to solve this issue. Take resident *i* with an AC unit as an example. The "Comfort Level Violation", CV_i, is defined by (5-2), and the mean value of the low and high threshold (user energy usage preferences) of the comfort temperature range $\frac{T_{L,i}+T_{H,i}}{2}$, is assumed as the perfect operating point. Then, CV_i stands for the distance between the present status and the perfect operating point. Therefore, the higher the CV_i value, the less comfortable the resident *i* feels. $CV_i > 1$ when temperature goes beyond the comfort temperature range.

$$CV_i = \left| \frac{2T_{RM,i} - T_{L,i} - T_{H,i}}{T_{H,i} - T_{L,i}} \right| \tag{5-2}$$

Substituting (5-2) into (5-1), the relationship between CV_i and reward rates can be expressed as (5-3).

$$RWR_{A,i} = \begin{cases} R_1 & ,if \quad CV_i \le 1 \\ R_2 & ,if \quad CV_i > 1 \text{ and } Com_i = 1 \\ R_3 & ,if \quad CV_i > 1 \text{ and } Com_i = 0 \end{cases} \tag{5-3}$$

To be fair to all the residents under the control of one RLA, whenever the RLA receives a DRR, it should try to maintain a similar comfort margin for each resident in the controlled area while performing the demand reduction. This issue can be solved by the optimal framework introduced in Section 5.2 since overall comfort levels have been considered in the objective function of the optimization problem formulation. However, there is still an issue among the residents with same *CV* values. To solve this issue, the RLA keeps a record on the DRR participation history of every resident. This way, whenever the residents have the same *CV* values, the RLA will choose the one with lower DRR contribution history to participate so as to maintain justice. For example, let's assume the contribution history for all the residents is as shown in Figure 30. If resident#2 and #3 have the same *CV* value and either resident#2 or #3 has to turn off their AC unit for a while, resident#2 will be selected according the aforementioned rules.

Furthermore, it needs to be noted that the record of DRR participation history and rewards distribution results will be kept in the RLA's data base. Those data will only be uploaded to the LSE every week or month which also help release the stress for LSE from having massive real-time bi-directional communication with tens of thousands of residents.

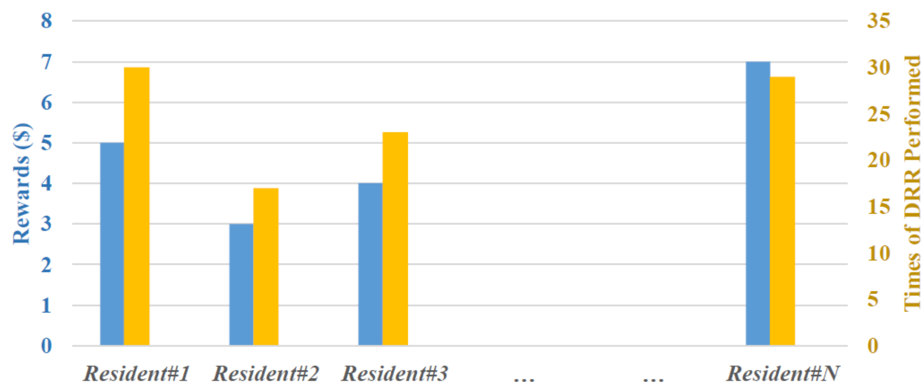


Figure 30. The Record of DRR Participation History

5.3.3 Discussion of Residents' Strategy

This optimal framework provides a chance for residents to gain financial rewards as a result of participating in DR program. As for a good reward system design, it must be able to attract more participants into the DR programs, and prevent any malicious manipulation. This reward system provides a platform which satisfies various residents with different needs. By customizing their preferences, residents can become involved in the DR program at different levels.

Here, a simple example of resident A, B and C with AC units under one RLA is used to perform a general analysis on different residents' strategies without performing complex optimization calculation. The preference settings of AC units for A, B, and C are shown in Table 9 as follow. The comfort temperature ranges of B and C are broader than A's; C chooses to compromise while A and B select not to.

Table 9. Preference Settings of Three Resident Example

Resident Name	***Comfort Temperature Range (°F)***	***Compromise?***
A	73-77	No
B	70-80	No
C	70-80	Yes

Assuming today is a hot summer day, resident A, B and C have exactly the same houses and AC units, and the present room temperature is the perfect operating point as mentioned in Subsection 5.3.2) (A:75 °F, B:75 °F, and C:75 °F). Hence, according to the description, Figure 31 shows the preference settings of the three residents. In Figure 31, the blue curve represents the reward rates they will get with different predicted room temperature during the demand reduction period, and the red dotted line is the initial room temperature before DRR.

Now, assume the RLA receives a DRR (CASE#1) asking for a one third reduction of total residential demands. Therefore, the RLA needs to turn down one of the ACs from these three residents. In CASE#1, because of the same houses, same AC units, and same initial room temperature. Since the estimated room temperature with executing this DRR is predicted as 77 °F for all three residents, the reward rate is the same for all of them. However, due to the concern of CV ($CV_A=1$, $CV_B=0.4$, $CV_C=0.4$), resident A is excluded, while B and C share the same possibilities to turn down their ACs. In CASE#2, the estimated room temperature with executing this DRR is 81 °F for all three residents. This 81 °F goes beyond the comfort temperature ranges for A, B, and C (CV_A, CV_B ,$CV_C >1$).

Due to the different preferences on “Compromise”, the reward rate for C is lower than A and B. Therefore, C will be selected to turn down his/her AC.

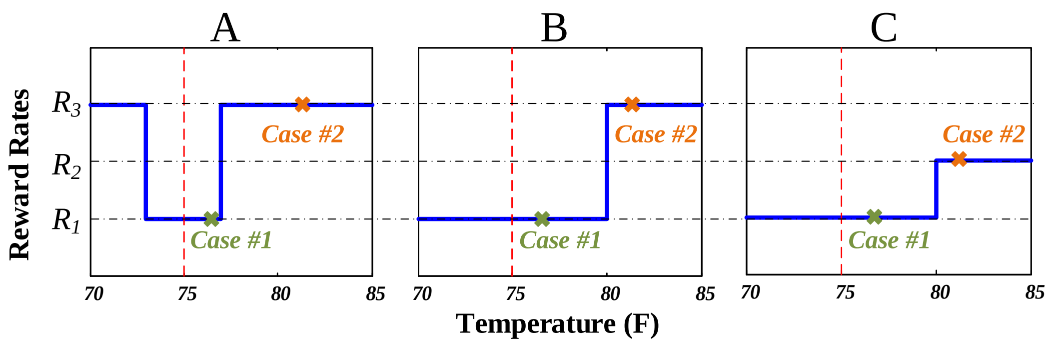


Figure 31. Reward Rate with Predicted Estimated Room Temperatures

In sum, this simple example shows clearly that resident C will most likely get the chance to perform a demand reduction and gain financial rewards, because resident C has the broadest comfort temperature range and willingness to compromise. The settings indicating that C is willing to sacrifice her/his comfort level more than the others.

This simple example is only used for generally demonstrating how the system works with various residents’ preferences. Meanwhile, the practical cases will be much more complex due to the differences in houses, appliance parameters, initial room temperatures, etc. Section 5.4 will provide the complete mathematical formulation of the optimization problem of the proposed optimal framework with this reward system.

5.4 Optimization Problem Formulation

The objectives of the optimal framework is to realize cost-effective DRR while trying to maintain the comfort levels of residents. In formulating the detailed mathematical model, there are several issues with the time length of DRR, temperature estimation, demand reduction accuracy, etc. Subsections from 5.4.1 to 5.4.4 will discuss these issues first and then formulate the complete optimization question into an MIQCP problem which is solvable using available optimization software tools.

5.4.1 Time Length of DRRs

A DRR contains two important factors:

1) total required demand reduction; and

2) time length based on how long demand reduction should last.

In order to prevent the uncomfortableness caused by performing one single DRR with a long time length, the time length of each DRR is set to be five minutes which means the long time length DRR will be treated as several continuous short DRRs.

There are several other advantages that come with dividing a long DRR into short time segments. This method ensures a stable calculation time and makes online optimization possible, because it keeps the size of the optimization problem same. Moreover, short DRRs reduce the errors in estimating temperature during DR events compared with longer term prediction, because the sensors' feedbacks will help correct the estimation.

Taking a one-hour long DRR with only ACs in winter as an example, the DRR will be divided into twelve five-minute DRRs. As shown in the schematic process chart in

Figure 32, after performing each of the short DRRs, the RLA receives the updated indoor air temperature data from each household, and then perform the next short DRR after five minutes. This method maintains the residents' comfort levels during DR events, reduces calculation errors, and makes the online optimal scheduling of DRRs online optimization feasible.

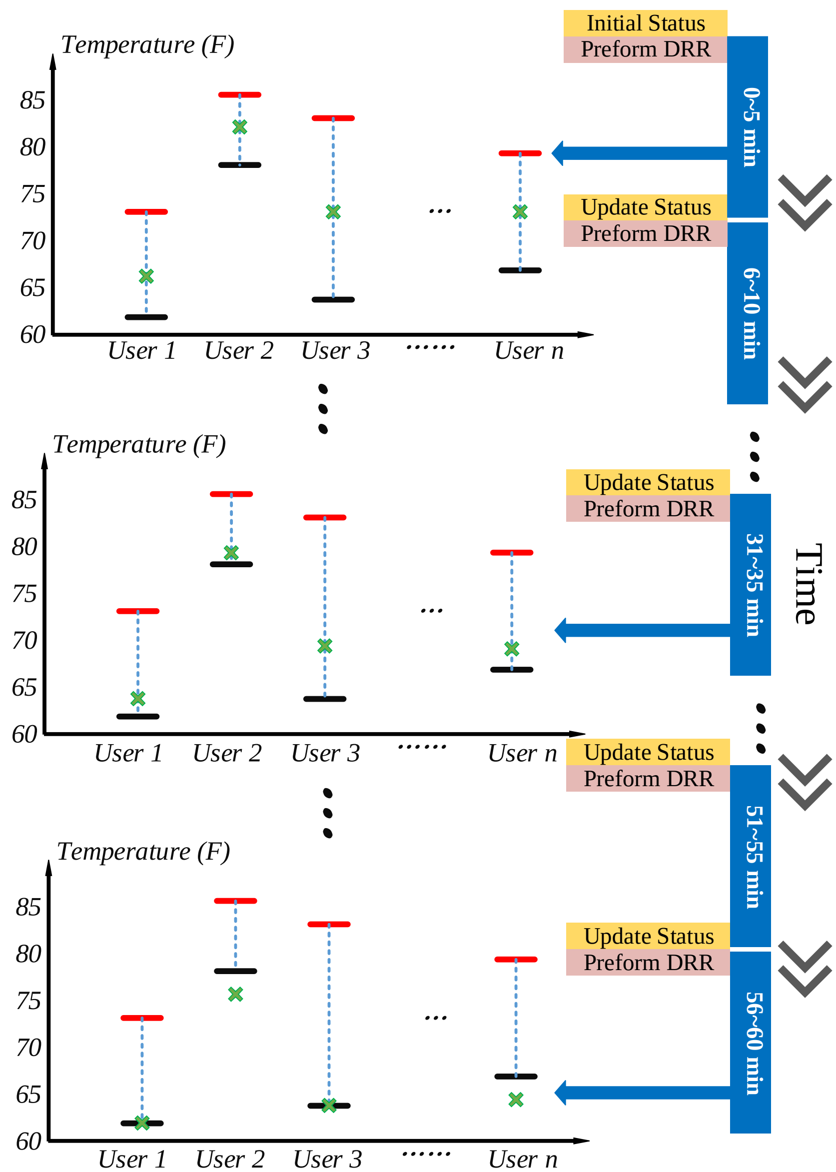


Figure 32. The Process Chart for Performing One Hour Length DRR

5.4.2 Temperature Estimation

Temperature estimation is vital in this model, because it determines the reward rates for the residents.

As for estimating the water temperature in EWHs, the general model has been discussed in [53-55]. The discrete state dynamics EWH model is applied here, since the time length of each DRR is set at five minutes which is fixed. Hence, the model can be described by (5-4):

$$T_{T,i} = -LR_{T,i} \cdot \left(T0_{T,i} - TA_i\right) + E_i \cdot PE_i \cdot SE_i \tag{5-4}$$

As for estimating the indoor air temperature with AC units, the ASHRAE has compiled modeling procedures in its fundamentals handbook [56]. The U.S. Department of Energy (DOE) has produced the Energy Plus program for computer simulation [57]. Also, the detailed model for simulating AC systems is given in [58, 59]. According to these studies, an accurate model needs to consider many factors including weather, season, building thermal resistance, solar heating, cooling effect of the wind, and shading. Unlike EWH which has constant and relatively accurate parameters, those parameters of AC are difficult to measure precisely, since they are always changing with the operating status. Compared with the complex model, the simplified model, which is faster but less accuracy, is a better for the proposed framework, due to the following reasons:

1) The errors of predicting the temperature for only five minutes ahead are limited;

2) The framework needs to perform online optimization.

Hence, the simplified model of estimating the indoor air temperature with ACs is implemented as shown in (5-5).

$$T_{RM,i} = -LR_{RM,i} \cdot \left(T0_{RM,i} - TA_i\right) + AE_i \cdot PA_i \cdot SA_i \tag{5-5}$$

Instead of executing complicated setting adjustments for ACs, the control variable for ACs is binary SA_i in (5-5). Therefore, the ACs will be controlled simply by ON/OFF.

It needs to be highlighted that the values of parameters $LR_{T,i}$, E_i, $LR_{RM,i}$ and AE_i are different for each resident. Because the RLA is able to receive feedbacks from the sensors, the values of those parameters can be obtained through performing regression on the historical data for each resident in practical application under the proposed framework. However, due to the lack of historical data, those parameters are only set by assumptions in the numerical case studies in Section 5.5.

5.4.3 Demand Reduction Accuracy Relaxation

The total demand can be reduced from n residents by executing the optimal control strategies over ACs and EWHs, which is expressed in (5-6) as:

$$TDR = \sum_{i=1}^{n} PA_i \cdot \left(1 - SA_i\right) + PE_i \cdot \left(1 - SE_i\right) \tag{5-6}$$

However, since SA_i and SE_i are both binary, *TDR* and demand *D*, which is the value requested to reduce, cannot usually be exactly the same. It is also possible for *D* to go beyond the capability of the RLA. Therefore, the constraint of the amount of demand to be reduced needs to relax according to the LSE requirement as expressed in (5-7).

$$(1-\delta)\cdot D \leq TDR \leq (1+\delta)\cdot D \tag{5-7}$$

The value of δ is set as 0.05 in the case study to be discussed in Section 5.5.

5.4.4 MIQCP Problem Formulation

According to the discussion in Subsection 5.3.1, in summer time, the reward rates of ACs and EWHs should be expressed by (5-8) and (5-9), respectively.

$$RWR_{A,i} = \begin{cases} R_1 & ,if \quad T_{RM,i} \leq T_{H,i} \\ R_2 & ,if \quad T_{H,i} < T_{RM,i} \text{ and } Com_i = 1 \\ R_3 & ,if \quad T_{H,i} < T_{RM,i} \text{ and } Com_i = 0 \end{cases} \tag{5-8}$$

$$RWR_{E,i} = \begin{cases} R_1 & ,if \quad T_{TL,i} \leq T_{T,i} \\ R_2 & ,if \quad T_{TL,i} > T_{T,i} \text{ and } Com_i = 1 \\ R_3 & ,if \quad T_{TL,i} > T_{T,i} \text{ and } Com_i = 0 \end{cases} \tag{5-9}$$

In order to formulate the optimization problem, (5-8) is converted into (5-10) (5-11) and (5-12) as the constraints of optimization problem.

$$RWR_{A,i} = R_1 \cdot \mu_i + R_2 \cdot (1-\mu_i) \cdot Com_i + R_3 \cdot (1-\mu_i) \cdot (1-Com_i) \tag{5-10}$$

$$T_{RM,i} - T_{H.i} \leq M \cdot (1-\mu_i) \tag{5-11}$$

$$T_{RM.i} - T_{H,i} > -M \cdot \mu_i \tag{5-12}$$

Similarly, (5-9) can be converted to (5-13), (5-14) and (5-15).

$$RWR_{E,i} = R_1 \cdot \upsilon_i + R_2 \cdot (1-\upsilon_i) \cdot Com_i + R_3 \cdot (1-\upsilon_i) \cdot (1-Com_i) \tag{5-13}$$

$$T_{TL,i} - T_{T.i} \leq M \cdot (1-\upsilon_i) \tag{5-14}$$

$$T_{TL.i} - T_{T,i} > -M \cdot \upsilon_i \tag{5-15}$$

where M is large enough constants, and μ_i and υ_i are the auxiliary binary variables [74].

Given the previous discussion in Subsections from 5.4.1 to 5.4.3, this optimization problem of minimizing total rewards payment while maximizing the residents' comfort levels (thereby minimizing comfort level violation) during the summer time can be formulated as:

$$\min \sum_{\mathrm{i}=1}^{n} RW_i + w \cdot \sum_{\mathrm{i}=1}^{n} CV_i^2 \tag{5-16}$$

s.t. Constraints (5-10), (5-11), (5-12), (5-13), (5-14), (5-15)

$$RW_i = PE_i \cdot (1 - SE_i) \cdot RWR_{E,i} + PA_i \cdot (1 - SA_i) \cdot RWR_{A,i} \tag{5-17}$$

$$TDR = \sum_{i=1}^{n} PA_i \cdot (1 - SA_i) + PE_i \cdot (1 - SE_i) \tag{5-18}$$

$$(1 - \delta) \cdot D \le TDR \le (1 + \delta) \cdot D \tag{5-19}$$

$$T_{T,i} = -AE_i \cdot (T0_{T,i} - TA_i) + E_i \cdot PE_i \cdot SE_i \tag{5-20}$$

$$T_{RM,i} = -LR_i \cdot (T0_{RM,i} - TA_i) + AE_i \cdot PA_i \cdot SA_i \tag{5-21}$$

$$CV_i = \left| \frac{2T_{RM,i} - T_{L,i} - T_{H,i}}{T_{H,i} - T_{L,i}} \right| + \left| \frac{2T_{T,i} - T_{TL,i} - T_{TH,i}}{T_{TH,i} - T_{TL,i}} \right| \tag{5-22}$$

Therefore, the optimization problem is formulated as a MIQCP problem, which is easy to solve using available software tools.

5.5 Case Studies

The proposed optimal framework is performed on both a ten-resident system and a much larger system with no more than 1000 residents whose parameters are from the residential energy consumption survey (RECS) created by U.S. EIA in 2009.

The first case study is designed to show how the optimal framework schedules every appliance and rewards each resident, since more detailed information can be demonstrated in a small scale case study. Also, this case study compares the simulation results under the optimal framework with the existing DR programs.

Further, the second case study is used to show changes in residents' comfort levels and total rewards costs for the LSE under different DRRs under the proposed framework.

The simulations have been done using the General Algebraic Modeling System (GAMS) which can solve large scale optimization problems. The MIQCP problem is solved by BONMIN solver in GAMS on a desktop with Intel Xeon 3.2GHz CPU, and 8 GB RAM.

5.5.1 Ten-Resident System

Based on the proposed framework and optimization problem formulation, several case studies have been carried out. The first test system is a ten residents' system considering only AC units. In this system, every residents has different personal preferences and house household parameters as shown in Table 10. The total demand of ACs is 13.6 kW.

Table 10. Ten-Resident Profile

ID	T_H	T_L	***PA***	***T0***	***Cop***	***AE***	***LR***
1	75	70	1.3	72.5	0	5	0.1
2	75	70	1.4	72.5	1	5	0.1
3	75	65	1.2	70	0	5	0.3
4	80	70	1.5	75	0	5	0.2
5	75	65	1.6	70	1	6	0.3
6	75	65	1.3	70	1	5	0.1
7	75	67	1.2	71	0	4	0.1
8	77	67	1.1	70	1	4	0.2
9	77	65	1.5	71	0	5	0.2
10	75	70	1.5	72.5	1	5	0.2

Here is an example of a conventional incentive-based DR programs offered in United States, referred to here as "IDR#1." On hot summer days, 3 to 5 times at most per month, a typical AC will be turned off for 20 minutes. A resident who enrolls in the program will get $8 off his/her monthly summer electricity bill as a reward. Assuming the power rate of the AC united is 1.5kW, if the utility company turns off the resident's AC unit 4 times, the cost would be equivalent to 33 cents/ (kW·5min). Here, reward rates R_1, R_2, and R_3 in the proposed framework are roughly set at 20, 40, and 60 cents/ (kW·5min) respectively, in which the lowest reward rate is a little lower than 33 cents/ (kW·5min). However, since the lowest reward rate ensures the residents' comfort levels and the median reward rate is higher than 33 cents/ (kW·5min), the settings of the reward rate in the optimal framework should be comparable to existing programs.

In this ten-resident case study, the RLA received two DRRs from the LSE.

5.5.1.1 DRR#1 with 4kW/ 20min

DRR#1 asked the RLA to reduce 4kW for 20 min among these ten residents' AC units. The results of residents' satisfaction as well as rewards distribution are shown in Table 11. CMFT stands for the percentage of time when the temperature was within comfort temperature ranges.

Table 11. DRR#1 Result (30% AC Demand Reduction)

ID	*min* $\boldsymbol{T_{RM}}$ *(℉)*	*max* $\boldsymbol{T_{RM}}$ *(℉)*	***CMFT*** *(%)*	***Rate***	***Rewards*** *($)*
1	70.8	74.5	100	R_1	0.38
2	70	74.3	100	R_1	0.56
3	71	72.8	100	R_1	0
4	70.1	74.1	100	R_1	0.3
5	70	70	100	R_1	0
6	66.4	70.1	100	R_1	0.78
7	70.3	72.9	100	R_1	0.24
8	70	74	100	R_1	0.22
9	67	69.8	100	R_1	0.4
10	70	74.8	100	R_1	0.3

As for DRR#1 results, all residents were within their comfort temperature ranges. Resident #6 received the most financial rewards, due to his broad comfort temperature range and low *LR* value. A lower *LR* indicates a lower temperature change when turning off the appliances, hence a low *LR* improved capability of residents participating in DRRs. Neither resident #3 nor #5 earned rewards, because they kept their ACs on to maintain the proper room temperature due to high *LRs*. As a result, the RLA did not turn their ACs off, as long as others were able to offer enough demand reduction.

5.5.1.2 DRR#2 with 8kW/ 20min

DRR#2 requests the RLA to reduce 8kW for 20 min among these ten residents' AC units. Residents' satisfaction results and reward distributions are shown in Table 12.

In DRR#2, the demand to be reduced was around 60% of the total regular demand which is tremendous. This can be traced to resident #2, #5 and #10 bear uncomfortable warm room temperature. Consequently, their financial rewards were relatively higher than others, because they were rewarded with R_2 when their room temperature went beyond their comfort temperature ranges. It needs to note that all three of these residents selected willing to compromise.

Table 12. DRR#2 Result (60% AC Demand Reduction)

ID	*min* $\boldsymbol{T_{RM}}$ *(°F)*	*max* $\boldsymbol{T_{RM}}$ *(°F)*	***CMFT*** *(%)*	***Rate***	***Rewards*** *($)*
1	70.8	74.5	100	R_1	0.58
2	70	75.8	75	R_1, R_2	1.28
3	71	72.5	100	R_1	0
4	73	79.1	100	R_1	0.6
5	70	80.2	50	R_1, R_2	1.28
6	68.8	72.8	100	R_1	0.78
7	72.2	74.6	100	R_1	0.72
8	72.6	76.1	100	R_1	0.44
9	72.8	76.3	100	R_1	0.6
10	71	76.3	75	R_1, R_2	1.2

5.5.1.3 Results Comparison

Table 13 clearly shows that, compared with the conventional incentive-based DR program IDR#1, the proposed optimal framework has the following advantages: 1) The optimal framework significantly increases the resident overall comfort levels during DR events; 2) The optimal framework reduces costs for LSEs to perform DRRs; 3) Residents are rewarded for the actual contribution they make which can attract more DR program participants.

Table 13. Result Comparison between DRR#1 and #2

	IDR#1		***Optimal Framework***	
	Ave. CMFT (%)	***Equivalent Rewards ($)***	***Ave. CMFT (%)***	***Rewards ($)***
DRR#1	49.7%	5.28	100%	3.18
DRR#2	46.3%	10.56	90%	7.48

As for the optimal framework itself, the calculation time for performing both DRRs is within 0.02s. Comparing the residents' profiles and the results of these two DRRs, all the appliances of the residents were fairly scheduled according to resident preferences and parameters. Moreover, Table. 13 shows that the increase in demands to be reduced may lead to a dramatic rise in terms of reward costs: The amount of DRR#2 was twice that of DRR#1, but the total reward cost to perform DRR2 was about 2.34 times that of DRR#1. Because, for large DRRs, the RLA has to violate some residents' comfort levels to reduce enough demand. The affected will be rewarded with R_2 which increases the total reward cost.

5.5.2 Large System Test

The parameters of a large system used in this study are found in the RECS by U.S. EIA. The RECS data sets contain information related to appliances that residents own, and their parameters as well as the usual settings for those appliances. The original RECS contained the information from more than 60,000 households. In this case study, no more than 1000 residents were selected, because the RLA is expected to solve practical problems within this scale.

The result turns out performing the optimization of 1000-resident system under the proposed optimal framework take less than 10 seconds of calculation time for each DRR.

5.5.2.1 The performance of a 500-resident system

A 500-resident system was studied with different DRRs. Figure 33 and Figure 34 show the change in resident comfort levels as well as the total rewards costs for the LSE performing the DRRs with different time lengths and demand reduction amounts.

The results are reasonable in that, they show how, with the increase of time lengths and the amount of the demand needs to be reduced in DRR, the resident comfort levels dramatically fall while total reward costs rise sharply.

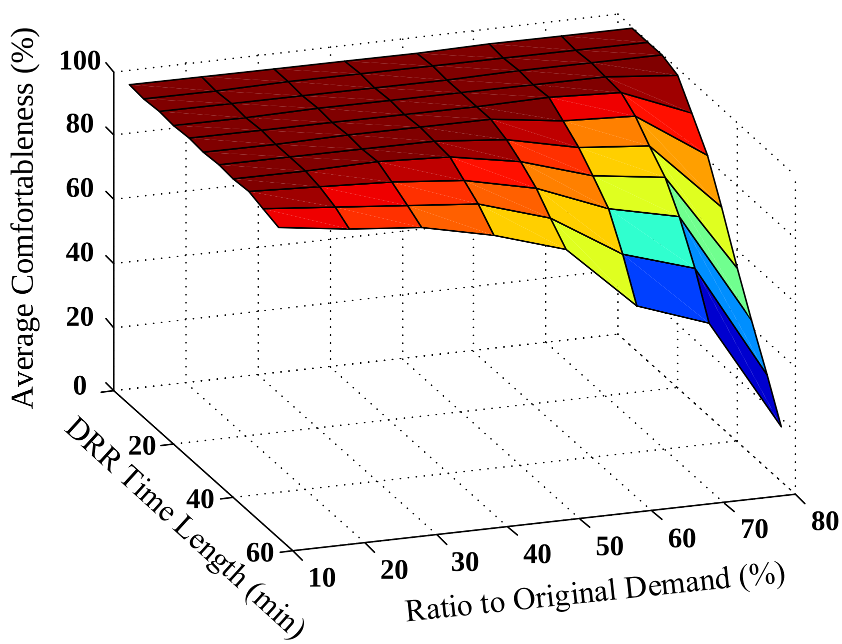


Figure 33. The Results of 500 Residents in Test#1

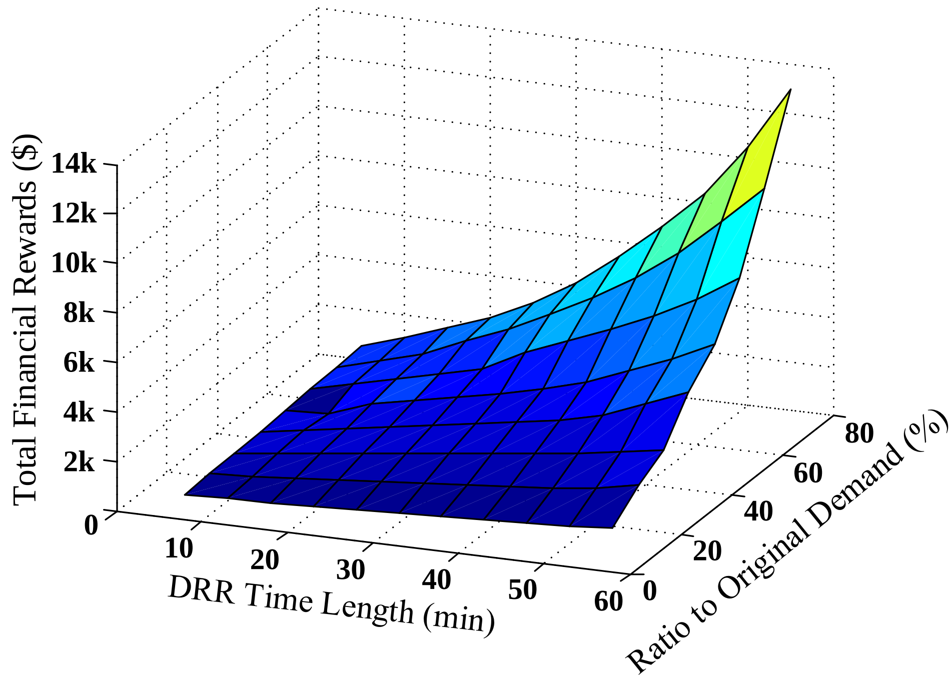


Figure 34. The Results of 500 Residents in Test#2

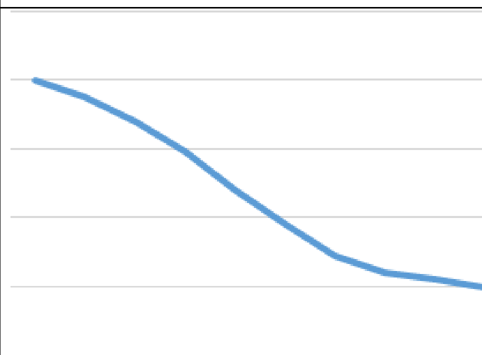
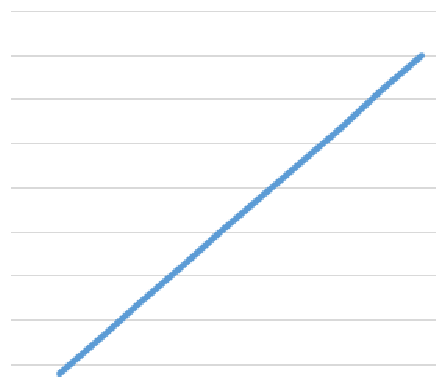
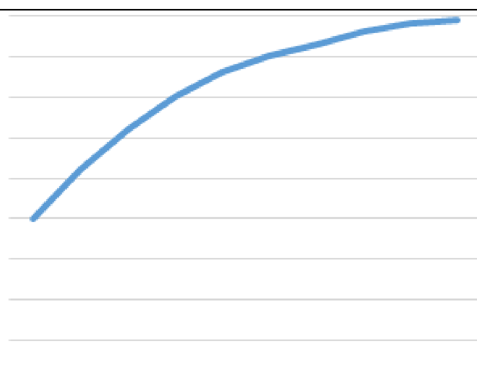
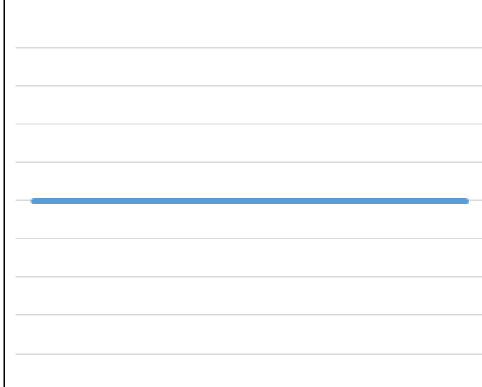
5.5.2.2 Scale Effect

Compared with the conventional incentive-based DR program, such as the aforementioned IDR#1, the proposed optimal framework is expected to have better overall performance as the number of DR program participants increase. With more DR program participants, the proposed framework will have more demand side resources available for scheduling. Hence, the resident overall comfort levels can be maintained in a very high level. Consequently, in most cases, the reward rates will be R_1, and the total cost for performing DRRs will be low. However, with more program participants, the cost of IDR#1 will have a linear increase. Moreover, since resident comfort levels are not considered as the objective of IDR#1, the difference in the number of participants will not influence the average comfort levels.

In order to verify the above discussion, the simulations regarding different number of DR program participants (from 100 to 1000) were performed. The simulation results about the changing trends of cost and residents' average comfort levels regarding different numbers of participants are summarized in Table. 14. It is clear that the simulation results support the statement that the proposed framework performs better with an increasing number of programs participants compared with conventional I-DR programs.

Table 14. Scale Effect Comparison

(X-Axis: Number of DR Program Participants)

	Optimal Framework	***conventional IDR#1***
Y-Axis *Total* ***DR*** ***Cost***		
Y-Axis ***Residents'*** ***Avg.*** ***CMFT***		

5.6 Conclusion

In Chapter 5, an optimal framework for RLAs is proposed. Under this framework, the RLAs serve as agents of LSEs. Their role is to not only allocate DDRs among residential appliances quickly and efficiently without affecting resident comfort levels, but to also strategically reward residents for their participation, which may stimulate the potential capability of loads optimized and controlled by RLAs in incentive based DR programs. The main contributions of this work are summarized as follows:

- For the LSE, RLAs reduce the size of the optimization problem and make dispatching DRR down to residential appliances feasible in real time.
- This framework minimizes total reward costs for LSEs to perform an efficient DRR in a DR program while maintaining the comfort levels for residents.
- The reward system is established to satisfy the needs for various types of customers. They can make a tradeoff between financial rewards and in home comfort levels by strategically and simply setting their preferences over the appliances.
- Compared with the conventional incentive based DR programs, the proposed framework has an economy of scale effect wherein its performance becomes better and more cost efficient with the increasing number of DR program participants.
- Moreover, since this framework benefits both LSEs and residents, it can stimulate the potential capability of residential appliances optimized and controlled by RLAs in DR programs. Eventually, with the growing electricity usage in residential aspect,

this framework will have the opportunity to become one of the most vital part in providing effective demand-side ancillary services for the whole power system.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Contributions

This work proposes a comprehensive optimal framework for aggregating residential demands and incorporates residential demand aggregation with current power system operation. The comprehensive solution may largely improve the capacity of demand-side ancillary, which helps maintain power system stability and security. The achievements of this work include:

1) Hardware design of a smart home energy management system

The SHEMS provides enabling technology for an incentive based residential demand aggregation. The design includes sensors to detect residents' activities, and then applies a machine learning algorithm to intelligently help residents reduce total electricity payment with very little involvements from the residents themselves. Moreover, it can achieve responsive control strategy over residential loads including EWHs, AC units, EVs, dishwashers, washing machines, and dryers. Most importantly, they may interact with LSEs to facilitate I-DR.

2) Model for assessing the capacity of responsive residential loads

Based on the residents' portfolios, this model can assess responsive residential demand in response to specific times, locations, and financial incentives. It solves issues with residents' versatile energy usage behavior towards I-DR. Also, the proposed model avoids the time-consuming procedure of communicating and makes the online implementation of I-DR feasible for LSEs.

3) Optimal framework for performing residential load aggregation

   This framework schedules the residential appliances in I-DR in real-time. This method not only allocates DRRs among residential appliances quickly and efficiently without affecting residents' comfort, but also strategically rewards residents for their participation.

To summarize, the comprehensive solution for incentive based demand aggregation benefits both LSEs and residents, and it may stimulate the potential capability of residential appliances enrolled in incentive based DR programs. Eventually, with the growing number of DR participants from residential aspect, this work has the potential to become one of the most vital parts in improving the system's operating stability, reliability and efficiency.

6.2 Future Works

The following directions are considered as future tasks of this comprehensive solution for incentive based residential demand aggregation.

1) The models of appliances implemented are simplified in the existing models. Future models of electrical vehicle and energy storage components will be more prevalent and are expected to show what they can do in test runs.

2) The advanced modeling technologies considering occupants' behavior are expected to improve the accuracy of assessing residential responsive demand.

3) The bi-directional electricity should be transferred between LSEs and common residents.

4) The field studies are expected to verify the functionalities of the proposed comprehensive solutions in aggregating residential demand. As a timely new research area teeming with unexplored extensions, the large-scale simulation can be used to exhibit designed functions. Meanwhile, practical pioneering projects can further verify the implementation of theoretical techniques and polish the existing models.

LIST OF REFERENCES

[1] Federal Energy Regulatory Commission, "Assessment of demand response and advanced metering", staff report Docket Number AD-06-2-00. Washington, D.C.: Federal Energy Regulatory Commission. See also http://www.ferc.gov/ legal/staff-reports/demand-response.pdf; 2006.

[2] Federal Energy Regulatory Commission, "National action plan on demand response", *Tech. Rep. Docket AD09-10*, 2010. [Online] Available: http://www.ferc.gov/legal/staffreports/06-17-10-demand-response.pdf.

[3] DOE Report, "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them", 2006. [Online] Available: http://westvirginia.sierraclub.org/.

[4] Albert Chiu, Ali Ipakchi, Angela Chuang, Bin Qiu, Brent Hodges, Dick Brooks, et al., "Framework for Integrated Demand Response and Distributed Energy Resources Models", 2009. [Online] Available: http://www.neopanora.com/.

[5] Michael Reid, Roger Levy, and Alison Silverstein, "Coordination of Energy Efficiency and Demand Response", Lawrence Berkeley National Laboratory, 2010.

[6] Mohagheghi S, Stoupis J, Zhenyuan Wang, Zhao Li, Kazemzadeh H., "Demand response architecture: integration into the distribution management system", *Proceedings of the 1st IEEE international conference on smart grid communications (SmartGridComm)*, 2010: p.501-506

[7] U.S. Energy Information Administration, "Monthly Energy Review," Apr. 2014, pp. 109.

[8] U.S. Energy Information Administration, "Electric Power Annual 2013," Mar. 2015, [Online] http://www.eia.gov/electricity/annual/html/epa_10_01.html

[9] U.S. Energy Information Administration, "Electric Power Annual 2013," Mar. 2015, [Online] http://www.eia.gov/electricity/annual/html/epa_10_05.html

[10] US DOE, "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them," *Report to the United States Congress*, February 2006. [Online] Available: http://eetd.lbl.gov.

[11] 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.

[12] R. C. Bilton M, Leach M, Devine Wright H, Johnstone C, D. Kirschen, "Demand Side Management", *delivering a low carbon electricity system: technologies, economics and policy*. Cambridge Univ. Press.

[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] R.L. Earle, “Demand elasticity in the California power exchange day-ahead market,” *Elect. J.*, vol. 13, no. 8, pp. 59-65, Sep. 2000.

[15] C. Goldman et al., “Customer Strategies for Responding to Day-Ahead Market Hourly Electricity Pricing”, Lawrence Berkeley National Laboratory, Berkeley, CA, 2005.

[16] S. Rassenti, V. Smith, and B. Wilson, “Controlling Market Power and Price Spikes in Electricity Networks: Demand-Side Bidding,” *Proc. Nat. Acad. Sci.*, vol. 100, no. 5, pp. 2998-3003, May 2003.

[17] Qinran Hu and Fangxing 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.

[18] G. Song, F. Ding W. Zhang and A. Song, “A Wireless Power Outlet System for Smart Homes”, *IEEE Trans. Consumer Electronics*, vol. 54, no. 4, pp. 1688-1691, 2008.

[19] P. Wang, et al., "Demand Side Load Management of Smart Grids using intelligent trading/Metering/ Billing System,” *IEEE PES General Meeting*, pp.1-6, 2010.

[20] D. Cook, M. Youngblood, E. Heierman, K. Gopalratnam, S. Rao, A. Litvin, and F. Khawaja, “Mavhom: An agent-based smart home,” *IEEE Proc. PerCom*, pp.521–524, 2003.

[21] S. Das, D. Cook, A. Bhattacharya, I. Heierman, and T. Lin., “The Role of Prediction Algorithms in the MavHome Smart Home Architecture”, *IEEE Wireless Communications*, vol. 9, no. 6, pp.77-84, 2003.

[22] M. A. A. Pedrasa, T. D. Spooner, and I. F. MacGill, “Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services,” *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp.134-143, 2010.

[23] A. Mohsenian-Rad and A. Leon-Garcia, “Optimal Residential Load Control with Price Prediction in Real-time Electricity Pricing Environments”, *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp.120-133, 2010

[24] E. Santacana, G. Rackliffe, L. Tang, and X. Feng, “Getting Smart,” *IEEE Power Energy Mag.*, vol. 8, no. 2, pp. 41–48, Mar./Apr. 2010.

[25] S. Mohagheghi, J. Stoupis, Z. Wang, Z. Li, and H. Kazemzadeh, “Demand Response Architecture: Integration into the Distribution Management System,” in *Proc. IEEE SmartGridComm*, Gaithersurg, MA, USA, Oct. 4–6, 2010, pp. 501–506.

[26] Gyuk I, Kulkarni P, Sayer J, Boyes J, Corey G, Peek G, “The United States of Storage: Electric Energy Storage” *IEEE Power Energy Mag*, vol. 3, no. 2, pp.31-39, 2005.

[27] Su Chua-Liang, Kirschen Daniel, "Quantifying the Effect of Demand Response on Electricity Markets", *IEEE Trans. on Power Syst.*, vol. 24, no. 3, pp. 1199-1207, 2009.

[28] Goldman C, et al. "Customer Strategies for Responding to Day-ahead Market Hourly Electricity Pricing". Lawrence Berkeley National Laboratory, Berkeley, CA, 2005.

[29] Kirschen Daniel, "Demand-side View of Electricity Markets", *IEEE Trans. on Power Syst.*, vol. 18, no. 2, pp.520-527, 2003.

[30] Borenstein S, Bushnell J, Wolak F, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market", *American Economic Review*, vol. 92, no. 5, pp. 1376-1405, 2002.

[31] 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.

[32] Xin Fang, Qinran Hu, and Fangxing Li, "Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities," *IEEE Trans. on Power Syst.*, in press, 2015.

[33] A. L. Ott, "Experience with PJM Market Operation, System Design, Implementation," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 528–534, May 2003.

[34] CAISO Department of Market Analysis, "Market Issues and Performance", 2010 [Online]. Available: http://www.caiso.com

[35] M. Chan, D. Esteve, C. Escriba, and E. Campo, "A Review of Smart Homes — Present State and Future Challenges," *Compute. Methods Programs Biomed.*, vol. 91, no. 1, pp. 55–81, Jul 2008.

[36] H. Farhangi, "The Path of the Smart Grid," *IEEE Power Energy Mag.*, vol. 8, no. 1, pp. 18–28, Jan./Feb. 2010.

[37] A. Vojdani, "Smart Integration—The Smart Grid Needs Infrastructure that is Dynamic and Flexible," *IEEE Power Energy Mag.*, vol. 6, no. 6, pp. 71–79, Nov./Dec. 2008.

[38] P. Zhang, F. Li, and N. Bhatt, "Next-generation Monitoring, Analysis, and Control for the Future Smart Control Center," *IEEE Trans. on Smart Grid*, vol. 1, no. 2, pp. 186–192, Sep. 2010.

[39] "The IBM Vision of A Smarter Home Enabled by Cloud Technology" [Online]. Available:http://www.ibm.com/smarterplanet/global/files/uk__uk_en__cloud__a_smarter_home_enabled_by_cloud_computing.pdf?ca=content_body&met=uk_smarterplanet_cloud_computingideas&re=spc

[40] "Manage Energy for Smart Control" [Online]. Available: http://panasonic.net/eco/zero-co2/manage/index.html

[41] Nucleus [Online]. Available: http://www.geappliances.com/home-energy-manager/index.htm

[42] "Building the Energy-smart Home" [Online]. Available: http://www.hpl.hp.com/news/2011/apr-jun/home_energy_manager.html

[43] M. Pedersen, "Segmenting Residential Customers: Energy and Conservation Behaviors" *ACEEE Summer Study on Energy Efficiency in Buildings*, 2008 [Online].Available:http://www.eceee.org/library/conference_proceedings/ACEEE_buildings/2008/Panel_7/7_671

[44] B. Sütterlin, T. A. Brunner, & M. Siegrist, "Who Puts the Most Energy into Energy Conservation? A Segmentation of Energy Consumers based on Energy-related Behavioral Characteristics," *Energy Policy*, vol. 39, no. 12, pp. 8137-8152, Dec. 2011.

[45] D. M. Gray, & B. Bean, "Can Social Marketing Segmentation Initiatives Be Used to Increase Household Electricity Conservation?" *Journal of Nonprofit & Public Sector Marketing*, vol. 12, pp. 269-305, 2011.

[46] D.S. Callaway, "Tapping the energy storage potential in electric loads to deliver," *Energy Conversion and Management*, vol. 50, no. 5, p. 1389–1400, 2009.

[47] C. Perfumo, E. Kofman, J.H. Braslavsky, "Load management: Modelbased control of aggregate power for populations of thermostatically controlled loads," *Energy Conversion and Management*, vol. 55, pp. 36-48, Mar. 2012.

[48] M. Heleno, M. A. Matos, J.A.P. Lopes, "Availability of thermal loads to provide reserve services," *IEEE PowerTech*, Grenoble, 2013.

[49] E. M. Tapia, S. S. Intille, and K. Larson, “Activity recognition in the home using simple and ubiquitous sensors,” in *Pervasive Computing*, 2004 [Online]. Available: http://web.media.mit.edu/~intille/papers-files/TapiaIntilleLarson04.pdf

[50] A. McCallum and K. Nigam, “A comparison of event model for naïve Bayes text classification,” *AAAI Workshop*, Madison, WI, USA, 1998.

[51] R. L. Rabiner and B. H. Juang, “An introduction to hidden Markov models,” *IEEE ASSP Mag.*, vol. 3, pp. 4–16, 1986.

[52] U.S. Energy Information Administration, “Annual energy review 2013,” Sep. 2014.

[53] L. W. Mays, “Water Resources Engineering”, 1st ed. Hoboken, NJ, USA: Wiley, 2001, p. 346.

[54] J. C. Laurent and R. P.Malhame, “A physically-based computer model of aggregate electric water heating loads,” *IEEE Trans. Power Syst.*, vol. 9, no. 3, pp. 1209–1217, Aug. 1994.

[55] C. Y. Chong and A. S. Debs, “Statistical synthesis of power system functional load models,” in *Proc. IEEE Conf. Decision Control*, Fort Lauderdale, FL, USA, 1979, F1.

[56] “ASHRAE Handbook: Fundamentals”, *America Society of Heating, Refrigeration and Air-Conditioning Engineering*, 1997.

[57] DOE Energy Plus [Online]. Available: http://apps1.eere.energy.gov/buildings/energyplus/

[58] W. Kempton, D. Feuermann, and A. E. McGarity, “I always turn it on super: User decisions about when and how to operate room air conditioners,” *Energy Buildings*, vol. 18, no. 3–4, pp. 177–191, 1992.

[59] R. H. Socolow, Ed., “Saving Energy in the Home”, Cambridge, MA, USA, pp. 231–254, 1978.

[60] “Charging at home” [Online]. Available: http://www.nissanusa.com/electric-cars/leaf/charging-range/charging/

[61] J. Seryak and K. Kissock, “Occupancy and behavioral effects on residential energy use,” in *Proc. Solar Conf.*, 2003, pp. 717–722.

[62] K. Ehrhardt-Martinez, K. A. Donnelly, and J. A. Laitner, “Advanced metering initiatives and residential feedback programs: A meta-review for household

electricity-saving opportunities," Jun. 26, 2010 [Online]. Available: http://www.aceee.org/research-report/e105

[63] Residential Energy Consumption Survey, U.S. EIA. [Online]. Available: http://www.eia.gov/consumption/residential/.

[64] American Time Use Survey, U.S. Depart of Labor. [Online]. Available: http://www.bls.gov/tus/.

[65] Qinran Hu, Xin Fang, Xiaojing Xu, Fangxing Li, Chien-fei Chen, Haolu Hu, "An Approach to Assess the Responsive Residential Demand to Financial Incentives," *IEEE PES General Meeting,* Denver, CO, Jul. 26-30, 2015.

[66] 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.

[67] A. Blaver, "Perth solar city annual report," Perth Solar City, Tech. Rep., 2011. [Online]. Available: http://www.perthsolarcity.com.au/annual-report/

[68] C. Dunstan, N. Ghiotto, and K. Ross, "Report of the 2010 survey of electricity network demand management in Australia," *Alliance to Save Energy Tech. Rep.,* 2011.

[69] J. H. Eto, C. Bernier, J. Kueck, J. Nelson-Hoffman, P. Young, B. Kirby, E. Parker, and D. Sheehan, "The demand response spinning reserve demonstration -

measuring the speed and magnitude of aggregated demand response," in *Proc. of the Annual Hawaii International Conference on System Sciences*, pp.2012-2019, 2011.

[70] "Demand management program interim report no. 3", ETSA Utilities, 2010. [Online]. Available: www.etsautilities.com.au/public/download.jsp?id=11891

[71] G. Heffner, C. Goldman, B. Kirby, and M. Kintner-Meyer, "Loads providing ancillary services: Review of international experience," Lawrence Berkeley National Laboratory Rep., May 2007.

[72] B. Kirby, J. Kueck, T. Laughner, and K. Morris, "Spinning reserve from hotel load response: initial progress," Oak Ridge National Laboratory and Tennessee Valley Authority, Tech. Rep, 2008.

[73] "Energy use in the Australian residential sector 1986–2020," Department of the Environment, Water, Heritage and the Arts, Tech. Rep., 2008.

[74] J. Fortuny-Amat and B. McCarl, "A representation and economic interpretation of a two-level programming problem," *J. Oper. Res. Soc.*, vol. 32, no. 9, pp. 783-792. Sep. 1981.

APPENDIX

List of Abbreviations

AC	Air Conditioner
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
ATUS	American Time Use Survey
CPP	Critical Peak Pricing
CURENT	Center for Ultra-Wide-Area Resilient Electric Energy Transmission
CV	Comfort Level Violation
DA	Day Ahead
DMS	Distribution Management System
DOE	Department of Energy
DR	Demand Response
DRR	Demand Reduction Request
EAB	Environmental Attitudes and Behaviors
ED	Economic Dispatch
EIA	Energy Information Administration
EV	Electrical Vehicle
EWH	Electrical Water Heater
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
HC	Heating-Cooling
HMM	Hidden Markov Model

I-DR	Incentive based Demand Response
ISO	Independent System Operator
LMP	Locational Marginal Price
LSE	Load Serving Entity
MTurk	Mechanical Turk
NBC	Naive Bayes Classifier
NYISO	New York independent system operator
RECS	Residential Energy Consumption Survey
RPR	Reduced Power Ratio
RT	Real Time
RTP	Real Time Pricing
SCRFI	Survey of Customers' Reactions to Financial Incentives
SHEMS	Smart Home Energy Management System
TOU	Time of Use
UI	User Interface
USDL	U.S. Department of Labor
UTK	University of Tennessee at Knoxville

Publications during Ph.D. Study

Related Journal Papers

[J1] **Q. Hu**, F. Li, X. Fang, and L. Bai “An Optimal Framework for Residential Load Aggregators,” *IEEE Trans. on Smart Grid*, under review, 2015.

[J2] X. Fang, F. Li, **Q. Hu**, and Y. Wei, “The Impact of FTR on Load Serving Entities’ Strategic Bidding Considering Coupon Based Demand Response and Wind Uncertainty,” *IEEE Trans. Industrial Informatics*, under review, 2015.

[J3] X. Fang, **Q. Hu**, F. Li, B. Wang, Y. Li, “Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities,” *IEEE Trans. on Power Systems*, in press, 2015.

[J4] **Q. Hu**, F. Li, and C. Chen, "A Smart Home Test Bed for Undergraduate Education to Bridge the Curriculum Gap Between Traditional Power Systems and Modernized Smart Grids," *IEEE Trans. on Education*, vol.58, no.1, pp.32-38, 2015.

[J5] **Q. Hu** and F. Li, "Hardware Design of Smart Home Energy Management System with Dynamic Price Response," *IEEE Trans. on Smart Grid*, vol. 4, no. 4, pp. 1878-1887, Dec. 2013.

[J6] 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, Jul. 2013.

Other Journal Papers

[J7] J. Mei, Y. Ji, C. Huang, **Q. Hu**, and X. Du, “Quasi-fixed-frequency Hysteresis Current Tracking Control Strategy for Modular Multilevel Converters,” *Journal of Power Electronics*, vol. 14, no. 6, pp. 1147-1156, 2014.

[J8] J. Mei, J. Yu, X. Du, T. Ma, C. Huang, and **Q. Hu**. “Balancing Control Scheme based on Virtual Loop Mapping with Fault-tolerance Capabilities for Modular Multilevel Converters," *IEEE Trans. on Industrial Electronics*, in press, 2015

[J9] X. Dou, K. Yang, X. Quan, **Q. Hu**, Z. Wu, B. Zhao, and P. Li, “An Optimal PR Control Strategy with Load Current Observer for A Three-phase Voltage Source Inverter of Battery Energy Storage System,” *Energies*, in press, 2015

[J10] X. Kong, L. Bai, **Q. Hu**, F. Li, and C. Wang, “Day-Ahead Optimal Scheduling Method for Grid-connected Microgrid Based on Energy Storage Control Strategy,” *to be submitted to Electrical Power System Research*, 2015.

Conference Papers

[C1] **Q. Hu**, X. Fang, X. Xu, F. Li, C. Chen, and H. Hu, “An Approach to Assess the Responsive Residential Demand to Financial Incentives,” *IEEE PES General Meeting 2015*, Denver, CO, Jul. 26-30, 2015.

[C2] X. Fang, F. Li, **Q. Hu**, Y. Wei, and N. Gao, “The Impact of FTR on LSE’s Strategic Bidding Considering Coupon Based Demand Response,” *IEEE PES General Meeting 2015*, Denver, CO, Jul. 26-30, 2015.

[C3] L. Bai, T. Ding, **Q. Hu**, F. Li, and H. Sun, “Robust Mean-Variance Optimization Model for Grid-Connected Microgrids,” *IEEE PES General Meeting 2015*, Denver, CO, Jul. 26-30, 2015.

[C4] X. Fang, F. Li, **Q. Hu**, N. Gao, "System Load Margin Evaluation using Mixed-Integer Conic Optimization," *47th North American Power Symposium (NAPS2015)*, Charlotte, NC, Oct. 4-6, 2015.

[C5] **Q. Hu**, J. Chan, D. Chen, and F. Li, “A Comprehensive User Interactive Simulation Tool for Smart Home Application,” *Australasian Universities Power Engineering Conference (AUPEC)*, Perth, Australia, Sept. 28-Oct. 1, 2014.

[C6] S. Adhikari, F. Li, **Q. Hu**, and Z. Wang, "Heuristic optimal restoration based on constructive algorithms for future smart grids," *16th International Conference on Intelligent System Application to Power Systems (ISAP),* Crete, Greece, Sept. 25-28, 2011.

Book Chapters

[B1] F. Li, P. Zhang, S. Adhikari, Y. Wei, and **Q. Hu**, "Vision of Future Control Centers in Smart Grids," Smart Grid Infrastructure & Networking, McGraw-Hill Professional, ISBN-10: 0071787747, Jun. 2012.

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