Hardware Design of Smart Home Energy Management System With Dynamic Price Response

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***Abstract*—The smart grid initiative and electricity market operation drive the development known as demand-side management or controllable load. Home energy management has received increasing interest due to the significant amount of loads in the residential sector. This paper presents a hardware design of smart home energy management system (SHEMS) with the applications of communication, sensing technology, and machine learning algorithm. With the proposed design, consumers can easily achieve a real-time, price-responsive control strategy for residential home loads such as electrical water heater (EWH), heating, ventilation, and air conditioning (HVAC), electrical vehicle (EV), dishwasher, washing machine, and dryer. Also, consumers may interact with suppliers or load serving entities (LSEs) to facilitate the load management at the supplier side. Further, SHEMS is designed with sensors to detect human activities and then a machine learning algorithm is applied to intelligently help consumers reduce total payment on electricity without or with little consumer involvement. Finally, simulation and experiment results are presented based on an actual SHEMS prototype to verify the hardware system.**

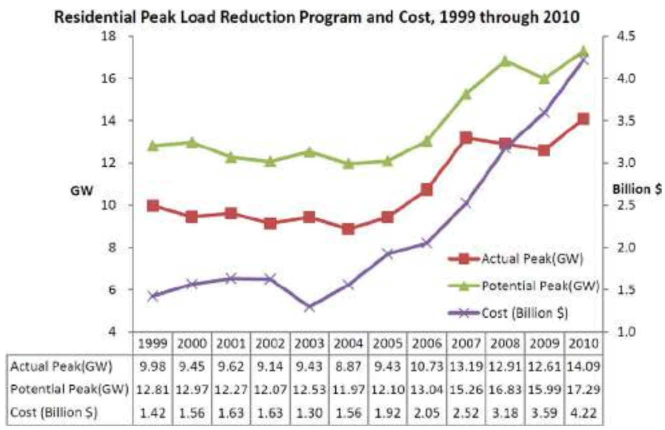
***Index Terms*—Controllable load, demand response, dynamic pricing, embedded system, machine learning, optimal control strategies, peak shaving, remote operation, smart home energy management system (SHEMS).**

NOMENCLATURE

F_i	Signals from sensors.
C	User's activity.
$X_T(t)$	Temperature in electrical water heater at time t, °C.
$X_a(t)$	Ambient temperature at time t, °C.
a	Thermal resistance of tank walls, W/°C.
$A(t)$	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 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 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 the user needs to pick up things from the dishwasher, the washing machine or the dryer.

I. INTRODUCTION

THE electricity prices in a competitive power market are closely related to the consumers' demand. However, the lack of real-time pricing (RTP) technologies presents challenges to electricity market operators to optimally signal and respond to scarcity, because electricity cannot be stored economically [1]. In the past a few years, the deployment of advanced metering infrastructures (AMI) and communication technologies make RTP technically feasible [2]. RTP, generally speaking, reflects the present supply-demand ratio and provides a means for load-serving entities (LSEs) and independent system operators (ISOs) to solve issues related to demand side management such as peak-load shaving. Applications of RTP enable consumers and suppliers to interact with each other, which also creates an opportunity for consumers to play an increasingly active role in the present electricity market with optimal control strategies at the demand side.



	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

Fig. 1. Residential peak load reduction program and cost.

According to the *Monthly Energy Review* in April 2012 by U.S. Energy Information Administration (EIA), the residential electricity use in the United States in 2011 is 1 423 700 million kWh [3], which includes 38%, the largest share, of the total electricity use. Fig. 1 is re-generated based on [4] and [5] to shows the increasing development and investment in demand side management, in particular, peak load reduction. In addition, for residential loads, both of the actual peak load reduction and the potential peak load reduction in the U.S. will continue to grow in pace. Thus, the device with a focus on demand side management has a bright market prospect.

In order to further optimize residential load consumption, it is reasonable to design a smart home energy management system (SHEMS) based on RTP response to reduce the total electricity payment cost for consumers, and meanwhile, to flatten demand peaks.

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 [6][7][8][9] point out that SHEMS will be an important and necessary component in future smart grid. As for the hardware prototypes, a wireless, controllable power outlet architecture is introduced in [10] 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 [11]. As for the design simulations, an agent-based smart home architecture is proposed in [12], in which prediction of inhabitant activity and related automated control is considered. Based on the architecture in [12], further analyses of the prediction algorithms and the automated control of an agent-based smart home are discussed in [13]. The real-time pricing issues in residential energy consumption scheduling are discussed in [14], [15]. In [14], residential distributed energy resources are collectively considered to give a coordinated scheduling. In [15], a dynamic price responsive algorithm which leads to significant reduction in users' payment is discussed. Also, there are some works related to home energy management documented in [16][17][18][19].

On one hand, the previous hardware prototypes in the literature rarely considered the implementation and design of machine learning to achieve the dynamic price responsive load management. On the other hand, many simulation studies in the literature rarely gave a SHEMS hardware design although they considered an individual issue from the "software" side such as machine learning algorithm, dynamic price responsive mechanism, and other challenges in practical applications.

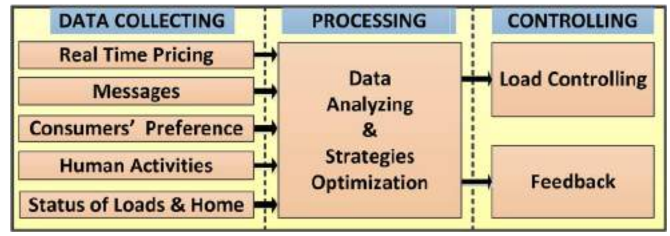


Fig. 2. Expected major functions of the proposed SHEMS

In contrast, this paper presents a SHEMS hardware design integrated with a machine learning algorithm to achieve dynamic price response. Thus, this work collectively considers both interests from the electricity supplier side and the customer side. Particularly, this paper presents a hardware design of a SHEMS system with communication, sensing technology, and machine learning. This paper also presents the experimental and simulation results based on a SHEMS prototype to verify the proposed hardware system.

Organization of this paper is as follows. Section II analyzes the functions that the proposed SHEMS design needs to implement. Section III presents the details of the SHEMS hardware design. Section IV discusses the machine learning algorithm applied to this work. Section V presents several typical appliance models and demonstrates a verification study based on the proposed design. Section VI compares the proposed design with other products and concludes the paper.

II. Functional Requirement Analysis

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

From the consumers' viewpoint, 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 or appliance at home in accordance with the variation of the real-time price, the preferred comfort level, the environmental temperature, and so on. As shown in Fig. 2, the primary function of the proposed SHEMS includes:

1) To collect useful information and other messages such as RTP, consumers' preference, human activities at home, status of load and battery;
2) To generate the optimal strategy by analyzing the collected data;
3) To modify or adjust the settings of loads based on the automatically generated strategy by the control algorithms; and
4) To send the feedback and other relevant data back to the load-serving entity (LSE).

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

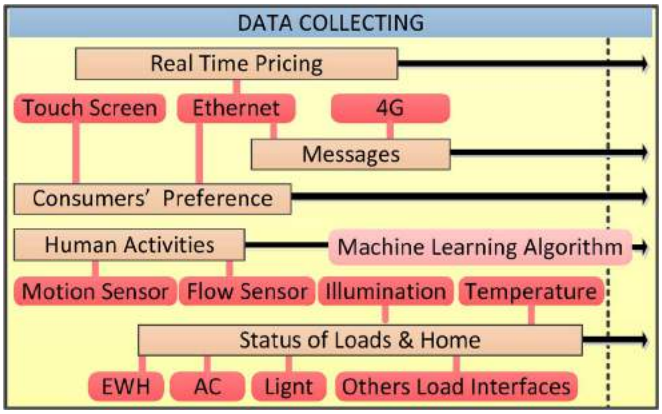


Fig. 3. Summary of the data collection part

A. Data Collection

1) Real Time Pricing: An Internet connection is necessary for reading the RTP signals from the supplier or LSE of the residential load. 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 consumers such as scheduled outages, weather alerts, and so on. Meanwhile, the consumers should be able to report issues related to electricity usage, which include meter-reading, billing, and payment. Note that 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) Consumers' Preference: In order to obtain the consumers' preference, a touch screen user interface is included for each consumer to manually change the settings at home. Also, with the Ethernet module already mentioned in 1), it is feasible for remote changes to the consumers' settings.
4) Human Activities: Motion and flow sensors need to be installed to collect useful data of human activities at home. By applying machine learning algorithms in the processing part, the consumer activities related to energy consumption can be predicted. For instance, the temperature settings of the consumer's electrical water heater (EWH) and heating, ventilation, and air conditioning (HVAC) unit may be changed to a lower setting if little human motion is detected. As such, SHEMS is able to further optimize residential load consumptions.
5) Status of Loads and Home: Interfaces need to be developed to obtain the status of loads at home, such as EWH, HVAC, electric vehicle (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.

Fig. 3 below summarizes this part. A notable highlight is that the design deploys both 4G and Ethernet in communication to make the system more robust.

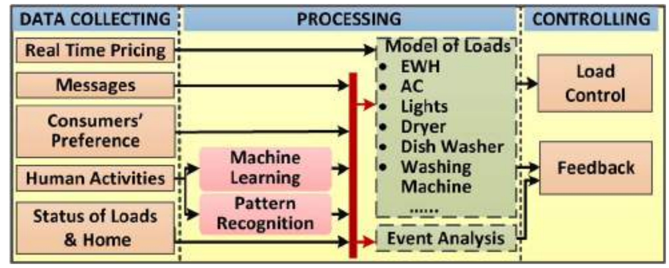


Fig. 4. Summary of the processing part.

B. Processing

The design will optimize the load consumption strategy based on the collected data by a processor that works as the brain of SHEMS. Below are tasks for the processor to perform.

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 to interact with the consumer. In addition, the processor may host a customized webpage on which remote control is implemented.
3) Event Analysis: The processor reminds the consumer about the messages from the utility supplier through a specific user interface. This information may affect the scheduling of the residential loads, and the proposed design should have the capability of analyzing these events and providing information such as whether the room temperature still meets the consumer's preference. 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 consumer's uncomfortableness. Further, SHEMS should alarm the consumer about whether the comfort level will be significantly impacted under any inclement event.
4) Human Activity Prediction: Machine learning and pattern recognition algorithms will be implemented to analyze and predict human activities based on data collected by motion and flow sensors. The prediction can provide important information for the processor to generate optimal strategy 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 consumer's living habits. That is, the longer the system is in use, the more accurate the predictions can be.
5) Load Optimal Strategies: Since all the useful information including RTP, consumer needs, special events, and human activities can be obtained, the processor will offer the optimal strategy for each load based on the models of different loads.

Fig. 4 summarizes the processing part. The collected data of human 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.

C. 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 all appliances. Meanwhile, in the proposed design the load interfaces are also expected to modify the settings of appliances according to the results calculated from the processing part.

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

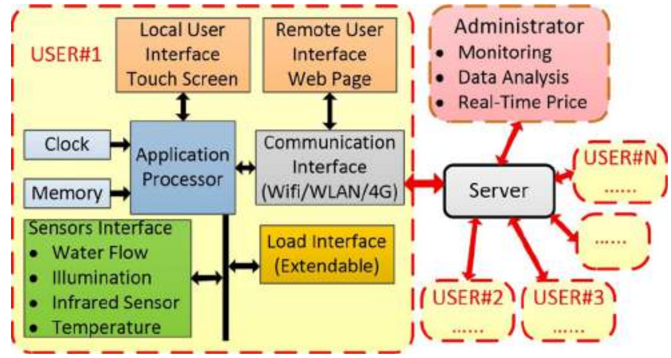


Fig. 5. Brief hardware design of SHEMS.

III. Proposed Hardware Designs

According to the functional requirement, the objective of SHEMS is to enable minimization of the consumer's total electricity payment cost meanwhile satisfying the consumer's needs in comfortableness such as the indoor temperature, the hot water temperature, and the indoor illumination. SHEMS will identify optimal load control strategy responsive to the electricity RTPs, the consumer's needs, as well as extreme scenarios. Further, SHEMS should also have the ability for administrators (utility suppliers) to monitor and analyze the real-time status of a specific area or home.

Fig. 5 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 consumer 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 RTPs, 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 (UI): Since ordinary consumers 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 consumer's side. The touch screen, which is driven by the processor, provides a local UI to the consumer. 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 consumer's needs after several weeks of automated training with the data monitored. In this approach, consumers 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 human 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 HVAC should work as a remoter to set the 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.

- Comfortable mode: In this mode, the highest priority of SHEMS is to ensure the most comfort level for consumers. That is, a consumer will always have sufficient hot water and prefect room temperature, and the consumer's comfort level will not be reduced by participating in the supplier's demand response program.
- Smart mode: In this mode, SHEMS will make a tradeoff between the comfort level and the payment saved. Occasionally, the consumer probably has to bear the water with a

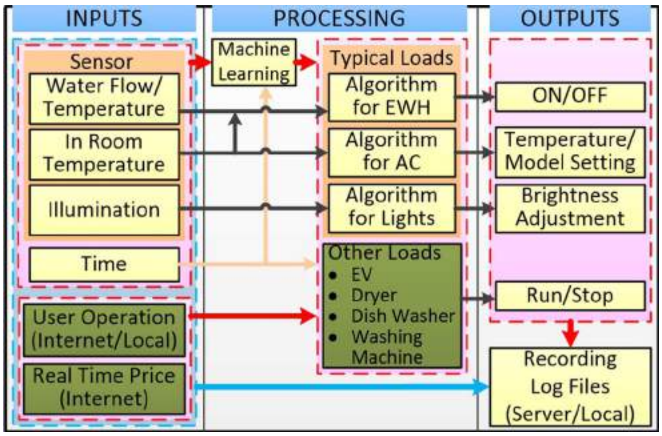


Fig. 6. Schematic design of SHEMS (user end).

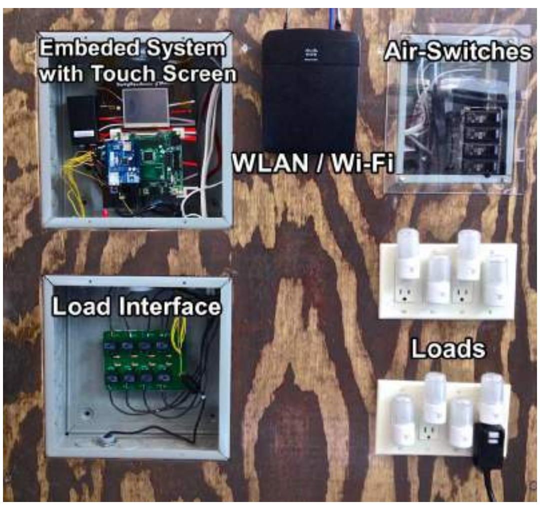


Fig. 7. Model platform of SHEMS.

little lower temperature than normal, and also a little difference (e.g., $\pm 3\ ^\circ\mathrm{C}$ or $5\ ^\circ\mathrm{F}$) in indoor temperature. SHEMS will take part in the load reduction program, if it does not affect the consumer's comfort level much.

- Saving mode: In this mode, the highest priority of SHEMS is to save the total electricity payment. In peak hours, consumers may have to bear the water with a lower temperature than normal, and also some difference (e.g., $\pm 5\ ^\circ\mathrm{C}$ or $9\ ^\circ\mathrm{F}$) 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 Fig. 6. It demonstrates how SHEMS processes the inputs, applies machine learning algorithm, calculates the optimal strategy, and uploads useful information to the server.

Based on the design described above, a model platform is established as shown in Fig. 7. The model platform of SHEMS is based on Stellaris LM3S9D96 MCU, and it realizes the functions mentioned in Section II. 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 tasks: 1) reading real-time prices; 2) providing optimal control strategy with automatically adjusted loads including EWH, HVAC, 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.

IV. Machine Learning Algorithm for SHEMS

A machine learning algorithm is implemented in the proposed SHEMS prototype design to analyze and predict human 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 [20]. In that experiment, sensors are installed in a single-person apartment collecting data about human 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.

A. 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 [21] given by $p(C|F_1,\ldots,F_n)$, 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

$$p(C|F_1,\ldots,F_n) = \frac{p(C)p(F_1,\ldots,F_n|C)}{p(F_1,\ldots,F_n)} \tag{1}$$

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

B. Hidden Markov Model

A hidden Markov model (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 [22]. 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

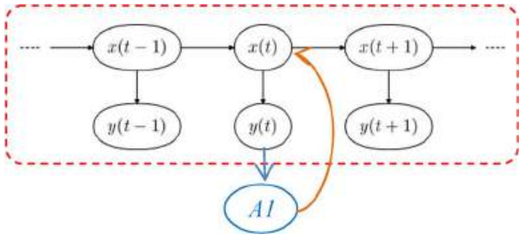


Fig. 8. The learning process of SHEMS.

TABLE I
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**

sensors as well as the previous classification results generated by NBC.

Markov matrix, 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 consumer's behavior.

Fig. 8 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.

C. Simulation Results

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

Fig. 9. Electricity end use of year 2011, USA.

TABLE II
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 °C)

TABLE III
WATER USAGE INFORMATION FOR TESTING

Residents (Persons)	4
Resident Type	Townhouse
Daily Water Demand	1000 Liter
Low Temperature Setting	40°C
High Temperature Setting	80°C

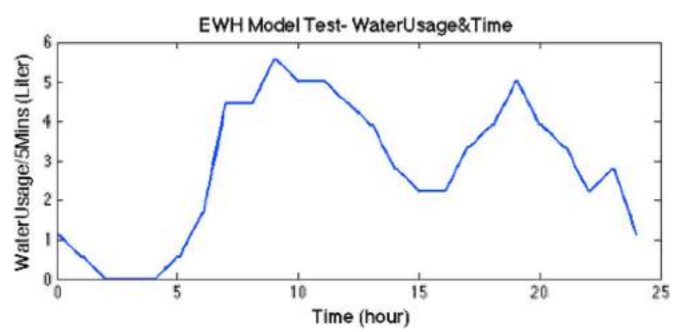


Fig. 10. Typical water usage curve for 24 hours.

V. APPLIANCE MODELS AND VERIFICATION RESULTS

In this section, various appliance models are studied first in Sections V-A to V-C. Then, test and verification studies about the effect of the proposed SHEMS system are presented.

Residential load profiles are inherently difficult to model. Each household has a different lifestyle and set of habits. There is also a wide variation in the load profiles of different appliances. According to [3], residential load is the largest share in electricity end use of year 2011, as shown in Fig. 9.

As for residential electricity use, EWH and HVAC hold two largest shares totaling 53% of the total residential electricity consumption [23], or 20% of the total electricity consumption. Hence, this section discusses the detailed model of EWH and HVAC with some testing results because these two have a great potential to be optimized by SHEMS. Nevertheless, the models of EV, dishwasher, washing machine and dryer are also briefly discussed since they have potentials in demand response programs as well.

A. Electrical Water Heater (EWH)

The general model of EWH has been discussed in [24]–[26]. The discrete state dynamics model is applied here, since the RTP

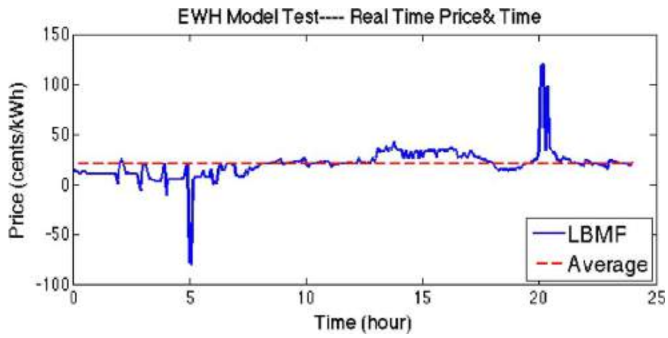


Fig. 11. Real time price curve for 24 hours.

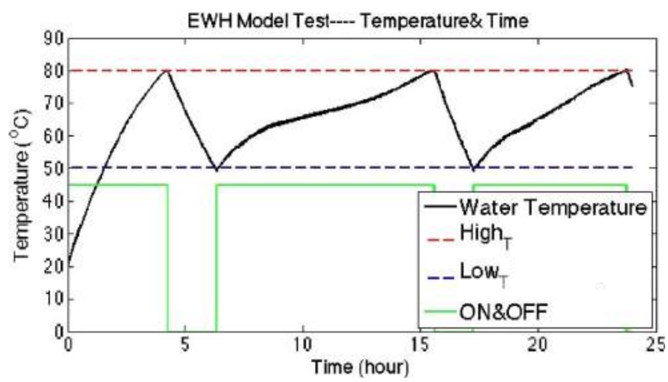


Fig. 12. Typical EWH strategy [26].

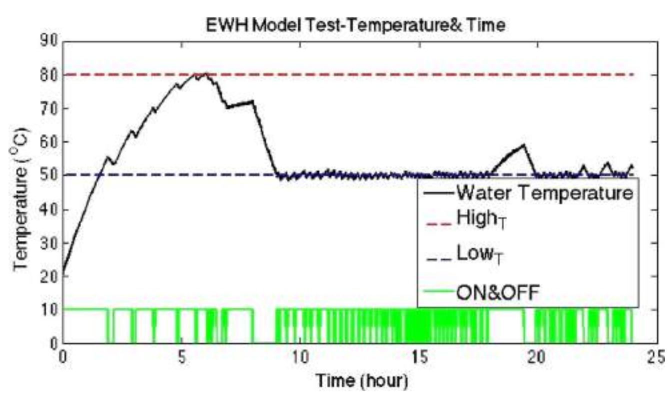


Fig. 13. Optimized EWH strategy.

signal may change as fast as every 5 minutes which is a discrete variable. The model can be described by:

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

Table II shows the specifications of EWH used in the experiment. For testing and simulation purposes, Table III shows some useful information applied here. Also, a typical water usage curve as shown in Fig. 10 is obtained from [25].

In this study, the locational marginal price (LMP) on a randomly selected day from NYISO is used as the real-time price, which is shown in Fig. 11. The result without SHEMS is shown in Fig. 12, and the results after applying an RTP-responsive algorithm to change the ON and OFF strategy of EWH is shown in Fig. 13.

The optimized strategy used in the test can be further improved in future algorithm/software studies, while this paper 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 consumer demand of water usage with a look-ahead consideration. For example, the algorithm will preheat the EWH to a higher temperature before the consumer takes a shower. The mathematical description is an optimization model given below.

$$\min \int_0^{24} RTP(t) \cdot m(t) \cdot P_{EWH} \quad (3)$$

$$\text{s.t.}: \quad \text{Eq. } (2)$$

$$T_{low} \leq X_T(t) \leq T_{high} \quad (4)$$

Since $RTP(t)$ refreshes every 5 minutes, this model given by (2), (3), and (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 consumer's needs.

The result verifies that SHEMS helps reduce the thermostat ON time by 14%, while reducing the consumer's 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 Fig. 13.

B. Heating, Ventilation, and Air Conditioning (HVAC)

The American Society of Heating, Refrigeration and Air Conditioning Engineers, Inc. (ASHRAE) has compiled modeling procedures in its Fundamentals Handbook [27]. The Department of Energy has produced the Energy Plus program for computer simulation [28]. Also, the detailed model for simulating HVAC systems is given in [29], [30]. 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 HVAC parameters are difficult to be precisely modeled with the possibility to change over the time due to other factors.

Thus, 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 HVAC unit.

In this experiment, the SHEMS optimizes the HVAC 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 IV shows the related parameters.

For comparison purpose, a parameter named "Comfort Level" is considered here. In market economics, a consumer 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

TABLE IV
HVAC PARAMETERS IN THE TEST

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

TABLE V
HVAC RESULTS WITH SHEMS

	Different Comfort Level		
	+/- 0°C	+/- 3°C (5.8°F)	+/- 5°C (9°F)
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%

means the difference between the actual indoor temperature and the temperature desired by the consumer.

Table V 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 the table, considerable reduction of energy consumption and payment is achieved. Further, if a consumer can tolerate a higher temperature difference, more payment or credit to HVAC from the supplier can be achieved. This is sensible from the standpoint of market economics.

C. EV, Dishwasher, Washing Machine and Dryer

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 electric vehicle (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 [15]. It is possible to charge the battery for 1 h, 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.

1) Electrical Vehicles: An EV should be fully charged, for example, at 8 A.M. 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 8 A.M..

As an interruptible load, the mathematical expression of the discrete model of EV can be expressed in (5) and (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.

TABLE VI
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

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

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

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 (7), (8), and (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.

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

$$\text{s.t. : } T_{hready} \leq T_{hstart} \leq T_{hend} \tag{8}$$

$$T_{hready} \leq (T_{hstart} + T_{huse}) \leq T_{hend} \tag{9}$$

D. Effects of SHEMS in Load Shifting

Based on the previous analysis on EWH and HVAC, it is rational to conclude that SHEMS can make substantial contribution to reduce home energy consumption from not only EWH and HVAC but also EV, dishwasher, washing machine, dryer, etc. To study the effect of SHEMS in a large-scale system, this section 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 HVAC parameters are the same as from the previous Sections V-B and V-C. The EV parameters are chosen based on Nissan Leaf [31] 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 VI.

The reduction of energy consumption from individual appliance is scaled up to simulate the optimized residential load consumption. The results are shown in Fig. 14, 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.

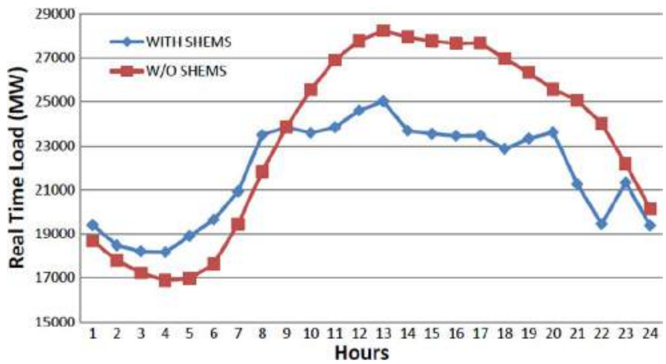


Fig. 14. Load curve comparison with and without SHEMS.

VI. Comparative Analysis and Conclusion

A. Comparative Analysis

As mentioned in the Introduction, there are several companies working on products related to demand response. However, those early products do not take full considerations of all aspects mentioned in this paper. 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" [32], [33]. 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 consumers 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 consumer wants to control HVAC 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 VII provides a high-level comparison of the proposed design and 4 SHEMS-like devices from commercial vendors. These 4 devices include Monitor12 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 VII. 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 HVAC.

TABLE VII
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

Note that 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 VII for future references.

B. Conclusion

This paper presents a hardware design of a smart home energy management system (SHEMS) with the application of communication, sensing technology, and machine learning algorithm. With the proposed design, consumers can achieve a RTP-responsive control strategy over residential loads including EWHs, HVAC units, EVs, dishwashers, washing machines, and dryers. Also, they may interact with suppliers or load serving entities (LSEs) to facilitate the management at the supplier side. Further, SHEMS is designed with sensors to detect human activities and then apply machine learning algorithm to intelligently help consumers reduce total electricity payment without much involvement of consumers. In order to verify the effort, this paper also includes testing and simulation results which show the validity 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, if this design can be widely used in the future, the administrator-user structure will provide good potentials for electricity aggregators. Most likely, utilities may not be interested or motivated to administrate all individual, millions of end consumers directly and simultaneously. Therefore, electricity aggregators can play as agents between consumers and utilities. This business mode may facilitate the popularity of SHEMS or similar systems and create win-win results for all players.

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