ABSTRACT

YAN, JIAHONG. Development and Implementation of a Time-of-Use Based Home Energy Management System. (Under the direction of Dr. Ning Lu).

Power system is experiencing rapid change on both supply and demand side. The increasing renewable generation, such as solar and wind generation, cause more variation of power supply and operation uncertainty, while the behind-meter solar and transportation electrification are reshaping the end-use demand curve. Such a change brings system operators a challenge to balance the system reliably and economically. On the other hand, load service entities are implementing time-varying electricity price to reflect the true cost of generation in a day, and energy consumers need to use energy accordingly. Thus, both system operators and energy consumers are seeking a tool to resolve the new problem raised by new trend in power system. In this dissertation, I focus on developing and implementing an Home Energy Management System (HEMS) with an objective to save residential costumers' energy cost and improve the energy demand curve for the power system.

Chapter 2 reviews the current technologies in HEM, and proposes a prototype of HEMS with both software and hardware design. A physical test system and graphical-user-interface of HEM is designed and implemented at FREEDM Center of North Carolina State University (NCSU). A demonstration case shows the functionalities and capability of an HEMS.

As an essential component in HEM, the household energy demand forecast is studied in Chapter 3. The proposed forecaster provides both day-ahead and hour-ahead demand forecast for HEMS. Considering the high volatility and randomness of house-level energy demand, progressive technologies are used to forecast the demand in both probabilistic and deterministic ways. In day-ahead, similar days are grouped based on the weather and "day of week" information, then a multinomial logistic regression model is used to estimate the probabilities of

household load levels. In hour-ahead forecast, the forecaster uses Kalman filter to recursively updates a state-space model to provide point estimate of hour-ahead load. Case study with 20 realistic house energy demand data show the effectiveness of the proposed forecasting approach.

Another core component of HEM is the scheduling algorithm. In chapter 4, controllable appliances are categorized in three main types and modeled according to their physical features. Instead of using mathematical optimization approach, the propose scheduling algorithm schedules smart load in a heuristic way based on different model types, such that it is computational effective and robust to demand forecast uncertainty. More important, the proposed HEM considers users' comfort preference and the cost saving expectation. A mechanism is developed to quantify users' cost saving expectation in return of comfort setting sacrifice. A case study shows the cost saving and load profile improvement are achieved by the proposed HEM.

In Chapter 5 of the dissertation, the aggregate impact of HEM is discussed. The main problem for high penetration HEM is the "loss of load diversity" issue. A control strategy is proposed to mitigate such an issue by introducing an artificial randomness in each individual HEMS. A case study with IEEE 123-node feeder system shows how the mitigation approach improve the system reliability and efficient. In addition, Chapter 5 discusses how the proposed HEMS can map the household-level smart appliance to demand response in wholesale energy market. A three-bus system example shows the aggregate HEM can relieve transmission congestion and reduce the total system cost.

Development and Implementation of a Time-of-Use Based Home Energy Management System

by
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DEDICATION

To my father Guoquan Yan, my wife Cuiyan Kong and my daughter Keira Yan

BIOGRAPHY

Jiahong Yan was born in Guangdong, China. He received his B.S. degree in electrical engineering from South China University of Technology, Guangzhou, China in 2010, and his M.S. degree in electrical engineering from Tianjin University, Tianjin, China in 2013. He is currently pursuing the Ph.D. degree in electrical engineering at North Carolina State University, Raleigh, NC. His current research interests include home energy management system, energy demand forecasting and optimization, and demand response in deregulated energy market.

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CHAPTER 1 INTRODUCTION

This chapter introduces the state-of-the-art of demand side management technologies, presents the technical challenges, and summarizes the main contribution of the thesis.

1.1 An Overview of Demand Side Management Methods

Traditionally, power systems operation applies a centralized, top-down approach. Electricity is generated by large, MW-level power plants. Power flows are normally one-directional in power distribution grid: from substations to the loads. In the past ten years, renewable generation resources are rapidly integrated to the grid from both the transmission and distribution level, causing significant increase in power variations and uncertainties in grid operation [1]. Furthermore, behind meter solar and the rapidly adoption of electrical vehicles are causing shifts in residential and commercial load patterns [2, 3]. The famous California daily "duck curve" illustrates the drastic change in daily load profiles at regional level caused by the increase in solar generation across the state. As shown in Figure 1.1, a deep valley is formed in the middle of the day. This causes a sharp decrease of energy consumption after the solar generation picks up the load in the morning right after a steep increase to the morning peak in the early evening (7 – 9 p.m.). This curve is not unique to California. Many grid operators in areas with high solar penetration feeders start to observe such load patterns.

The "duck curve" brings two main issues to the power system operators and planners: maintain enough conventional generation capacity to supply peak load while solar generation is not available and maintain enough flexible ramping resources to follow the variations caused by both the load and the renewable generation resources.

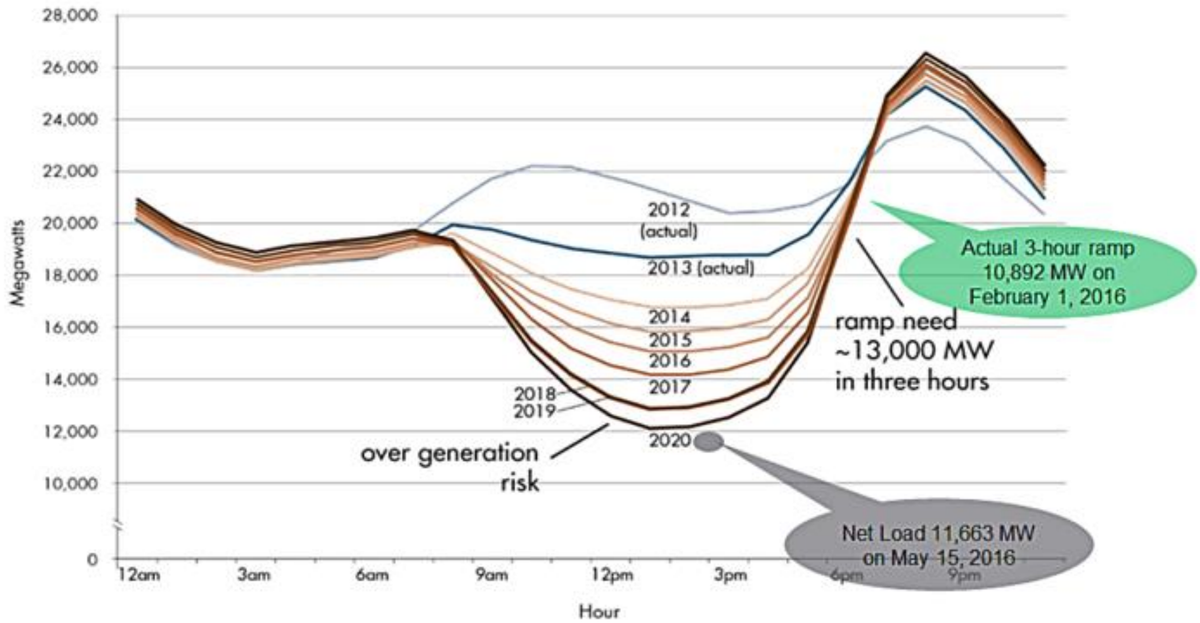


Figure 1.1 CAISO's 2013 illustration of the "duck curve"[4]

Demand Side Management (DSM) is the demand side solutions to alleviate the power system stress of energy balancing. Main DSM applications include load shifting [5], peak shaving [6], load following [7], frequency response [8], and smoothing of intermittent generation resources [9] using distributed energy resources such as energy storage, distributed generators, electric vehicles, or controllable loads. Traditionally, DSM was mainly used for peaking shaving and load shifting for hedging price spikes, investment deferral, or low-frequency load shedding [10]. In recent years, there are some new trends in DSM due to the smart grid initiative and new pricing schemes in electricity market operation:

- Using the data collected in DSM programs for advanced data analytics such as load forecast, end use pattern detection, nonintrusive load monitoring, fault detection, etc.
- Accurate real-time load control. The reduction in the cost of wireless communication makes it affordable for more accurate real-time load control via smart meters or smart switches.

- Time-varying retail prices are implemented by the Load Serving Entities (LSE) to reflect the wholesale electricity market (if applicable) price dynamic or system status. It requires intelligent DSM to help energy consumers to adjust their demand patterns accordingly.
- The DSM promotes the distributed generation consumed locally, deferring new transmission line expansion or reducing energy storage requirement.
- In the past, the DSM is mainly "utility driven", it moves towards "customer driven" in the future.

These new trends in the DSM draws increasing attention from both research and industry on developing advance energy management systems for energy consumers, especially for residential consumers. According to U.S. Energy Information Administration (EIA), the residential electricity use in U.S. is over one third of the total electricity use [11], which is the largest share sector. The DSM on residential load is expected to provide significant response to enhance the power system reliability, economic, and eco-friendly. Therefore, I selected the topic of my Ph.D. thesis in the area of design and implementation of a robust and cost-effective Home Energy Management System (HEM) for benefiting both the power system and residential consumers.

1.2 Home Energy Management System

The research of HEM was started in 1990s [12-14] in order to extend the DSM policy to domestic customers. However, due to the lack of 2-way communication infrastructure and tariff incentives, the interest of developing HEM was minimal until the emerging of "smart home" in recent years [15]. Basically, the smart house consists of monitorable and controllable appliances/devices, which are managed by the HEM. Figure 1.2 shows the schematic diagram of a smart house.

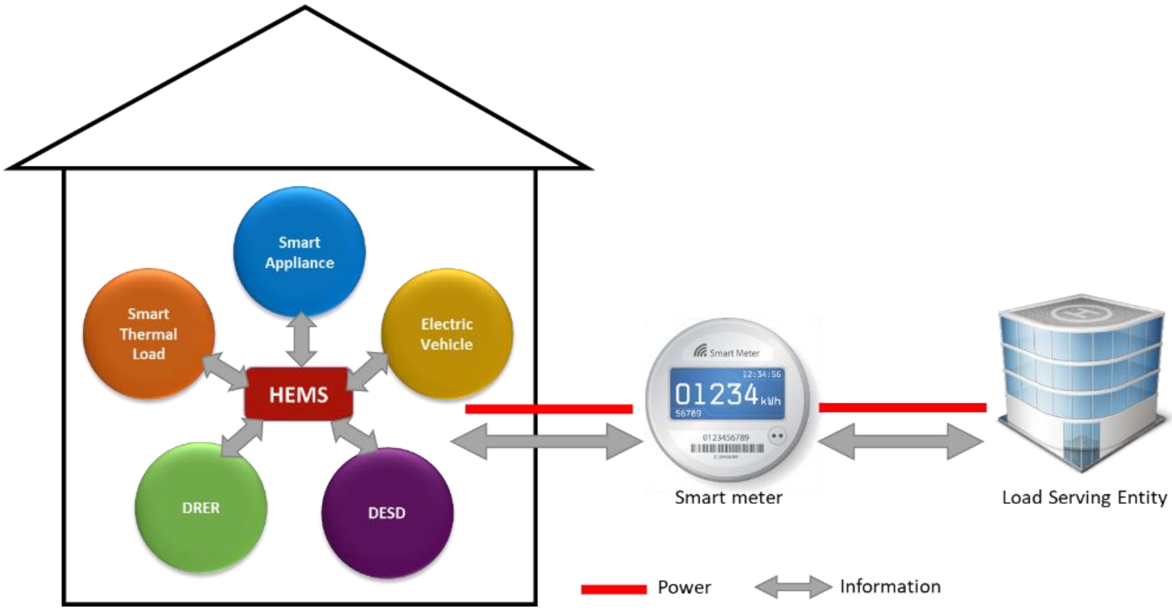


Figure 1.2 Smart house schematic diagram

Nowadays, many companies are developing varied smart home products, including intelligent home security, smart TV, smart appliance (e.g. washer & dryer), smart thermostat [16, 17] and smart light bulb, etc. The HEM is an essential sub-system in a smart home to make it "smart" and "green". The HEM manages the household energy consumption in order to improve the users' comfort and energy cost saving, especially in the present of time-varying residential retail pricing schemes [18], such as Time-Of-Use [19, 20], Real-Time-Price [21,22], Critical-Peak-Price [23], Incremental-Block-Rates [23], Demand Charge [24] and some monetary incentives/credits [25]. In general, the HEM communicates with external information (e.g. DSM request, weather) and household devices, and finds the optimal schedules of the energy consumption/production of the device. The HEM can reduce the household energy cost as well as help the power grid as a DSM tool. In addition, other advantages of using HEM include minimization of energy waste, detection of device inefficiency, be eco-friendly and educating residents energy saving behaviors.

At present, the research of HEM focuses on two aspects: the architecture design of HEM and the HEM control algorithm/strategy development. The HEM architecture design includes the connection topology of household device [26, 27], communication protocol [28, 29], data collection and visualization [30], and controller location (e.g. centralized or distributed) [31, 32, 33]. In the development of HEM control algorithm, there are three main approaches of device scheduling: the mathematical optimization [34-36], model predictive control [37, 38], and heuristic control [39-41]. The data requirement, computation complexity and optimality can be significantly different among different approaches.

Regarding to these two research aspects of HEM, there are two phases in my thesis. The first phase is to develop a cost-efficient and user-friendly HEM prototype embedded in a smart microgrid system, including hardware and software architecture design and implementation. The second phase is to develop HEM control algorithms for demand forecasting and scheduling, with the consideration of consumers' involvement and aggregate impact on system profile.

1.3 Technical Challenges

There are various barriers for the deployment of the HEM:

- *Increasing Communication*: Though the reducing cost of bidirectional communication technique makes affordable for HEM communication, the increasing HEM communication can lead to a high installation and operation cost. Also, the communication between grid and HEM can be vulnerable by the hacks. For example, a theft can hack the HEM data and know when the house is not occupied. How to develop a cost-efficient and secure communication system for HEM is a main issue right now. In Chapter 2, this problem will be further discussed.

- *Future Consumption Uncertainty*: In order to schedule the demand, HEM usually needs a forecaster to provide the future (1 hour or 24 hours ahead) energy consumption. However, an accurate forecast of household demand is challenging, due to the uncertainty of dwellers' energy consumption behavior, occupancy, weather condition and (for some houses) the roof-top PV production [42]. In Chapter 3, I will present the forecasting algorithms to be used by the HEM algorithms I developed and discuss the accuracy of the proposed algorithm.
- *Diversity of Electrical Devices*: There are various types of electrical devices in each household, and the ownership rate of different devices is also significantly different [43]. The HEM should be flexible to handle different type of household device, including the interface with each device and the control strategy for each unique device. In Chapter 4, I will present the modeling of controllable appliances and the operational constraints of those appliances.
- *Multiple Objectives*: The HEM algorithms schedule the controllable appliances based on the forecast of future energy consumptions as well as the operational constraints of each devices. The control objectives include minimizing cost, maximizing comfortableness, maintaining certain load profiles, and maximizing self-consumption. There are constant tradeoffs among different objectives so the HEM problem formulation needs to be flexible and robust when coping with multiple control objectives. In Chapter 4, I will introduce a heuristic-based HEM algorithm for home load scheduling.

The obstacles for HEM implementation include the cost of implementation as well as the easiness to use. For a customer, the cost saving and other benefit brought by the HEM may not be sufficient to cover the installation and operation cost. Most customers do not have enough knowledge of the electricity price as they are billed once a month, and do not fully understand the benefit for changing the way and time they use energy. On the other hand, it is difficult for the LSEs to estimate the residential load elasticity, and the response from residential load is not guaranteed. Though with the help of the HEM system and Advance Measurement Infrastructure (AMI), it takes a long time for the LSEs to develop and fine tune the price-and-load model, since the retail price is usually review every two or three years. However, the rapid expansion of renewable generation, including the Distributed Energy Resource (DER), will be the fundamental driver for a large deployment of HEM in near future, as it will change the wholesale and retail prices, net load profiles and the regulatory policies (e.g. encouraging more HEM to improve the energy efficiency). Therefore, in this thesis, I focused my research on 5 main aspects: 1) implement the HEM in a cost-efficient and user-friendly way; 2) provide an accurate forecast for load scheduling; 3) model different types of load as well as user's involvement in decision making; 4) develop a robust and computationally-efficient algorithm for load scheduling; 5) consider both energy user and provider's requirement of HEM.

1.4 Overview of Thesis Framework

This research is part of the Green Energy Hub (GEH) project in the Future Renewable Electric Energy Delivery and Management (FREEDM) Systems Engineering Research Center at North Carolina State University. In the GEH project, a lab-scale testing system is developed for integrating and demonstrating the three main components in FREEDM system [44]: Solid State Transformer (SST) with Distributed Grid Intelligence (DGI), Fault Isolation Device (FID), and a microgrid with smart homes, Distributed Energy Storage Device (DESD) and Distributed Renewable Energy Resource (DRER) (e.g. rooftop PV and wind turbine). As one of the energy cell in the GEH, the smart home managed by HEM cooperates with other energy cells in the system. Figure 1.3 shows the research framework of HEM within the GEH.

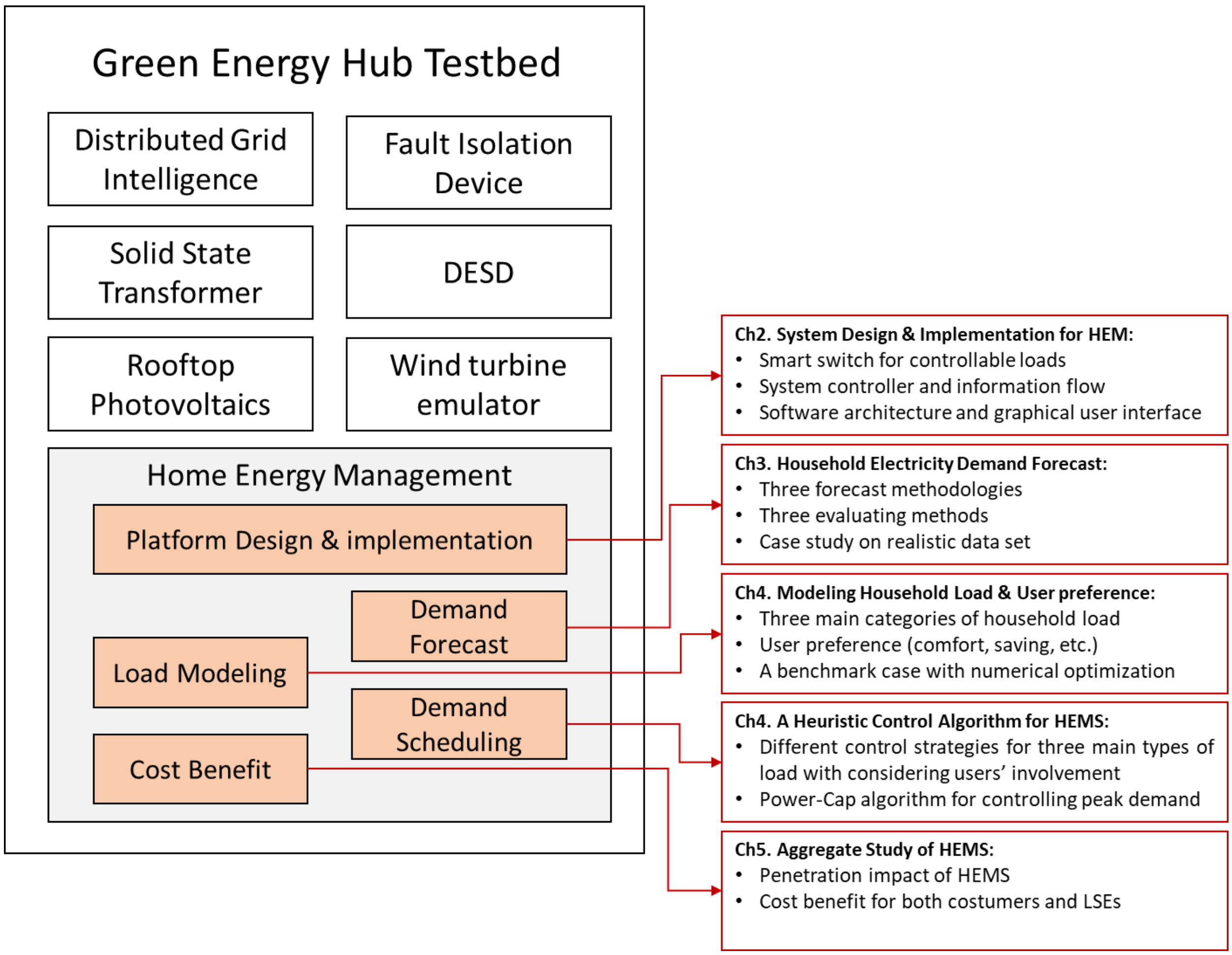


Figure 1.3 GEH research project framework

This dissertation presents the author's work on design and implementation of a Home Energy Management System considering the DRER integration, consumers' benefit and impact on utility. In the first step, I developed a smart house platform within the GEH to testify the FREEDM functionalities with different load conditions. In Chapter 2, it presents the hardware and software design and consideration of the smart house. These includes the smart switch for controllable devices, an HEM controller, different software modules and a graphical user interface (GUI). This smart house testing system can be used for generating the dynamic of household load by setting different user's preference (room temperature, schedule, etc.), price information (TOU, RTP, CPP, etc.) and other external inputs (e.g. weather) [45].

Based on such a design of HEM, I extend the research in the second step to develop the control algorithms for HEM, which including the works of forecasting algorithm development, household load modeling, and a heuristic control algorithm that is feasible and affordable for the HEM. In Chapter 3, three household electricity demand forecasting methodologies are developed to deal with the randomness and volatility of household load, which include two deterministic approaches and one probabilistic approach. These three methods are evaluated with realistic household data showing different application conditions for different approaches. In Chapter 4, I focus on modeling the household load behaviors and residential customers' engagement, then a heuristic control algorithm is developed based on this model such that it is computationally feasible for the HEM.

In the last step, I study the cost benefit of proposed HEM in terms of costumers' cost saving, comfortableness, distribution system impact as well as renewable integration. By the increasing penetration of HEM, the load diversity would be reduced, thus a control strategy is developed to alleviate the "rebound effort". Moreover, the aggregate HEM can be an effective DR resource to relieve transmission congestion and reduce system cost.

1.5 Contributions of the Thesis

In this thesis, I focused my effort on developing a practical HEM for better manage the household energy consumption considering the energy users and providers' benefit. The contributions of my thesis are summarized as follows:

- In Chapter 2, a smart home testbed is developed with controllable load and distributed renewable energy. The modular design and open-access platform allow users to test their smart home designs, such as control algorithms, price designs, communication delay, and etc.
- In Chapter 3, based on the analysis of the characteristics of household load, I develop three forecast methodologies for household electricity demand forecast. These three approaches can offer day-ahead forecast for load scheduling with different perspectives. The first one sets up the baseline for the scheduling horizon based on historical similar day information. The second one can adjust the forecast in real-time and provides an accurate forecast for near term load scheduling or adjustment. The third one predicts the probabilities of the electricity demand levels (high, medium, low). They are all computational affordable for the local controller of HEM.
- In Chapter 4, I model the controllable household load in three main types: the thermostatically control appliance, task-base appliance and electrical vehicle. This set of model consider both the load characteristics (e.g. thermal dynamic, task sequence, etc.) and the user preference. It models the trade-off between users' comfort and cost saving using a user-defined penalty function. This model can improve the transparency of electricity demand elasticity. A heuristic control algorithm is developed based on the model in Chapter 4, aiming to provide a robust and computationally efficient way to optimize the household energy consumption. Meanwhile, a power-cap control algorithm is developed based on priority-list method, helping the dwellers to avoid high demand charge. A cause study is conducted in order to validate the performance of the proposed HEM algorithms.

- In Chapter 5, it investigates the impact of increasing penetration of HEM in the system. The proposed HEM is able to help LSEs to alleviate the “rebound effort” in the TOU pricing scheme. In addition, the proposed HEM is used to quantify the demand elasticity in terms of cost saving, so that a virtual power plant model of aggregated HEM DR can be created.

1.6 Organization of the Thesis

The rest of this thesis is organized as follows. Chapter 2 introduces the hardware platform and software architecture design and implementation of HEM. Chapter 3 presents three forecast methodologies for residential demand. In Chapter 4, major load in a household is modeled with the consideration of user’s involvement. Using the developed load model, a set of heuristic scheduling algorithm is developed. Chapter 5 presents impact of increasing HEM on the power system. The final conclusions and some future research directions are presented in Chapter 6.

CHAPTER 2 DESIGN OF HOME ENERGY MANAGEMENT SYSTEMS

This chapter introduces principles of the home energy management (HEM) system design and requirements for each HEM components. The implementation of the HEM system on a smart house test bed is also discussed.

2.1 Background

There are two important HEM design considerations: control algorithms development and hardware implementation. In [46-49], the authors discussed the design of hardware and communication topology. In [46], the authors discussed communication requirements of the home area network (HAN) for HEM related applications. In [47], the authors designed a wireless controllable power outlet to control the on/off of household devices. In [48], the authors proposed the design of a hardware test bed for testing HEM. In [49], the authors compared different communication network design and discussed the impact of communication on the performance of the HEM algorithms.

In literature [50 - 52], HEMS control algorithms are developed and provide simulation results. In [50], the HEMS is modeled and a dynamic programming algorithm is used to optimize the load scheduling. In [35], an agent-based HEMS architecture is proposed and it applies game theory to determine the schedule for each individual agent. Literature [36, 53] discuss the methodologies to improve the HEMS capability of predicting dwellers' behaviors or electricity demand patterns. In addition, some researchers study the impacts of pricing schemes on cost reduction and demand responsiveness [54-60].

There are several research institutes have worked on HEMS and published related reports. In Pacific Northwest National Laboratory (PNNL), they developed a home energy model integrated in a distribution simulation platform "GridLAB-D" [27]. They also develop the controller called “Grid Friendly Appliance” [61] that enables device-level control for providing demand response. In Lawrence Berkeley National Laboratory (LBNL), they mainly focus on HEMS modeling with dynamic price response [62]. We can also find some commercial vision of HEMS products [63-65], pointing out the functionalities and benefits of HEMS for costumers.

On one hand, these previous work rarely consider the implementation of algorithms in the hardware prototype, making it less practical to manage the dynamic demand. On the other hand, some publications over complicate the control algorithms that are either not computationally feasible for a local HEMS controller or significantly increase the cost of HEMS installation and operation. In this research, it aims to design an efficient and low-cost HEMS prototype, then develop a robust control algorithm based on this prototype, so that the HEMS is an easy-to-use product for customers and practical for deployment.

2.2 Optimization Objectives and Key Functionalities of the HEM System

In general, a HEM system is designed to reduce the total electricity cost and improve comfortableness for residential consumer, while helping load serving entities (LSEs) to deploy the HEM systems in the residential sector. The optimization objectives include:

- *Minimizing the electricity cost and the cost of control.* Costs are predominant factors in HEM problem formulations. Costs include financial cost saving/reward gaining, system installation and operation cost, device wear-and-tear and battery deterioration. In my design, minimizing the cost saving expectation of the customers is the main objective.
- *Maximizing customer comfort.* Customer comfort includes deteriorated quality of energy service, delay in tasks, or forced change customer consumption patterns. In this research, the household appliances/devices are modeled in terms of comfort setting (e.g. task time,

preferred temperature), and the comfortableness criteria are defined to evaluate the performance of the HEM.

- *Maintaining target power or energy consumptions.* Load profiling is desirable for both LES and consumer, for example reducing peak demand for the utility and reducing the grid dependence for customers. The load profile objectives include: peak shaving [5], target profile following [66], load shifting [67], and self-sustainable [68]. In this research, the proposed HEM can improve the individual household load profile to avoid high demand charge, as well as improve the aggregate system load profile to alleviate the "rebound effort"[69] by the TOU pricing.

To achieve the above objectives, the proposed HEM operation include four primary functions: information collecting, data processing, decision making, and command executing, as shown in Figure 2.1.

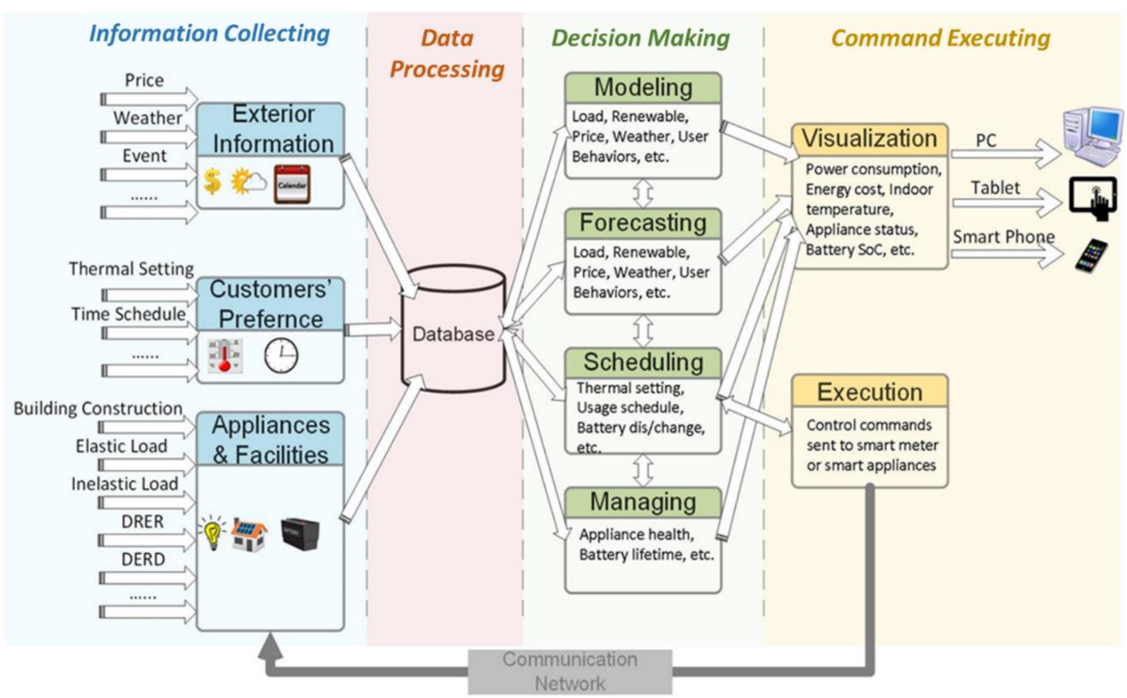


Figure 2.4 Lifecycle of an HEM Operation Forming the OODA Loop

- The *information collecting* collects three main inputs: ambient information (e.g. outdoor temperature, solar radiation, and electricity prices), user preferences (e.g. indoor temperature, task schedule, and cost saving expectation), and measurements from smart appliances and controllable devices inside the household.
- The *data processing* can process the collected data by specific algorithms, such as data reorganization and eliminating bad data. Then the data is stored in corresponding databases.
- The *decision making* consists of four categories of algorithms: modeling, forecasting, scheduling and managing. The modeling algorithm calculates the model parameters of load and DER/DESD. The results can then be used by the forecasting algorithm to produce the energy demand and supply forecast for day-ahead, hour-ahead or intra-hour. Based on the forecast results, the Scheduling algorithm schedules the appliance usage to fulfill control objective, such as minimizing the energy cost, enhancing the comfortableness, and following a load profile target. Management algorithm takes care of the appliance status and health and gives feedback to scheduling algorithm.
- The *command executing* sends the control commands to the smart switches and appliances, as well as visualizes the appliance status and energy saving with a Graphical User Interface (GUI). The two-way communication closes the HEM operation loop, providing data to the HEM information collecting unit.

2.3 The Proposed Hardware Prototype

The proposed HEM consists of three main hardware components: an HEM controller, a set of executors (i.e. smart switches and smart thermostats), and a home-area communication network. The general topology of proposed HEM is shown in Figure 2.2. This section reviews the design idea of these three components and their implementation will be discussed in section 2.5.

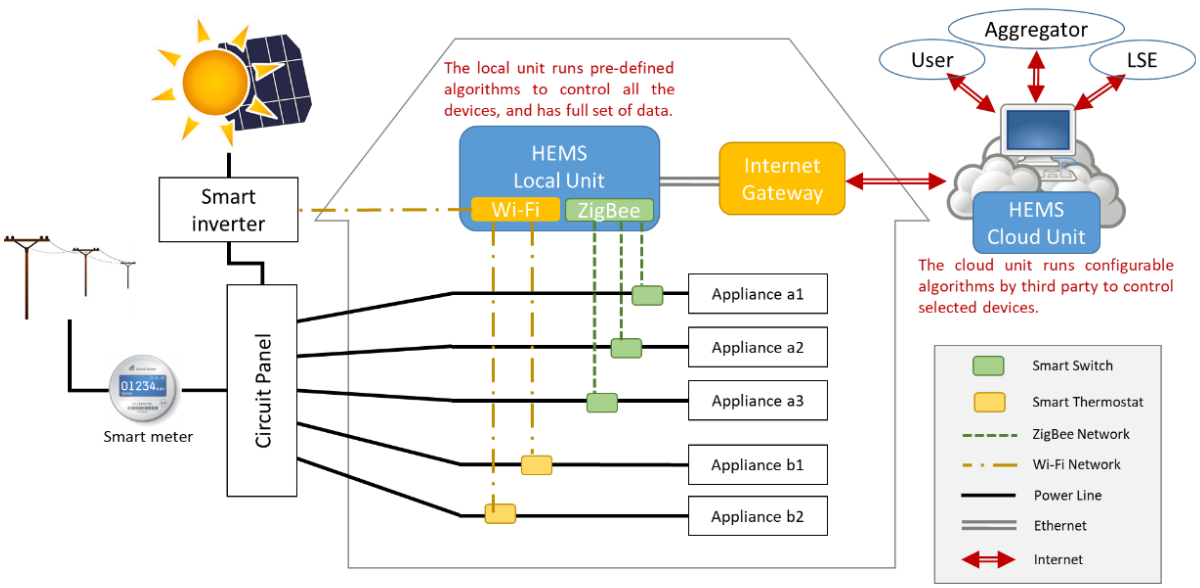


Figure 2.5 HEM hardware system overview

2.3.1 HEM Controller

The HEM controller is the brain of the system. In order to balance the trade-off between computational capability and cost effectiveness, the proposed design uses a “hybrid” controller: a local-centralized unit and a cloud-based unit. The local unit uses control algorithms that requires less computational resource, while communicates with each of the controllable device/appliance frequently. It also has the detail energy consumption information in the house. The cloud unit uses the shared pools of configurable algorithms (developed by a third company) to control specific large-energy-consume devices (e.g. HVAC and EV) and to cooperate with other HEM to achieve some upper level control target. The cloud unit can run more advanced control algorithms with the cloud computer, and it communicates with the household devices less frequently and keeps necessary data in order to protect user information privacy. In general, the local unit is the main commander for controllable device in the house, but in some cases, the cloud unit can overwrite or substitute the local unit commands, such as local unit blackout or power system contingency.

2.3.2 Smart Switch and Smart Thermostat

The HEM uses two types of executors to manage the controllable load: smart switch and smart thermostat. The smart switch can measure the appliance energy consumption (both voltage and current), then send this information to HEM controller, and turn it on/off accordingly. Similarly, the smart thermostat needs to measure the room/water temperature, monitor the house occupancy, then transmit the data to controller, and decide to turn on/off the device or adjust the temperature setting.

2.3.3 HEM Communication Network

The HEM operation heavily relies on the communication network in the home area. There are three types of networking technologies are used in the proposed HEM: Zigbee, Wi-Fi, and Ethernet.

The Zigbee network is mainly used by the smart switch, which requires low energy consumption, frequent communication and flexibility of expansion. ZigBee is a short-range, low-data rate, energy efficient wireless technology based on the IEEE 802.15.4 standard. It uses a duty-cycle to access to transmit the data, meaning a ZigBee module is active (wakes up) for certain time to send/receive data to/from other module, then it falls asleep again.

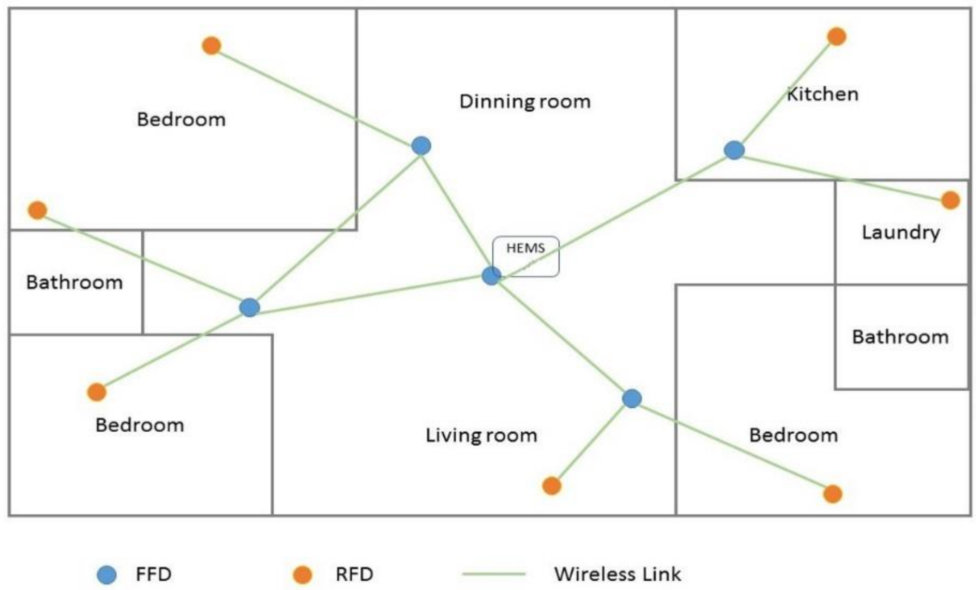


Figure 2.6 Mesh ZigBee network topology of HEM

The ZigBee communication range is between 30 to 70 meters, varied by the obstacle indoor (e.g. walls). Thus, in my design, it uses the mesh network topology in Figure 2.3. There are two types of ZigBee devices, full function device (FFD) and reduced function device (RFD). FFDs can be interconnected with their peers in the mesh topology, while the RFDs can be used at end nodes. In the smart house, the RFD smart meters or sensors are placed in bedrooms or bathrooms, FFD smart meters and sensors are placed in hallway or living room. Also there is a FFD module connecting to the local controller unit as a ZigBee coordinator, working in a beacon mode to define the duty cycle. The ZigBee module configuration is detailed in the section 2.5.

Other controllable devices, such as smart inverter and smart thermostat, use Wi-Fi network to communicate with HEM controller. These devices exchange large amount of data package but in a lower frequency (e.g. every 5 minutes), thus the Wi-Fi network is applied in this case. The HEM local controller unit collects the data through ZigBee and Wi-Fi, connects to local gateway by Ethernet cable, then communicate with the cloud controller unit via Internet.

2.4 The Proposed Software Architecture

2.4.1 Software Layers and Interfaces

The proposed HEM software can be divided into three bottom-up layers: library layer, host layer and application layer, as shown in Figure 2.4.

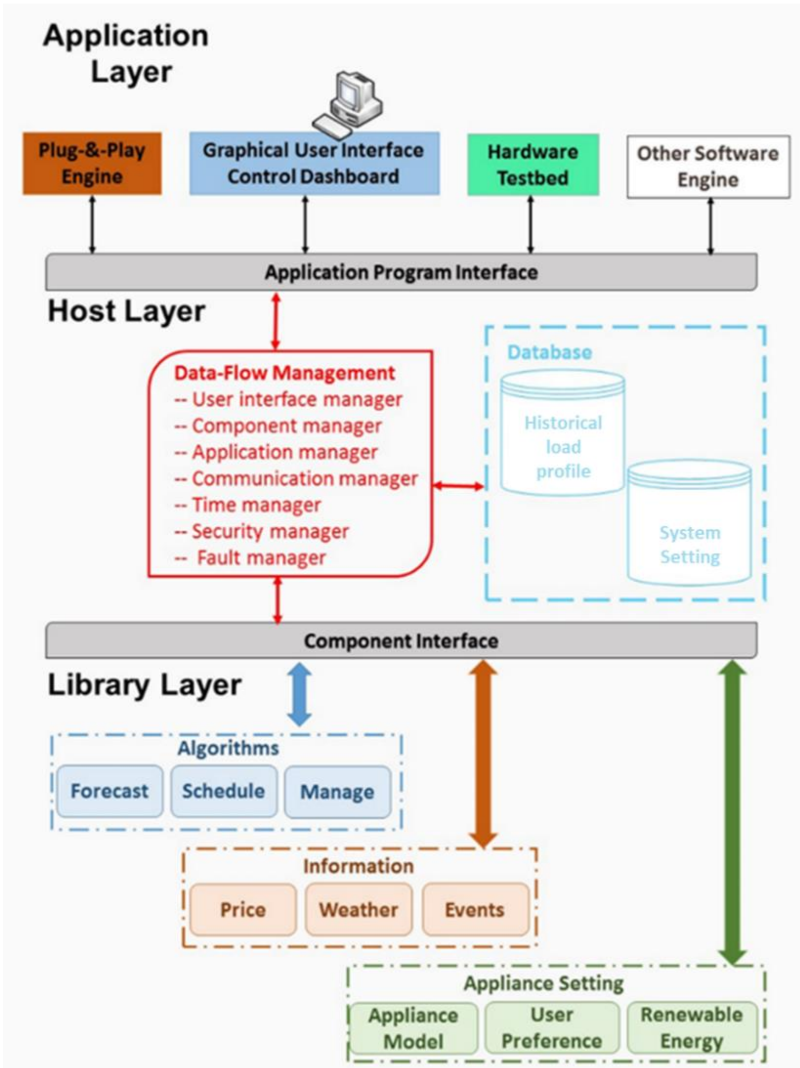


Figure 2.7 HEM software framework

The bottom layer is the library layer, which is the repository of three main components in HEM: HEM setting/parameter, external information, and control algorithms.

- HEM setting/parameter: the proposed HEM models different commonly-used household appliance, such as HVAC, water heater, washer and dryer, etc. Users can input the appliance setting, such as the thermal setting or usage schedule of the appliances. Also, the model can allow users to define the price response preference, indicating their demand elasticity.
- External information: this component reads external information that may impact the HEM operation, including prices, weather information and special events.
- Algorithms: the proposed HEM has three main types of algorithms: 1) Forecasting algorithms provide load or renewable energy forecast for a define horizon; 2) Scheduling algorithms can schedule load and DRER based on different objectives; 3) Managing algorithms can be even more extensive, such as battery lifetime evaluation, energy efficiency monitoring and etc.

The middle layer is called host layer. It has two main components: the database and the data-flow management. The database stores the historical load profiles and system setting, such as appliance setting and user preference. The data-flow management controls the time series of data, and formats the data input and output from/to different layers via the interface.

The upper layer is the application layer. It has a Graphical User Interface (GUI) to visualize the data and to allow users input the settings. It is also the layer that connects to the hardware system take in/sent out appliance information.

For research purpose, the HEM software allows researcher to customize some software components (e.g. control algorithms, pricing schemes, etc.), while the data input/output is standardized.

2.4.2 HEM Information Flow

There are multiple controllable appliances in a house, but the HEM doesn't require the information collected simultaneously in order to avoid more hardware cost. Instead, it measures the appliances sequentially in a period for multiple times, then averages the measurements of each appliance as the real-time value. In this design, the smart switch and smart thermostat measures the appliance 3 times in a minute, and sends the average measurements to HEM controller as the real-time value. Since the HEM controller has local and cloud units, they have different data process rate. Figure 2.5 shows the information flow among appliance, local controller and cloud controller. Basically, the smart switch and thermostat measure the appliance couple times in a minute and send the data to HEM local controller with the average values. Once the local control gets all the appliance data, it updates the forecast and schedule, and sends back to those smart devices. The local unit sends some of the appliance data (e.g. HVAC, water heater) to the cloud unit every 5 minutes. Then based on the cloud unit control command, the local unit adjusts the schedule for smart device execution.

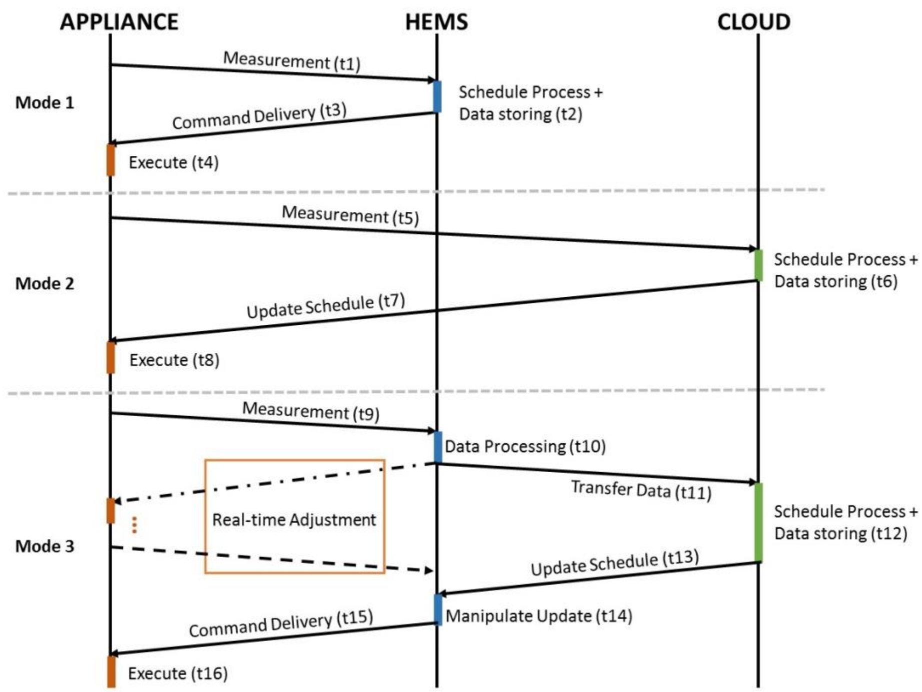


Figure 2.8 Information flow among smart device, local and cloud controller

2.4.3 HEM Algorithms Overview

In this thesis, it focuses on developing two main types of algorithm: demand forecasting algorithm and load scheduling algorithm. There are three key settings for this two algorithms: forecast/schedule horizon, update frequency and resolution. Figure 2.6 shows the timeline of how the forecasting and scheduling algorithm work interactively. In this design, the proposed HEM forecasts both day-ahead and hour-ahead household electricity demand. The day-ahead forecast algorithm predicts electricity demand in 15-minute resolution for the next 36 hours. It updates once a day at 11:45AM, one interval ahead of the forecast horizon (12:00-00:00 next day). The day-ahead can provide demand forecast for “long-term” schedule, such as charging EV overnight. For hour-ahead forecast, the forecasting algorithm predicts demand in an hour ahead with 5-minute resolution, it updates every 5 minutes. The scheduling needs to schedule the load for 24-hour ahead with a 5-minute resolution. It updates every 5 minutes right after the hour-ahead demand forecast update. Basically, the load scheduling algorithm uses the day-ahead demand forecast to plan the electricity usage in long-term, such as allocate the dishwashing task, charging the EV. Meanwhile, with hour-ahead demand forecast, the load scheduling algorithm can adjust power consumption plan to avoid high demand charge (it is usually based on the average of power consumption in 15 minutes) or achieve a load profile target. All the forecasting and scheduling algorithm publish the results one interval before the cover horizon begins.

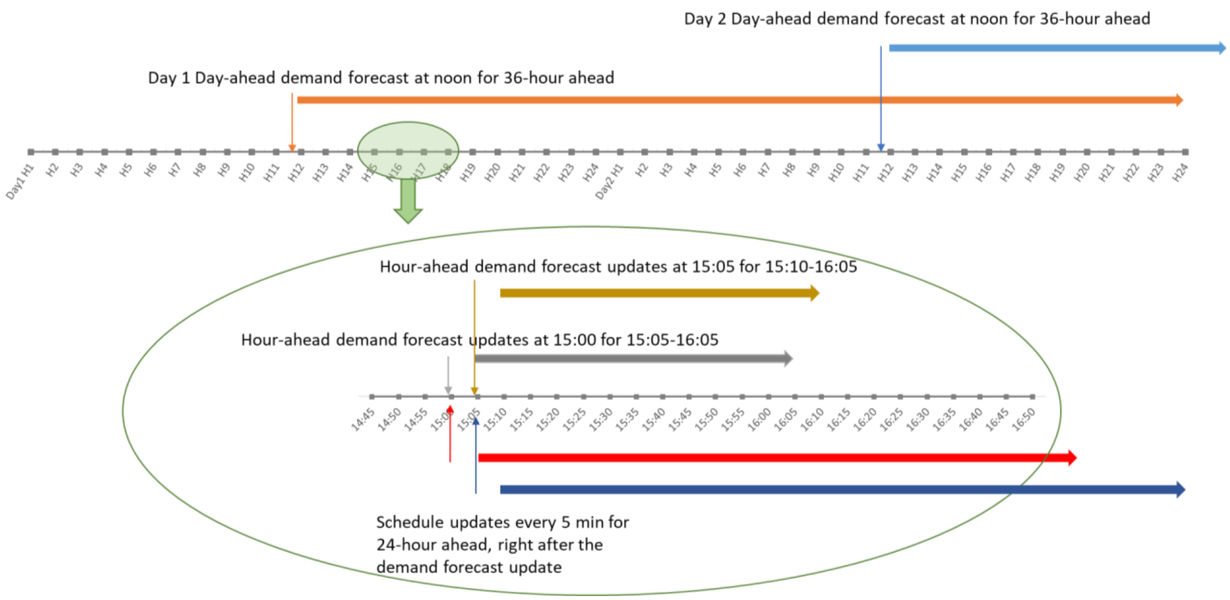


Figure 2.9 Timeline of forecasting and scheduling algorithm horizon and update frequency

Different than system-level energy management, the HEM needs to use unique methodologies to forecast and schedule energy demand at household level. In this design, the forecasting algorithm provides both deterministic and probabilistic demand forecast based on the granular data from smart devices. It also uses unique methods to evaluate the forecast accuracy. On the other hand, the scheduling algorithm schedules the controllable device based on their usage patterns respectively, such as thermostatically-control-appliance, task-base-appliance, and energy storage device. Moreover, the customer cost saving expectation is considered by scheduling algorithm, so that it can bridge the gap between user electricity demand elasticity and LSE time-varying electricity price or DR incentive. To achieve the optimal load schedule, the proposed HEM uses heuristic algorithm, instead of using mathematical optimization algorithm. In this way, it significantly reduces the computational burden while enhance the algorithm robustness to the demand uncertainty. The forecasting and scheduling algorithms are presented in Chapter 3 to Chapter 5.

2.5 HEM Testing System Implementation

In the FREEDM envisioned “Energy Internet” [44], an ac/dc hybrid microgrid system that enables flexible energy sharing is proposed. A 1-MWh hybrid microgrid testbed called Green Energy Hub [45] is constructed based on several key technologies. As shown in Figure 2.7, the Solid State Transformer (SST) connects the smart house microgrid to distribution grid. Within the smart house, all household appliances, home-owned energy storage and distributed generation resources (primarily PV) are managed by an HEM. In this section, it shows the HEM hardware testbed and the Graphical User Interface (GUI). A showcase demonstrates the HEM testbed capability.

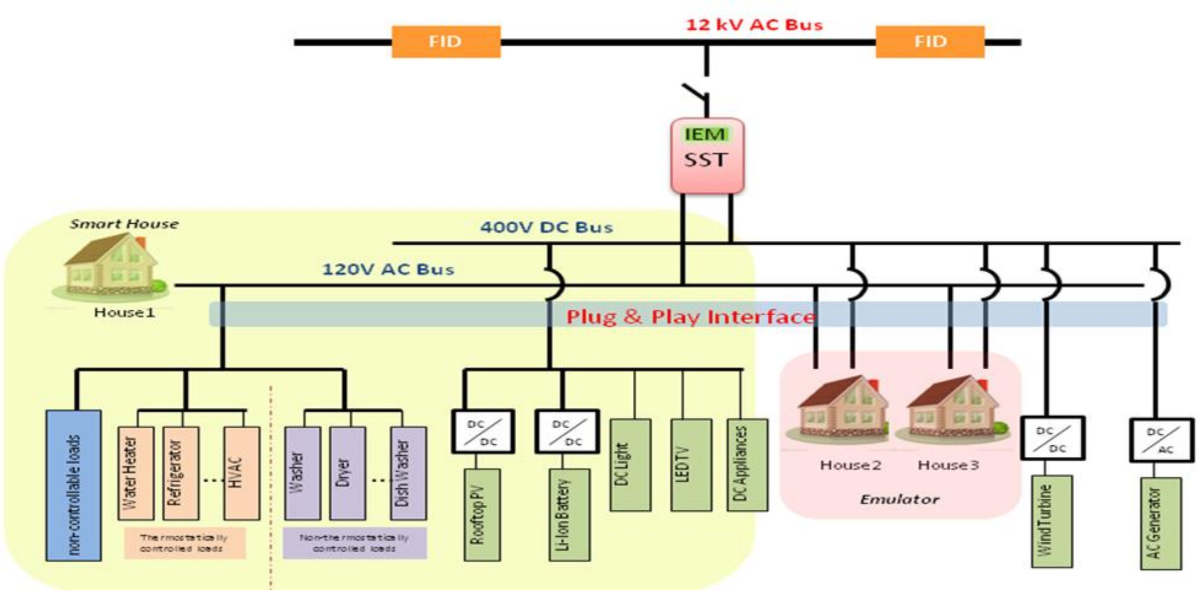


Figure 2.10 1-SST Test System Schematic Diagram

2.5.1 *HEM Hardware Testbed*

A physical hybrid smart house is setup to provide capability for researchers to validate control algorithms in a realistic residential microgrid system, as shown in Figure 2.8. The house includes ac and dc appliances, rooftop PV as DRER, Li-Ion battery as DESD. More specifically, the dc loads include LED lighting, LED TV, battery (simulating EV) and a dc emulator. AC loads can be categorized into thermostatically control appliances (TCA) (e.g., HVAC, refrigerator), task-based appliances (e.g., clothes washer & dryer, EV) and random loads. Hybrid household loads can also be emulated by ac and dc load emulators (4 kW and 2.5 kW each) so that the whole smart house test system can be scaled up to 3 houses.

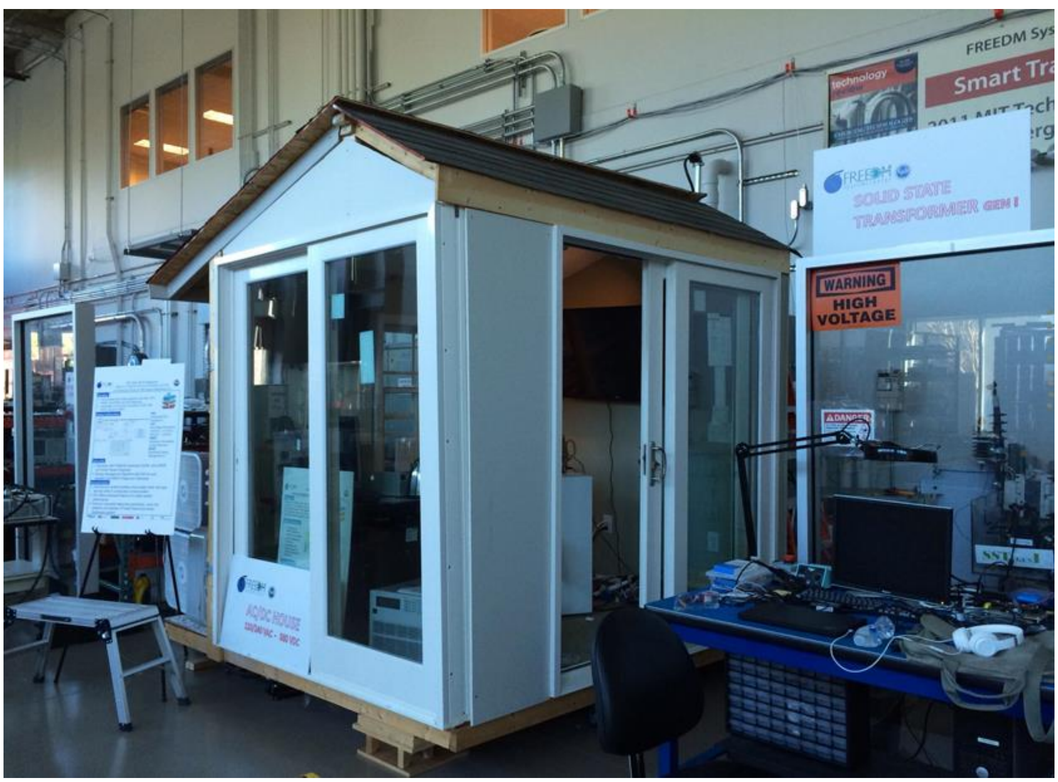


Figure 2.11 Physical HEM testbed in FREEDM System Center

The proposed HEM local controller unit is currently implemented on a PC in the testbed with Matlab as the programming language. This is an efficient way for implementation at a development stage, and it is easier to use GUI to demonstrate the results on PC screen. Actually, for future deployment, it can be implemented on a mini computer, such a BeagleBone Black or Raspberry Pi. The local controller unit uses ZigBee network to communicate with smart switches, and XBee Series 2 is used as the Zigbee RF modules in this design. On the controller side, it connects with a ZigBee coordinator via RS232. On the smart switch side, the micro-controller (Microchip PIC16F877A in this design) manages the data flow as shown in Figure 2.9.

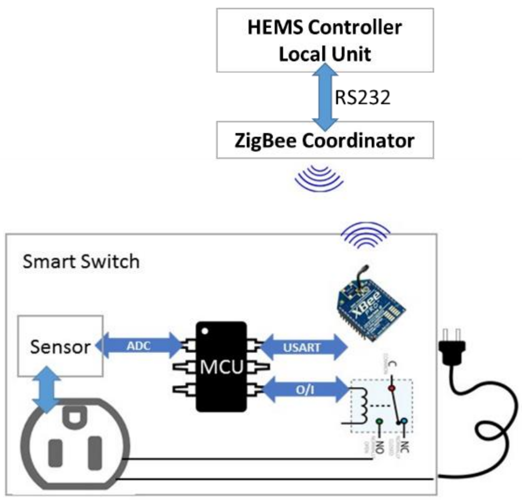


Figure 2.12 Smart switch diagram

The proposed HEM cloud controller unit is also implemented on a local PC in order to communicate with the local unit within university network domain (university network restraints external visits on internal local machine). To control the smart thermostat, the cloud controller unit runs a JavaScript program to send JSON file to Ecobee API to change the settings and events based on the scheduling results.

2.5.2 Graphical User Interface

The GUI provides the users an easy way to set up the simulation and to observe the step-by-step results. A Matlab-based GUI [30] is developed for the HEM testbed, as shown in Figure 2.10. Here list the functionality in each section/window:

① Appliance setting

② Control strategy selection

③ Actual and forecast load profile

④ Renewable energy: PV and energy storage SOC

⑤ Appliance status

⑥ External information

⑦ Appliance monitoring

⑧ Cost comparison before/after control

Figure 2.13 A Matlab-based Graphical User Interface

The HEM GUI is used to modify the resource status and control parameter settings, user comfort settings, price signals in demand response program, and visualize the results.

1) Appliance parameter setting: For TCAs, whose load profiles are mostly related to outside and room temperature, researchers can set the temperature setpoint and deadband of these appliances.

For task-based appliances, researchers can set the estimated turn-on time and turn-off time, during which interval the task should be finished.

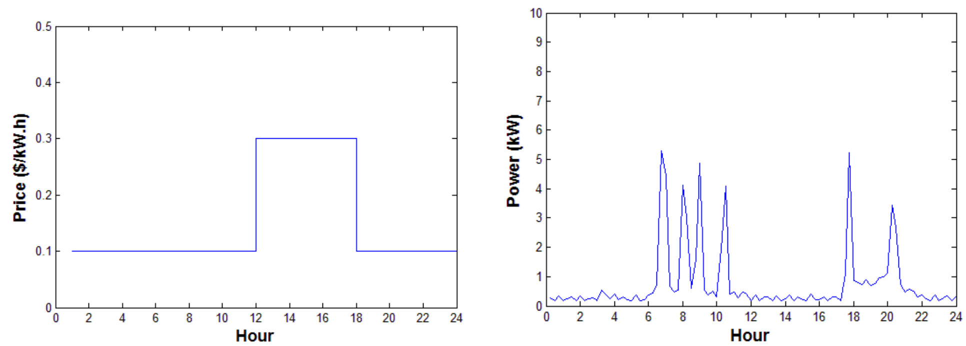
2) Control strategy setting: The HEM currently provides three basic control algorithms for researchers to select: price-cap control, power-cap control and consensus control. For example, in price-cap control strategy, some appliances will be shut down when the price is higher than the pre-set price cap. Appliances are turned off according to a priority list calculated by an optimization algorithm. Power-cap control will shift or shed loads to keep the power consumption within the pre-set value. The effect on consumer comfort level will be minimized. Users can also easily implement their control algorithms using the “CUSTOMIZE” function, which requires users to clarify input/output information in a Matlab programming environment.

3) Input information setting: Before running simulation, input information should be defined, including pricing scheme, outdoor temperature, and power/price cap.

The main window provides various real-time information, such as actual and forecasted total power consumptions, solar generation status, battery charging status, and demand response capabilities. With those displays, researchers can easily access test system status for testing and validating the effectiveness of their algorithms. In the following section, a demonstration case is carried out using this GUI to setup and view the results.

2.5.3 A Demonstration Case of HEM Testing System

The showcase demonstrates the capability of HEM scheduling household load under time-of-use pricing scheme in a typical summer day. The peak hours are from 12 p.m. to 5 p.m with an energy charge of \$0.3/kWh while the off-peak hours energy price is \$0.1/kWh. Demand charge is not considered in this case. Uncontrolled base load is produced by the load emulators. The price curve and base-load curve are show in Figure 2.11.



(a) (b)

Figure 2.14 Case setting (a) TOU price curve, (b) base-load

A. Modeling Setup

In each algorithm testing and validation process, the test system needs to be setup in the following steps.

1) Set up the communication parameters. The users need to configure the smart switching and metering devices as controllable or metered. In the current test system, the communication frequency between devices and HEM can be at every 5 second. Although ZigBee technology allows much faster communication, but communication delay or losses will increase when there are more devices in the network. This is one of the key reasons that a realistic test system needs to be used for testing and validating control algorithms.

In addition, a droop control technology is used to regulate the SST output voltage level. Therefore, there are fluctuations in load measurements. 5-sceond data turns out to be the optimal communication interval that allows measurements to be collected with good resolution to filter out the spikes in the measurements.

2) Set up the control and monitor parameters for appliances. The following actual appliances can be used in the test system: air-conditioner (A/C), water heater (WH), clothes washer (CW), clothes dryer (CD), and dish washer (DW), lighting and TV of both ac and dc, and battery. An example setting of each controllable appliance is shown in Table 2.1.

3) Select other auxiliary inputs. Auxiliary inputs may be needed based on the control strategies selected. For example, if one needs to minimize the electric payment under TOU pricing scheme, TOU prices need to be fed to the communication interface. If peak-shaving is selected, a signal for executing peak-shaving command will be fed to the communication interface. Ambient temperatures and user comfort settings and user defined schedules will be needed to schedule appliance operations.

Table 2.1 Appliances setting

Appliance	*Rating*	*Setting*
A/C	4.5 kW	Setpoint: 68 °F, deadband: ±4 °F
WH	2 kW	Setpoint: 135° F, deadband: ±15 °F
CW	1 kW	Scheduled interval: 8 a.m. to 10 p.m.
CD	3.5 kW	Scheduled interval: 8 a.m. to 10 p.m.
DW	1.5 kW	Scheduled interval: 10 a.m. to 6 p.m.
Battery	2 kW * 2h	--

B. Modeling Results

Figure 2.12 shows the testing results collected from 9 a.m. to 9 p.m., including scheduled load profile and measured demand curve. We can see that, before peak hour, the demand increases due to the pre-cooling process and charging battery for later usage. During peak hour, the battery partly supplies the demand. There is a small peak after peak hours.

It can be seen that the measured demand curve is slightly different from the scheduled one, which is caused by the communication delay between devices. Also, the transient starting processes of appliances can be captured by the metering system, the value of which may mislead the HEM to trigger a peak shaving signal. This demo case shows the importance of using real devices to test the HEM algorithms.

Figure 2.13 shows a zoom-in view of the demand curve with corresponding ac and dc bus voltage at the SST end. Generally, both ac and dc voltage variations are within ±2%, though voltage spikes can occur when large appliances are switching in and out. This case demonstrates that providing SST a realistic smart house load can effectively test the SST voltage regulation algorithms.

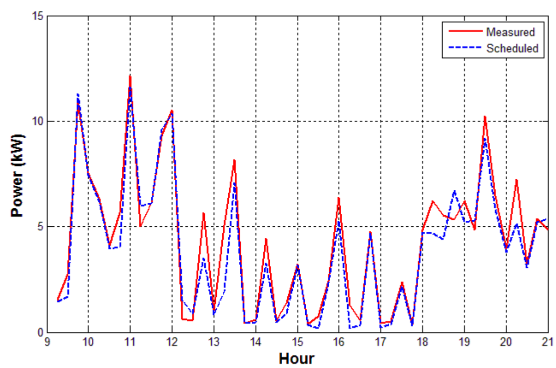


Figure 2.15 Demonstration case results

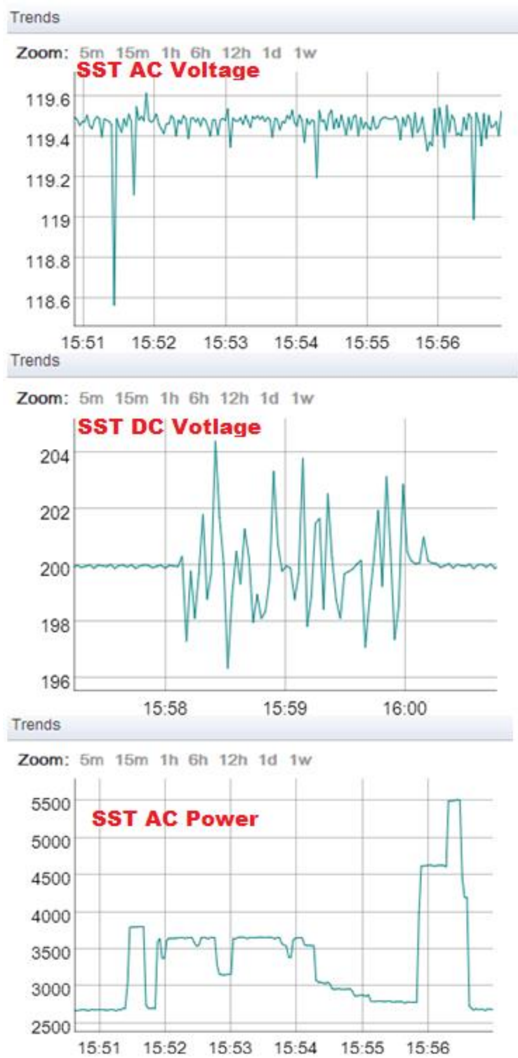


Figure 2.16 Voltage and Power at the SST side

CHAPTER 3 A HOUSEHOLD ELECTRICITY LOAD FORECAST APPROACH FOR HOME ENERGY MANAGEMENT SYSTEM

This chapter introduces the load forecasting algorithms for day-ahead (DA) and hourly-ahead (HA) residential load forecasting.

3.1 Introduction

Traditionally, load forecasting is often conducted at the system level. This is because the utility engineers only have access to the load measurements at the feeder head, where supervisory control and data acquisition (SCADA) data is available. The deployment of smart meters as well as smart switches possessing metering functions allows the home owners and utilities to have access to energy consumption data at household level with intra-hour resolution [70]. To implement different control functions of a Home Energy Management System (HEMS), a load forecaster is often needed for estimating the energy consumption of appliances in a scheduling period, which is normally for one day ahead.

Today, many load forecasting techniques have been deployed for forecasting system level aggregate load, such as linear regression model [71-74], similar day approach [75,76], neural network model [77-79], support vector machine approach [80, 81], etc. However, at the household level, because of the randomness in customer consumptions, load is highly volatile. Therefore, the methods developed for forecasting the aggregated load are not applicable for forecasting the individual household loads. Some publications have provided study of residential load forecasting [82, 83]. In [82], it clusters the residential load profiles and summarizes residential load pattern regarding individual customer attributes, such as house type, number of residents, age, and number of appliances, etc. [83] uses the smart meter data to identify some residential characteristics on predicting household load. These researches need a large amount of household data, so they may not be applicable to forecast individual household demand. Some researches [83, 84] focus on individual household energy usage disaggregation using either intrusive or non-intrusive methods, providing information for household appliances modeling. Some advanced forecast techniques, such as ANN and SVM, are applied on house level load forecasting [85-87], but they are either system specific or need high computational effect that HEMS control micro-process can't handle. Also, most of the residential load forecast related publications neglect the forecast horizon. Just as system level load forecasting, a household demand forecaster should consider both short-term (intra hour) and mid-term (day ahead) energy consumption.

In this chapter, I developed a progressive residential load forecasting method using a combination of k-mean, multinomial logit regression, and Kalman filter methods to provide the HEMS with DA and HA load forecast. To obtain the DA load forecast, I used the k-mean based algorithm to cluster the historical daily electricity load profiles based on their daily weather conditions. Then, a multinomial logit regression method is applied to subsets of the clustered load data to forecast the probabilistic of the load level (high, medium, and low) of each 15 minute for day ahead. To obtain the HA forecast, a state-space model with its coefficients recursively updated by a Kalman filter is used. The forecaster is tested and validated using realistic smart meter measurements collected from 20 households in Austin, TX. Euclidean distance and Weighted Mean Absolute Scaled Error (WMASE) are used to quantify the accuracy of the DA and HA forecast respectively.

The rest of the chapter are organized as following. Section 3.2 presents the forecasting methodology of DA and HA household energy demand forecast. Section 3.3 shows the case study with 20 household data in both summer and winter case, as well as the household demand forecast evaluation criteria. Section 3.4 concludes this chapter.

3.2 Methodology

The proposed forecaster consists of two main processes: DA forecast and HA forecast. Instead of forecasting a point value, the DA process predicts a 15-minute resolution probability of three load levels: high, medium, and low, so that HEMS moves schedulable load from higher demand period to lower demand period. The DA process is updated once a day at noon. The HA process predicts the deterministic value of load in one hour ahead with 5 minute resolution. HEMS uses this information to adjust energy usage in real time, for example, if HEMS foresees a high demand in 10 minutes later, it can postpone a rescheduled dishwasher at that time to a later time slot. The DA and HA forecaster allows HEMS to largely schedule a load in day ahead and to fine tune the usage in real time.

The proposed HEM forecasting processes is shown in Figure 3.1. There are two steps in DA process: (1) find a data set of similar days to the forecasted day based on the weather condition and day of the week, (2) use the similar days as training dataset to estimate the parameters in a logistic regression model of load level probabilities. In HA process, it uses the historical load and weather condition in a state-space model, and applies Karmel filter to recursively updated the model parameters.

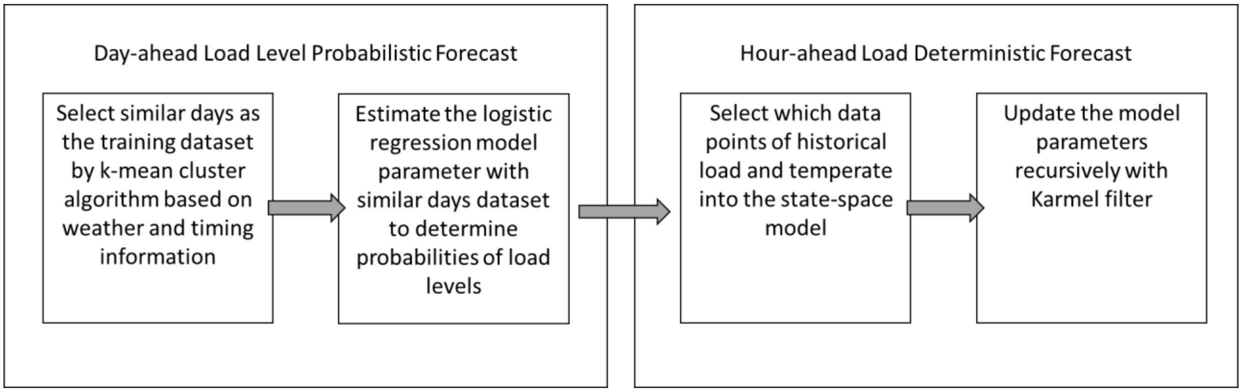


Figure 3.17 Household electricity load forecast process: DA and HA

3.2.1 Day-ahead load level probabilistic forecast

<u>Step 1: Clustering load profiles to find similar days</u>

Although residential load profiles vary significantly each day, the probability for high, medium, and low consumption periods remains stable for similar day types. This is because weather sensitive loads usually dominate the household energy consumptions. For example, Figure 3.2 shows the temperature and a realistic household load summer daily change. It indicates that the load changing interval is correlated with the temperature range during the day. Thus, we can use the weather information as a criteria to group daily profiles based on an assumption that a similar weather condition can result in a consistent load range.

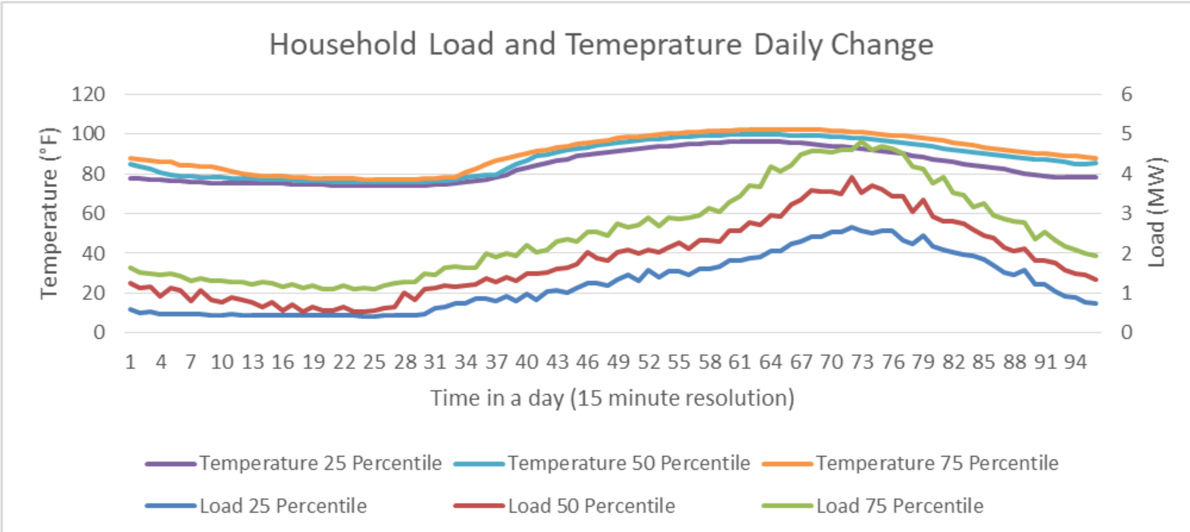


Figure 3.18 A household load and temperature daily change

The inputs of this step include: five months of data (the past two months and three months last year) and the corresponding weather data (i.e. outdoor temperature, precipitation, humidity, and wind speed). For example, if March 1, 2018 is the forecasted day, the historical data set should be January 1st 2018 to February 28th 2018, and February 1st 2017 to April 30th 2018. The output of this step is day groups with similar external conditions. The goal of this step is to select load profiles that have the highest probability to match the forecast day load profile.

To cluster the load profiles, the K-mean algorithm is used. Then, the Davies-Bouldin (DB) index [88] is used to determine the most suitable number of cluster. Eq. 3.1 – 3.5 define the DB index.

Eq. 3.1 calculates the scatter within the cluster C_i, X_j is the n-dimensional feature vector assigned to cluster C_i. A_i is the centroid of C_i and T_i is the size of the cluster i.

Eq. 3.2 calculates separation between cluster C_i and cluster C_j. $a_{k,i}$ is the kth element of A_i.

Eq. 3.3 is a measure of how good the clustering scheme is. The lower the value indicates the better the separation of the clusters and the 'tightness' inside the clusters.

$$S_i = \left(\frac{1}{T_i} \sum_{j=1}^{T_i} \left| X_j - A_i \right|^p \right)^{1/p} \tag{3.1}$$

$$M_{i,j} = \left\| A_i - A_j \right\|_p = \left(\sum_{k=1}^{n} \left| a_{k,i} - a_{k,j} \right|^p \right)^{\frac{1}{p}} \tag{3.2}$$

$$R_{i,j} = \frac{S_i + S_j}{M_{i,j}} \tag{3.3}$$

$$D_i \equiv \max_{j \neq i} R_{i,j} \tag{3.4}$$

$$DB \equiv \frac{1}{N} \sum_{i=1}^{N} D_i \tag{3.5}$$

Eq. 3.4 and 3.4 define the DB index, which consider the worst case with the value equals to $R_{i,j}$ for the most similar cluster to cluster *i*. A lower DB index is means that within an individual cluster, the load profiles are similar to each other and each cluster is well separated.

Once the appropriate number of cluster is identified, the historical day and forecasted day meteorological data will be used as the input and clustered separately on a 24-hour basis. The output is the cluster indices of each day, then the days with same index as forecast day will be used in the second step —probabilistic day-ahead load forecast.

Step 2: Probabilistic forecast with multinomial logistic regression

In the second step, a tri-level load forecast (i.e. high, medium and low) is conducted. This is because customer consumptions are highly random so capture the exact value of the energy consumption is often impossible. In addition, to conduct peak shaving or load shifting, it is usually important to know when an appliance is turned on whether or not it will create a load peak. To define the low, medium, and high levels, we used the following criterion:

1. If the consumption is low, then turning on the largest appliance in the household (e.g. a 4 kW air compressor unit) total load can still remain in medium level. Thus, HEMS can schedule any load to this time slot without creating a peak.
2. If the consumption is medium, then turning on the largest appliance in the household (e.g. a 4 kW air compressor unit) will make the total load consumption reach 80% of the predefined peak values.
3. If the consumption is high, then turning on the largest appliance in the household (e.g. a 4 kW air compressor unit) will exceed the predefined peak;

To find the thresholds of the low, medium, and high load levels, a statistical analysis is conducted based on the predefined peak values and the rated value of the largest appliances. For example, in Figure 3.3 of a sorted household load in summer time, one can see that the peak demand is about 11.5 kW. If the largest appliance power rating is 4 kW, we can define the high/medium threshold is 5.2 kW (11.5*0.8-4), and the medium/low threshold is 1.2kW. With these threshold, HEMS can schedule the appliance to low load periods, or remove some appliance for some high low periods.

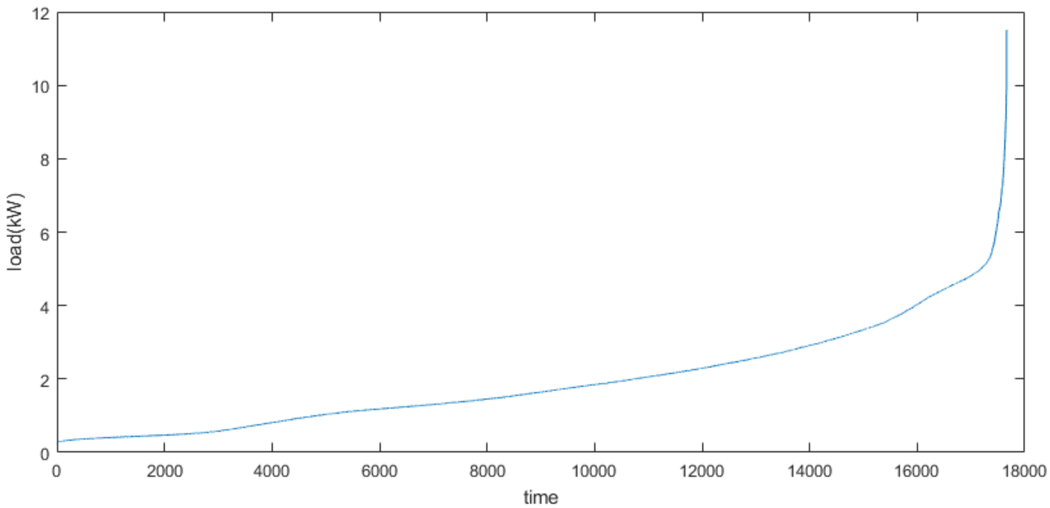


Figure 3.19 An example of sorted household load

In order to determine the load level probability, a multinomial logistic regression is used to model the continuous values of predictors (such as temperature, previous load value, time of the day, etc.) to a probability of load levels between 0 to 1. In a multinomial regression, a logit function is used to link the odd ratio of an outcome (the probability of an event over the probability of a reference event) to a linear combination of the predictor variables, so that the probabilities are restricted between zero and one [89]. Assuming that there are *N* observations in the dataset with *p* predictor variables, and there are *J* categories of outcome. The problem can be described as in Eq. 3.6 and 3.7 below.

$$\log\left(\frac{P_{ij}}{P_{i1}}\right) = \beta_{0j} + \beta_{1j}x_{i1} + \beta_{2j}x_{i2} + \ldots + \beta_{pj}x_{ip}, \quad j = 2, \ldots, J, i = 1, \ldots, N \tag{3.6}$$

$$\sum_{j=1}^{J} P_{ij} = 1 \tag{3.7}$$

Eq. 3.6 shows that the logarithm of odd ratio for category *j* to category 1 (reference category) is a linear combination of predictor variables. The x_{ip} represents the p predictor variable in observation i, and β_{pj} is the coefficient of predictor p for category j. The model coefficients are estimated by using maximum likelihood. All the probabilities in one observation is subjected to 1 as shown in Eq. 3.7.

In Figure 3.4, it shows the data structure in this application. There are three load levels (so J = 3) for the dependent variable: high, medium, and low. The total observation number depends on the data pool selected from last stage. For one day with 15 minutes as a time interval, there are 96 observations. In each observation, the predictor variable includes timing information, weather information, and HEMS control information (i.e. if the appliances had been controlled). In the case study section, it shows how to select predictor variables. The multinomial logistic regression model in this application can be formulated as Eq. 3.8 and 3.9 with using low load level as the baseline.

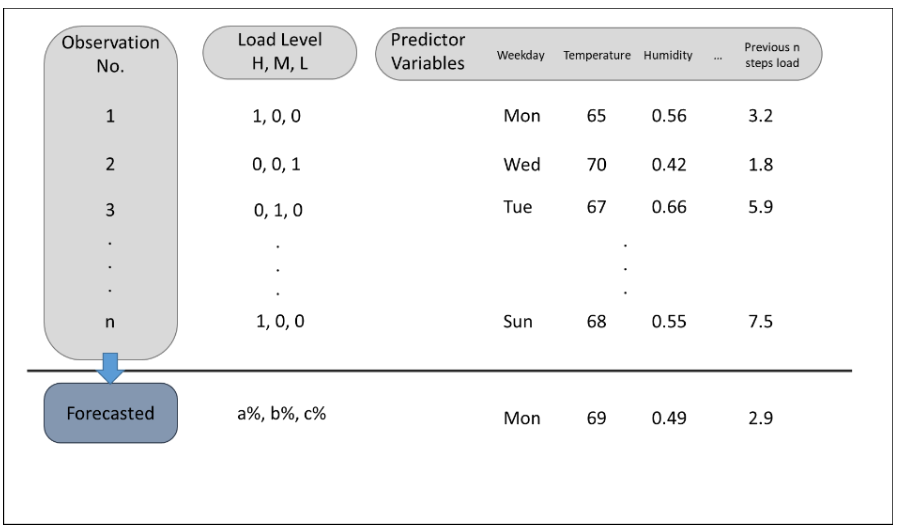


Figure 3.20 Data structure for multinomial logistic regression

$$\log\left(\frac{P_{\mathrm{H}}}{P_{\mathrm{L}}}\right) = \beta_{0\mathrm{H}} + \beta_{1\mathrm{H}} x_{i1} + \beta_{2\mathrm{H}} x_{i2} + \ldots + \beta_{p\mathrm{H}} x_{ip} = x_i^T \beta_{\mathrm{H}} \tag{3.8}$$

$$\log\left(\frac{P_{\mathrm{M}}}{P_{\mathrm{L}}}\right) = \beta_{0\mathrm{M}} + \beta_{1\mathrm{M}} x_{i1} + \beta_{2\mathrm{M}} x_{i2} + \ldots + \beta_{p\mathrm{M}} x_{ip} = x_i^T \beta_{\mathrm{M}} \tag{3.9}$$

$$P_{\mathrm{H}} + P_{\mathrm{M}} + P_{\mathrm{L}} = 1 \tag{3.10}$$

Then the forecasted load level probabilities ($\hat{P}_{\mathrm{H}}$, $\hat{P}_{\mathrm{M}}$, $\hat{P}_{\mathrm{L}}$) can be calculated from Eq. 3.11- 3.13 with forecast input x_f.

$$\hat{P}_{\mathrm{L}} = \frac{1}{1 + \exp\left(x_f^T \hat{\beta}_{\mathrm{H}}\right) + \exp\left(x_f^T \hat{\beta}_{\mathrm{M}}\right)} \tag{3.11}$$

$$\hat{P}_{\mathrm{M}} = \exp\left(x_f^T \hat{\beta}_{\mathrm{M}}\right) \hat{P}_{\mathrm{L}} \tag{3.12}$$

$$\hat{P}_{\mathrm{H}} = \exp\left(x_f^T \hat{\beta}_{\mathrm{H}}\right) \hat{P}_{\mathrm{L}} \tag{3.13}$$

3.2.2 Hour ahead load forecast with Kalman filter

The HA load forecast provides the hour-ahead deterministic load forecast in 5-minute resolution so that the HEMS can adjust its schedules timely. In this stage, a state space model is constructed for load forecasting based on recent past load and temperature information. Then the Kalman filter is applied to determine the optimal estimates of model state given the time series of observable measurements available at time t. In general, it is a recursive algorithm that consists of two sets of equations: Prediction equations and Updating equations. Here lists the key equations of state space model and Kalman filter. The detailed derivation of Kalman filter in state space model can be found in [90].

$$y(t) = C(t)x(t) + v(t) \tag{3.14}$$

$$x(t+1) = A(t)x(t) + w(t) \tag{3.15}$$

$$K(t) = \left[A(t)P(t)C^T(t)\right]\left[C(t)P(t)C^T(t) + Q_2\right]^{-1} \tag{3.16}$$

$$\hat{x}(t+1) = A(t)\hat{x}(t) + K(t)\left[y(t) - C(t)\hat{x}(t)\right] \tag{3.17}$$

$$P(t+1) = \left[A(t) - K(t)C(t)\right]P(t)\left[A(t) - K(t)C(t)\right] + K(t)Q_2K^T(t) \tag{3.18}$$

Where:

t is the time step,

$x(t)$ is n*1 system states,

$A(t)$ is n*n time varying state transition matrix,

y(t) is m*1 measurement vector,

$C(t)$ is m*n time-varying output matrix,

$w(t)$ is n*1 system error and $v(t)$ is m*1 measurement error, with covariance matrices of Q_1 and Q_2 respectively.

The first two equations are the general form of a state space model. The Eq. 3.14 is the measurement equation, describes the relation between the observed time series, $y(t)$, and the state $x(t)$. $v(t)$ is the measurement noise, which is assumed to model as Gaussian error term, $v(t) \sim$ N(0, σ_v). The Eq. 3.15, the transition equation, describes the evolution of the state variables as being driven by the stochastic process of $w(t)$, which is typically modeled as a Gaussian error term, such that $w(t) \sim$ N(0, σ_w)

To use the Kalman filter on state estimation, the Kalman gain in Eq. 3.16 is calculated firstly. It is the relative weight given to the measurements and current state estimate. With a high gain, the filter places more weight on the most recent measurements *y(t)*. In this equation, *P(t)* is the error covariance matrix, which is a measure of the estimated accuracy of the state estimate. The Q2 is the covariance matrix (noise level) of $v(t)$. After getting the Kalman gain, a new state and the error covariance matrix can be update by Eq. 3.17 and 3.18 respectively.

To forecast the hour-ahead load, a dynamic load model is created as Eq. 3.19, which is a linear combination of previous load and temperature variables in the moving window shown in Figure 3.5.

$$
\begin{aligned}
L(t+h) &= a_0(t+h-1) + a_1(t+h-1)L(t+h-t_1) + a_2(t+h-1)L(t+h-t_2) + \cdots + a_{n1}(t+h-1)L(t+h-t_{n1}) \\
&\quad + b_1(t+h-1)T(t+h-t_1) + b_2(t+h-1)T(t+h-t_2) + \cdots + b_{n2}(t+h-1)T(t+h-t_{n2}) \\
&= \begin{bmatrix} 1 \\ L(t+h-t_1) \\ L(t+h-t_2) \\ \vdots \\ L(t+h-t_{n1}) \\ T(t+h-t_1) \\ T(t+h-t_2) \\ \vdots \\ T(t+h-t_{n2}) \end{bmatrix} \times \begin{bmatrix} a_0(t+h-1) & a_1(t+h-1) & a_2(t+h-1) & \cdots & a_{n1}(t+h-1) & b_1(t+h-1) & b_2(t+h-1) & \cdots & b_{n2}(t+h-1) \end{bmatrix} \\
&= C(\tau)\chi(\tau)^T
\end{aligned}
$$

…… (3.19a)

In Eq. 3.14a, t is the current time stamp, *h* is time steps ahead (e.g. one time step ahead, h=1). $L(t)$ is the load at time t, and T(t) is the temperature value at time t. The $t_{n1/n2}$ is the selected data points prior to the forecasted point. Figure 3.5 shows an example of selected data points in forecasting t+2 load at time t. If a 15-minute resolution is used in the forecast model (i.e. there are 96 points in a day), then the model in Eq. 14a associated with figure 3 is as Eq. 19b. Please note that when forecasting 2 steps ahead, it uses the predicted values at t+1.

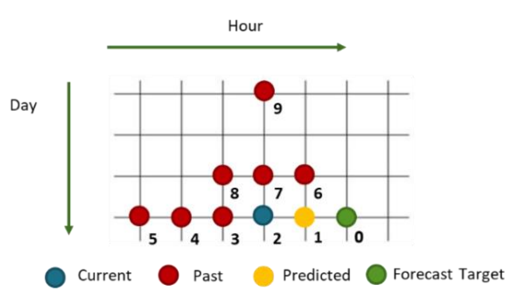


Figure 3.21 Moving window of data points selected in the load forecast model

$$
\begin{aligned}
L(t+2) = {} & a_0(t+1) + a_1(t+1)\hat{L}(t+1) + a_2(t+1)L(t) + a_3(t+1)L(t-1) + a_4(t+1)L(t-2) \\
& + a_5(t+1)L(t-3) + a_6(t+1)L(t-95) + a_7(t+1)L(t-96) + a_8(t+1)L(t-97) + a_9(t+1)L(t-288) \\
& + b_1(t+1)\hat{T}(t+1) + b_2(t+1)T(t) + b_3(t+1)T(t-1) + b_4(t+1)T(t-2) \\
& + b_5(t+1)T(t-3) + b_6(t+1)T(t-95) + b_7(t+1)T(t-96) + b_8(t+1)T(t-97) + b_9(t+1)T(t-288)
\end{aligned}
$$

…… (3.19b)

The dynamic load model of Eq. 3.19a can be summarized as $L(\tau) = C(\tau)\chi(\tau)^{\mathrm{T}}$ that is fitted into the Kalman filter state space model with the following definitions and calculation steps:

The load $L(\tau)$ in Eq. 3.19a is the measurable (observable) value (scalar) as $y(t)$ in Eq. 3.14. The load-temperature vector, $C^{\mathrm{T}}(\tau)$ in Eq. 3.19a is the output matrix C(t) in Eq. 3.14. It changes at each time step.

The $\chi^{\mathrm{T}}(\tau)$ of parameter vector is the state matrix x(t) in Eq. 3.14, which is estimated by Kalman filter. It represents the 1+n1+n2 parameters in the model.

The state transition matrix $A(t)$ in Eq. 3.15 is assumed to be an identity matrix with corresponding dimension to state matrix. In this case, it a (1+n1+n2)* (1+n1+n2) matrix.

The v(t) and w(t) are modeled as Gaussian white noise, and Q2 is assumed to be 1.

At the beginning, it initializes state matrix x(0) and error covariance matrix P(0) by a priori estimate. Then, it sets the time step t and forecast target time *t*+*h*. It collects the previous load and temperature data to generate the *C*(*t*) matrix and calculates the Kalman gain *K*(*t*). Then, the state matrix and error covariance matrices can be updated, with which a new forecasted *L*(*t*+*h*) is calculated. Please note that Kalman filter may produces a negative forecasted value of *L* due to the small magnitude of load, so in the last step of algorithm, it needs to change the negative value to zero. The algorithm flowchart is shown in Figure 3.6.

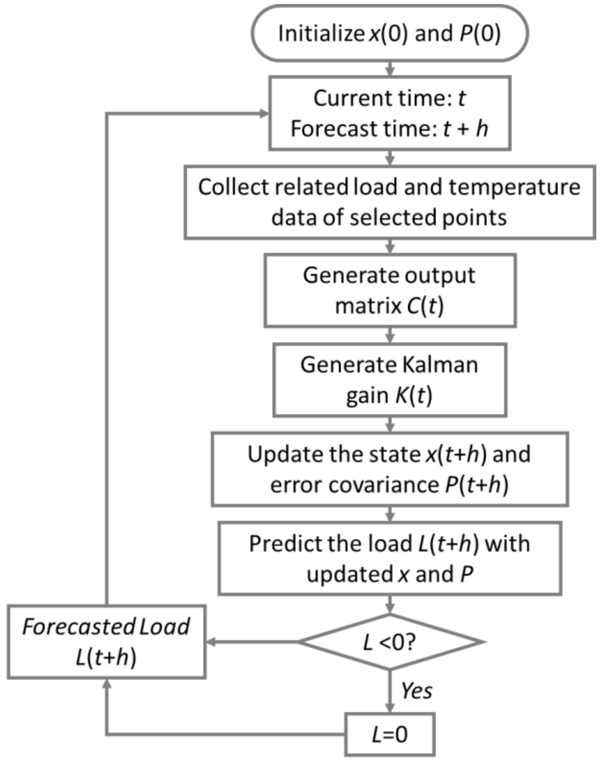


Figure 3.22 State-space Kalman filter algorithm flowchart

3.3 Case study

3.3.1 Data preparation

The approach is tested and validated with the high resolution data from 20 individual houses in Austin, TX provided by Pecan Street Inc. [91]. The data of each house includes 1-minite total household electricity load for the whole year 2015 and 2016. The corresponding weather data is also downloaded from Pecan Street Inc., and in this case, it uses temperature, humidity, precipitation intensity and cloud cover information. Note that in this case study, it use the actual weather information to forecast the load, and no weather forecast error is considered. In reality, the weather forecast error may impact the load forecast accuracy.

For DA probabilistic forecast, it requires to define the range of high, medium, low load levels, as discussed previously. In this case, 15% and 85% of sorted historical load are considered to be the thresholds of load level: historical load below 15% threshold is in low load level, and historical load above 85% threshold is in high load level, and load in between 15% and 85% is in medium load level. Please note that the historical data pool for DA forecast includes the most recent three months, and same month and two adjacent months in previous year.

To verify the effectiveness of the proposed forecasting approach, 10 summer days and 10 winter days in 2016 are forecasted for these 20 houses. All the data before forecasted day or forecasted hour with be used as historical data to train the model.

3.3.2 Accuracy Measurement

Different methods are used to measure the accuracy of the DA and HA forecast results. For probabilistic forecast in DA, its accuracy is measured based on a geometry distance concept shown in Figure 3.7 (a). The three angles on the “forecast error triangle” represent the high, medium and low load level probability. The low load level probability and high load level probability are on the opposite sides of x axis, while medium load level probability is on the y axis. The distance from the three angles to the origin is one, meaning the maximum probability of load level is one. Also the actual load level probability can only locate at one of these three points. The distance between a forecasted point to the actual angle point is the forecast error. Such a design considers the fact that a high load level forecast to low load level forecast is worse (longer distance) than medium load level forecast to low level actual, and vice versa.

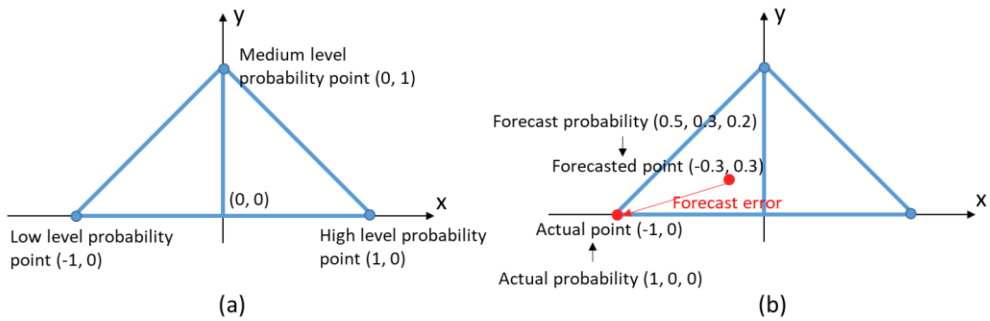


Figure 3.23 Illustration of probabilistic forecast error triangle

Figure 3.7(b) gives an example: the actual load is in low load level, so the actual point is (-1, 0). If a forecasted probability is (0.5, 0.3, 0.2) for low, medium and high level respectively, then the distance (error) is $\sqrt{(0.2-0.5+1)^2+(0.3)^2}=0.76$. Obviously, the longest distance or worst forecast error is 2, and best forecast error is 0. The forecast error, distant d, is formulated in Eq. (15) for each individual probabilistic forecast i. $\hat{P}_i$ and P_i are forecast and actual probability respectively. Again, there is one and must be one of $P_{(\mathrm{H,M,L}),\, i}$ equals to 1. The average distant (error) for a forecasted day is shown in Eq. (3.21).

$$d(\hat{P}_i, P_i) = \sqrt{(\hat{P}_{\mathrm{H},i} - \hat{P}_{\mathrm{L},i} - P_{\mathrm{H},i} + P_{\mathrm{L},i})^2 + (\hat{P}_{\mathrm{M},i} - P_{\mathrm{M},i})^2} \tag{3.20}$$

$$D = \frac{1}{n}\sum_{i=1}^{n} d(\hat{P}_i, P_i) \tag{3.21}$$

For HA deterministic forecast, a Weighted Mean Absolute Error in Eq. 3.22 is used to evaluate the forecast accuracy. Because there are multiple forecast intervals in one forecast shot and the evaluation should weight the forecast error of each forecast interval. For example, in the case study, the HA forecast has 5 minute resolution with 12 forecast intervals, so the MAE of a particular HA forecast should be a weight average of these 12 intervals. Such a design considers the fact that the forecasted value in HEMS application at an earlier time step is more important than the one at a later time step, because the HEMS relies on most recent forecast information. For example, at 10:55am, the forecaster predicts the load from 11am to 12am with 5 minute resolution. Then at 11am, the forecaster predicts the load from 11:05am to 12:05am, but the forecasted value of 11am won't be updated. So HEMS requires the load forecast in 11am interval be as accurate as possible when it schedules load at 10:55am.

$$\begin{aligned} &\mathrm{WMAE} = \frac{\sum_{i=1}^{T} w_i \left|\hat{L}_i - L_i\right|}{T} \\ &\sum_{i=1}^{T} w_i = T \end{aligned} \tag{3.22}$$

T is the total time steps in this forecast, for the HA forecast with 5-minute time steps, there are totally 12 intervals, so T = 12. $\hat{L}_i$ is the forecasted value at time interval i, and L_i is the actual value at time interval i. w_i is the weight for forecast error in interval i. In this case, it defines $w_i = \frac{3}{2} + \frac{1-2i}{2T}$, so that it is summed up to one.

In addition, it is helpful to evaluate the error in terms of percentage, however traditional measures such as percentage error are not suitable due to the low magnitude of house-level load. Some very bad instances can overshadow the other good forecasts. For example, a load of 0.5kW is forecasted as 1kW, so the Mean Absolute Percentage Error is 100%, but in house-level forecast, it should be considered as an acceptable forecast. So an Average Mean Absolute Percentage Error (AMAPE) is used to shown the error percentage over a whole forecast period.

$$\mathrm{AMAPE} = \frac{\sum_{n=1}^{N} \mathrm{WMAE}_n}{\sum_{n=1}^{N} L_n} \tag{3.23}$$

In Eq. 3.23, N is the total number of time steps in the forecast period, for example, in a day with every 5 minutes as a time step, then N =288.

3.3.3 Results

3.3.3.1 Data Clustering

The first stage is to prepare the data pool for DA forecast with a K-mean cluster algorithm, selecting the days with similar weather conditions. In this study, it considers temperature, humidity, cloud cover, and precipitation intensity. These factors are normalized, then weight averaged as a composite weather time series, which is used to determine the cluster. The optimal cluster number K is determined by the DB index. As mentioned before, the cluster dataset of each forecasted day include six months data. For example, when forecasting a day in June 2016, the cluster dataset includes April 2016 to June 2016, and May 2015 to July 2015. In Figure 3.8, it shows the chart of DB index of different cluster number in different months and highlights the optimal values in red. The optimal Ks for May, June and August are 4, since their weather patterns a lot with their adjacent months as shown in Figure3. 9. The optimal Ks for March, July and August are 3, and rest of the months' optimal K is 2. Figure 3.10 and 3.11 show the clustering results of daily temperature for an August forecasted day and a February forecasted day respectively.

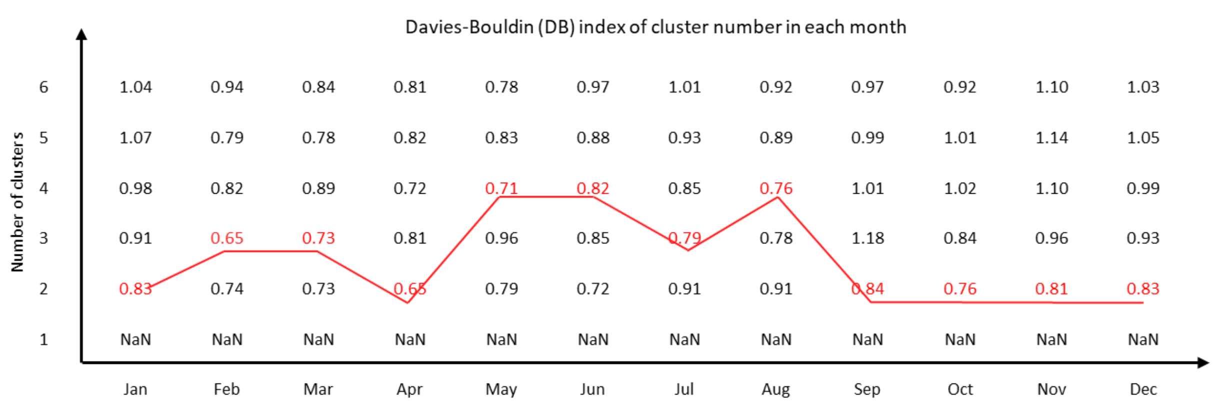


Figure 3.24 DB index of different cluster numbers in different months

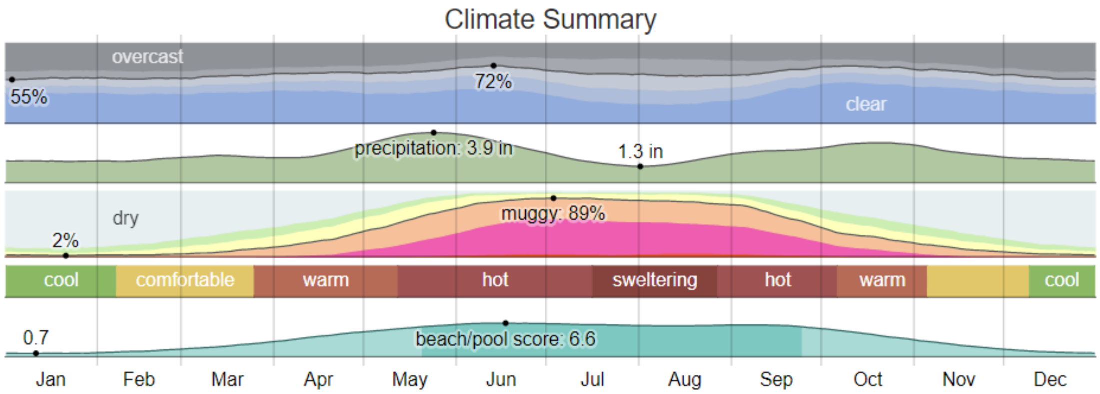


Figure 3.25 Average Weather in Austin, TX [92]

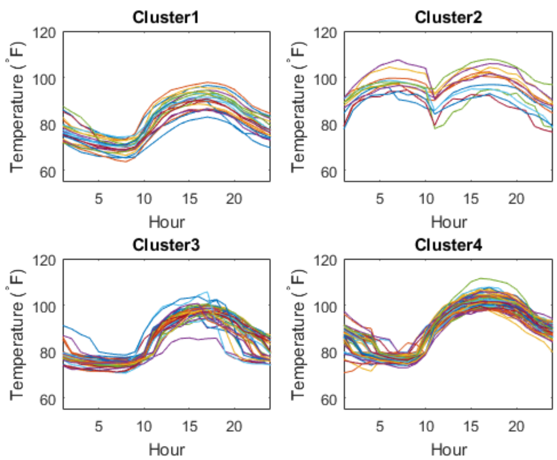


Figure 3.26 An August forecasted day cluster results of daily temperature

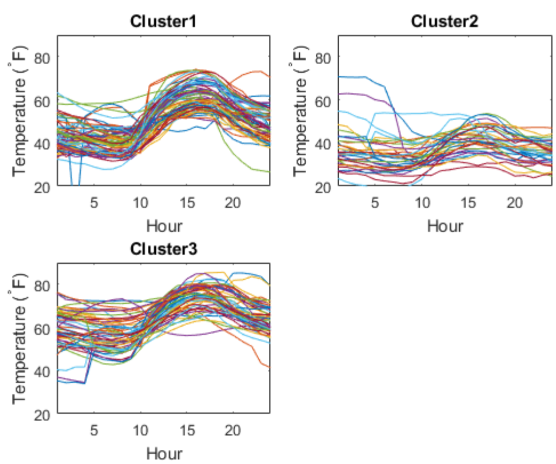


Figure 3.27 A February forecasted day cluster results of daily temperature

As shown in in Figure 3.10, there are 4 clusters for an August day, the cluster 1, 3 and 4 have similar shape but are different in the temperature range. Also, cluster 1 has lower temperature in early morning. Cluster 2 has some days of abnormal weather. The winter day cluster result in Figure 3.11 has three clusters, and they are different in temperature range as well as daily shape. These results show the clustering stage can narrow down the historical data and prepare the similar days for next stage of DA forecast.

3.3.3.2 DA probabilistic forecast

The probabilistic DA forecast is conducted with 15-minitue resolution. In this case study, it uses the following predictors in the model: month, time of the day, previous day load, previous two days load, temperature, humidity, cloud cover and precipitation intensity. The model is trained with the "similar day" from last stage. Both summer case and winter case are studied. Figure 3.12 is the DA probabilistic forecast result for one house (house ID 77 in the raw database) on Aug.31, 2016, it shows the probabilities of load level at each 15-minute interval. Three different color bars represents the three load level probability, the longer the bar, the higher probability the load level is. For example, during H7 to H10, the low level bars are longer than the others, meaning the load is most likely to be low during that time period. Figure 3.13 shows the actual load and selected load level thresholds. Comparing Figure 3.12 and 3.13, one can see that the forecast can predict the higher load in the early morning, also predict that the load is mostly likely to be at low level from H4 to H8. The forecast error defined in Eq. 3.15 for each interval is shown in Figure 3.14, with an average daily error of 0.53.

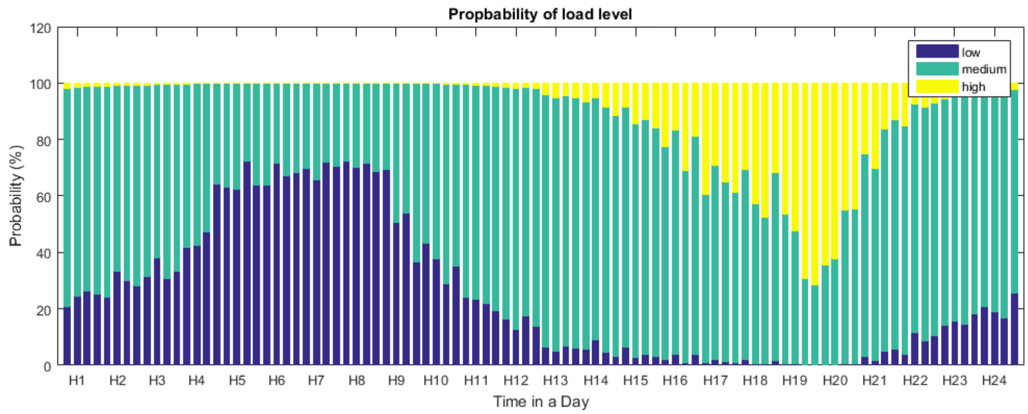


Figure 3.28 DA probabilistic forecast result for one house on Aug.31, 2016

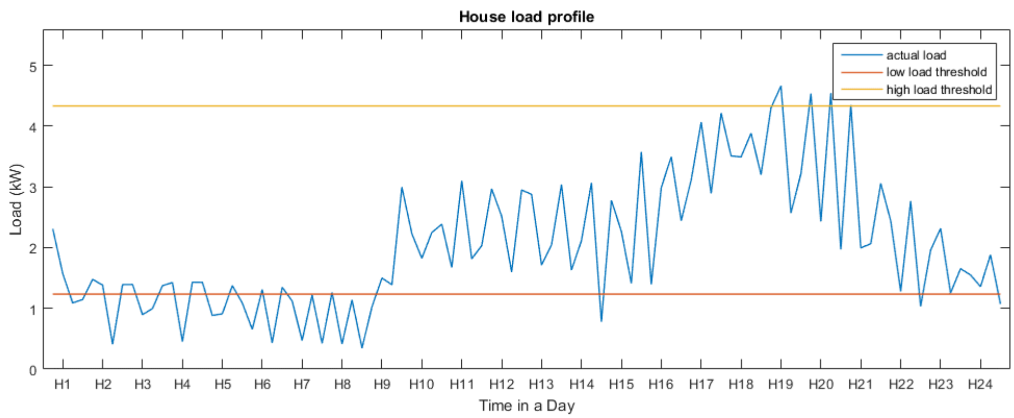


Figure 3.29 Actual load and selected thresholds for one house on Aug.31, 2016

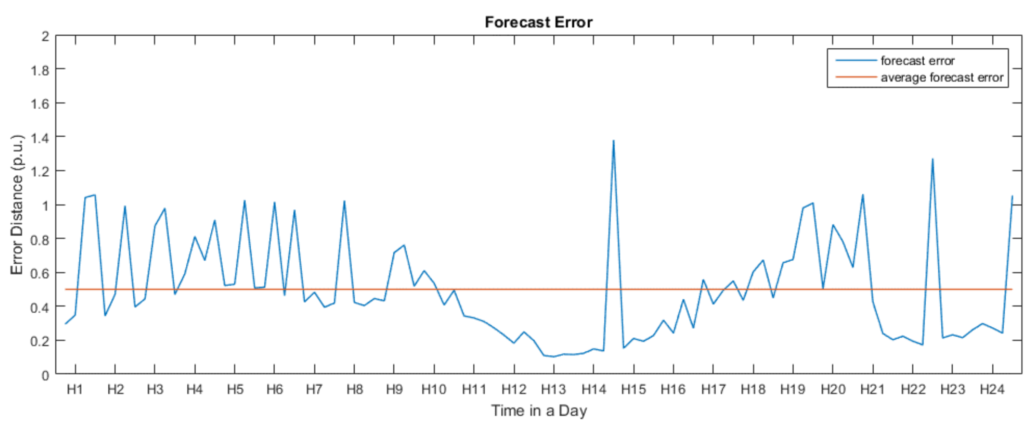


Figure 3.30 DA forecast error for one house on Aug.31, 2016

The winter case results for the same house are shown in Figure 3.15, 3.16 and 3.17. One can see that the forecaster can predict that the load will be at medium level most of the time in day ahead. There is one load spike at H17 that forecaster didn't predict. The overall forecast error of the day is 0.3.

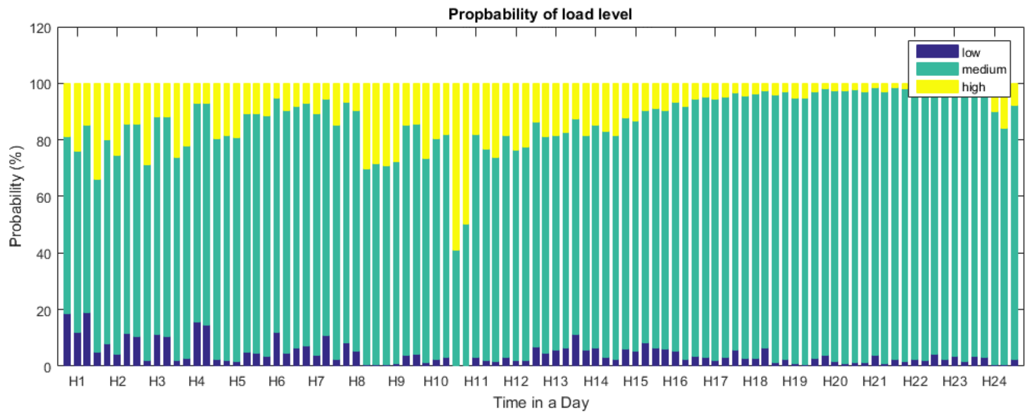


Figure 3.31 DA probabilistic forecast result for one house on Dec. 22, 2016

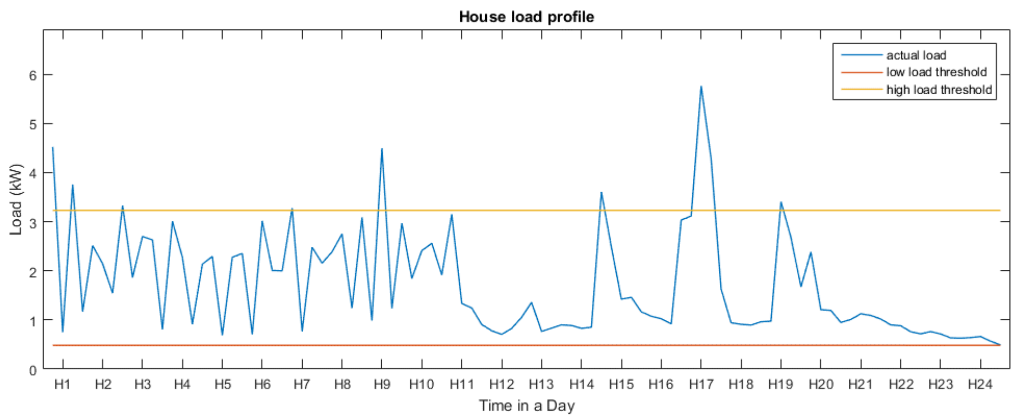


Figure 3.32 Actual load and selected thresholds for one house on Dec. 22, 2016

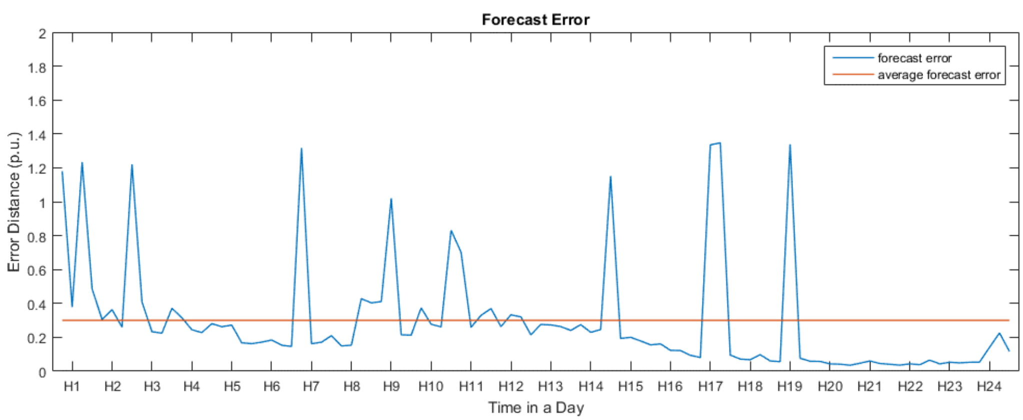


Figure 3.33 DA forecast error for one house on Dec. 22, 2016

The DA probabilistic forecaster is also evaluated by 20 houses in 2 summer and winter weeks. The results are shown in Table 3.1. On average of all houses' forecast error, the summer forecast is 0.6, which is higher than winter forecast error 0.48. This is due to the higher electricity demand level as well as demand volatility in summer.

Table 3.2 DA forecast error of 20 houses in 2 summer and winter weeks

	Summer			Winter		
House ID	Min	Mean	Max	Min	Mean	Max
26	0.54	0.63	0.74	0.20	0.45	0.70
77	0.46	0.55	0.61	0.24	0.42	0.59
114	0.50	0.60	0.78	0.13	0.51	0.72
545	0.47	0.59	0.75	0.17	0.43	0.62
624	0.58	0.66	0.78	0.41	0.51	0.67
744	0.27	0.46	0.62	0.10	0.44	0.58
781	0.54	0.63	0.86	0.37	0.50	0.68
1192	0.46	0.58	0.67	0.38	0.48	0.64
2129	0.50	0.59	0.72	0.37	0.49	0.64
2233	0.42	0.56	0.66	0.47	0.59	0.82
2755	0.53	0.62	0.70	0.39	0.53	0.72
3367	0.55	0.64	0.71	0.18	0.52	0.77
3456	0.45	0.57	0.70	0.22	0.54	0.76
3538	0.49	0.60	0.71	0.38	0.49	0.60
3918	0.47	0.53	0.60	0.06	0.36	0.59
3935	0.49	0.66	0.92	0.44	0.56	0.78
3967	0.37	0.56	0.75	0.27	0.50	0.72
4373	0.51	0.63	0.75	0.34	0.52	0.64
4767	0.30	0.65	0.74	0.10	0.44	0.68
4957	0.55	0.63	0.71	0.22	0.42	0.63

3.3.3.3 HA forecast

The HA load is forecasted in a 5-minute resolution and updated every five minutes, thus there are 12 forecast intervals in an hour. Every time interval has 12 update from 1 hour ago to 5 minutes ago, meaning the load at a time interval will be forecasted 1 hour ago, then updated every 5 minute, until 5 minutes before it. According to Eq. 3.19, the proposed model selects 14 previous points of load and temperature as shown in Figure 3.18.

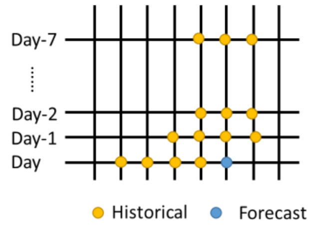


Figure 3.34 A moving window of selected point in HA model

The forecast effectiveness is verified by 20 houses in both summer week and winter week. Figure 3.19 shows the HA forecast result of a house load in a summer day. In this figure, it compares the actual load with four forecast updated 5 minutes ahead, 15 minutes ahead, 30 minutes ahead and 1 hour ahead. One can see that the later the forecast is updated, the closer it is to the actual. That is because the model has more information when getting to the time interval. An interesting fact is that all the forecast are close to each other when the load is smooth or has less change in time, such as time H7 to H9 in Figure 3.19. When the load change significantly, the 5-minute ahead forecast curve can pick up the change in the next interval, while the 1 hour ahead forecast curve reflect the change in a later time. For example, between H14 and H15 in Figure 3.17, the actual load changes a lot, and the 5-minute ahead forecast can predict the change closely. However, the 1-hour ahead forecast is lower than actual at H14 but forecasts a higher load at H15. Therefore, the volatility has more impact on longer term.

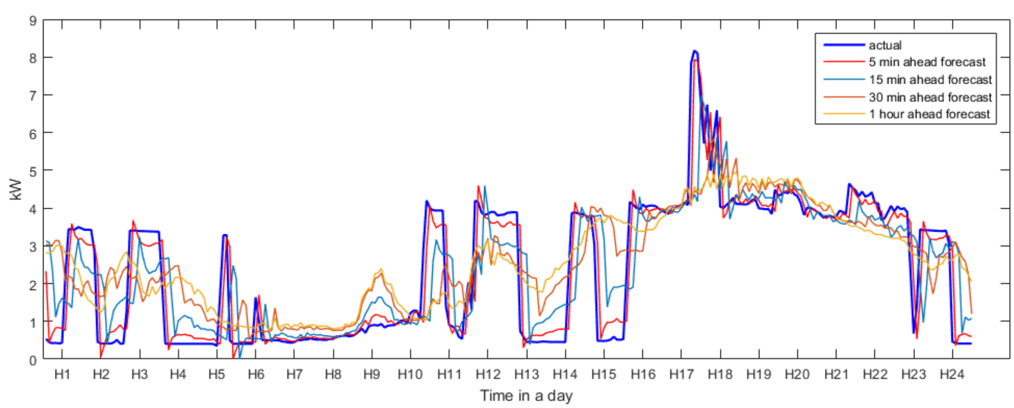


Figure 3.35 HA forecast of a house load in a summer day

Figure 3.20 plots out the WMAE of the result in Figure 3.19. It shows that the WMAE is high when the load change a lot in a short time. The forecaster can adjust itself quickly to reduce the error. The daily AMAPE is 35.8%.

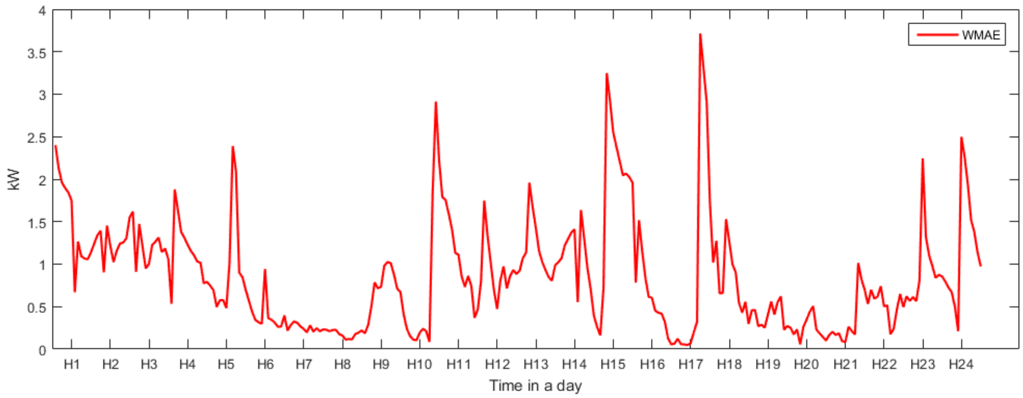


Figure 3.36 WMAE of HA forecast of a house load in a summer day

The winter results are shown in Figure 3.21 and 3.22. The winter load has less volatility, so the forecasted curves at different time frames are close to each other at most of the time. Thus the WMAE is within 1 kW for most of the day, expect one large error due to big load jump around H18. The daily AMAPE is 30.1%.

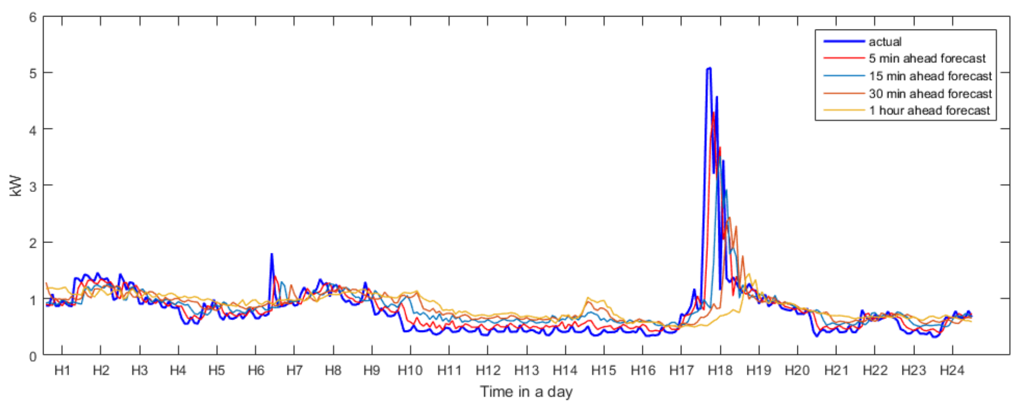


Figure 3.37 HA forecast of a house load in a winter day

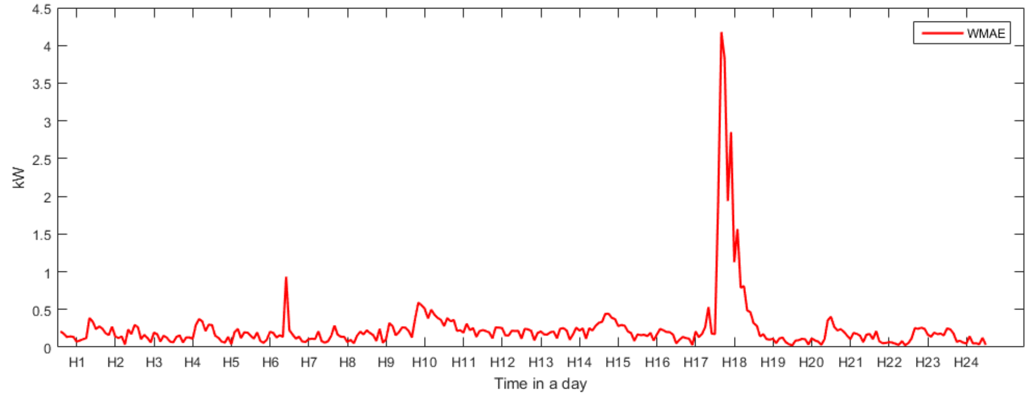


Figure 3.38 WMAE of HA forecast of a house load in a winter day

The HA forecast model is also testified by 20 houses. The results of AMAPE over a summer and winter week long time period are shown in Table 3.2. In general, the winter error is smaller than summer error.

Table 3.3 AMAPE of HA forecast for summer and winter case

House ID	*Summer week AMAPE*	*Winter week AMAPE*
26	33.74%	23.94%
77	40.60%	29.12%
114	32.86%	25.74%
545	34.76%	14.73%
624	57.08%	47.93%
744	24.48%	14.50%
781	44.71%	33.44%
1192	38.67%	26.77%
2129	30.30%	13.08%
2233	21.97%	20.63%
2755	41.76%	45.95%
3367	37.11%	31.75%
3456	51.31%	29.27%
3538	49.65%	27.38%
3918	16.28%	2.84%
3935	17.57%	24.87%
3967	34.33%	35.13%
4373	39.44%	41.59%
4767	28.61%	20.67%
4957	33.63%	12.34%

3.4 Summary

HEMS needs to schedule household load based on an energy demand forecaster. Due to the high volatility of household load, the proposed forecaster predicts the load level instead of exact value in day ahead, while it provides short-term forecast in hour ahead. In this way, HEMS can schedule tasks with less impact of demand uncertainty in day ahead, then fine tune schedule in real-time with the HA forecast results.

The DA forecast includes two steps: (1) similar day clustering with k-mean algorithm and (2) probabilistic forecast of load levels with multinomial logistic regression. The first step groups daily load profiles in order to narrow down the training dataset for the second step. The DB index is used to determine the suitable groups of similar day based on their weather similarity. Statistic shows that weather is the main factor that impacts daily load level. The second step uses the similar day group data to estimate the load level probability based on weather and timing information. The load level threshold selection is discussed, which is based on a pre-defined peak and the largest power rating of household appliances. An "Error Distant" concept is proposed to evaluate the forecast accuracy. Case study shows the effectiveness of the proposed DA forecast approach that is on average 57% more accurate than the "naïve method" (assuming the load level probabilities are equally distributed through the day).

The HA forecast uses a state-space model updated with Kalman filter algorithm. In this application, the past 14 point values (a 5-min time step) of load and weather are used as the inputs. It shows the forecasted load has high correlation with the values in last half-hour and some time in previous day. The AMAPE is used to evaluate the accuracy of the forecast. Further forecast horizon will results in lower accuracy, reducing from 13% in 5 minutes ahead to 42% in

1 hour ahead. Also, the HA forecast has better performance in winter than in summer, which are 26% AMAPE and 35% AMAPE respectively.

The proposed forecast approach is computationally economic, and it can help HEMS to be robust to demand uncertainty.

CHAPTER 4 LOAD MODELING AND CONTROL STRATEGY FOR HEMS WITH HEURISTIC APPROACH UNDER TIME-OF-USE PRICING

In this chapter, HEMS scheduling methodology is presented. The controllable load is categorized and modeled in three main types according to their physical characteristics. With this model set, a heuristic based control strategy is developed to manage the controllable appliance in order to maximize the household cost benefit and improve the energy demand profile under TOU price.

4.1 Introduction

The increasing household smart appliances allow residential users to consume the energy in a smart way, in which they can save the electricity bill, have greater control of their comfortableness, and even reduce their carbon footprint. At the same time, LSEs expect to use the smart appliances to reduce the peak demand and reshape the load profile, so that they can improve the energy efficiency and defer some facility upgrade. In addition, nowadays time-varying pricing schemes are used by most of the LESs to guide consumers' energy usage. Thus, an HEMS can help residential users to schedule their smart appliances and help LSEs to fulfill the demand side management strategy. In this chapter, it focuses on developing scheduling algorithm of HEMS from the perspectives of cost saving and peak demand reduction.

There are several residential demand side management techniques and algorithms are proposed in the literature [93 – 99]. Most of them model the household load mathematically and solve it with minimization programming algorithms. However, most of literature provides a generic model, which may not well represent some characteristics of certain appliance. Some papers [100–102] use only one or two appliances as control object, and design specific control algorithms for that appliances. In the future of smart grid, there will be variety of types of controllable appliance in a smart house, thus, an HEMS should be able to include all types of smart appliances. On the other hand, most of the proposed control algorithms are based on mathematical programming [96, 103,104], which needs a lot of computational resource to solve the question. In reality, HEMS controller uses less powerful processor, so a rule-based or heuristic-based approach can be more tangible for an HEMS. In this chapter, a heuristic-based HEMS scheduling approach is proposed for the future of smart grid, which aim to handle a variety of controllable devices with different usage patterns. Such a scheduling approach should be computationally achievable for local HEMS controller's micro-processor and robust to forecast inaccuracy. Most important, the proposed scheduling approach considers user's preference setting and their expectation of cost saving, which bridges the local HEMS scheduling to upper system requirements.

The smart appliances are firstly categorized and modeled in three main types: Thermostatically Controlled Appliance (TCA), Task Based Appliance (TBA) and Electric Vehicle (EV). TCA represents the appliances that operates according to its temperature setpoint, such as air conditioner, space heater, water heater and refrigerator. This model needs to consider the thermal dynamic, operation limits (minimum on/off time) and user's preference of temperature setpoint. TBA is a category for appliances whose usage pattern is based on timing, such as dish washer, clothes washer and dryer. A user assigns a task and expects the task will be finished before certain time. This model considers the task/sub-task running time of the appliance and user's timing setting. The EV model considers both EV charging rate and EV state of charge (SoC), which impact the charging time needed. It also needs to consider user's expected SoC target and timing setting (arrive/leave).

A heuristic-base control strategy and algorithm are developed for each type of controllable load. The control strategy aims to find a right controllable value (e.g. temperature setpoint, task start time, EV charging rate) and the right time to optimize the energy usage under the time-varying electricity price. The control strategy uses rule-base and greedy search approach to find the optimal solution, considering user's preference and demand forecast. The control strategy is combined with a "cost-saving" mechanism that allows users to quantify their saving expectation in terms of control values (e.g. setpoint, task end time, EV SoC). In addition, a power-cap control algorithm is developed to control household load based on a rolling priority list, such that it can limit the maximum demand and flatten the load profile. A case study is conducted to demonstrate the effectiveness of the proposed control algorithm with criteria of total cost, peak demand, comfortableness affect, and peak-to-average ratio.

The rest of the chapter are organized as following. Section 4.2 presents the models of three different types of controllable load. Section 4.3 introduces the heuristic control strategy and the power-cap control algorithm of HEMS. Case study in Section 4.4 shows the effectiveness of the proposed control algorithm and discusses the performance sensitivity to power cap selection. Section 4.5 concludes the chapter of HEMS scheduling.

4.2 Controllable Load Modeling

In a house, the HEMS monitors the total household electricity load and controls the operation of major appliances. Based on customer usage patterns and physical characteristics, we categorize the house controllable loads into three categories: Thermostatically Controlled Appliance (TCA), Task Based Appliance (TBA) and Electric Vehicle (EV). There are two main constraints in the problem formulation: operational constraints of the appliances and consumer comfort constraints.

4.2.1 TCA Modeling

The first type of controllable loads include appliances such heating, ventilation, and air conditioning (HVAC) units, electric water heaters (EWH), and refrigerators. They are controlled mainly by adjusting the temperature setpoint within a customer/manufacturer defined deadband. Figure 4.1 shows an example of the water temperature dynamic and operation cycle of a EWH with a setpoint T_{set} =130°F and deadband [T_{L} , T_{U}] = [125°F, 135°F]. When the water temperature falls lower than the lower bound T_{L} , the heating coils turns ON to heat up the water. When the water temperature reaches the upper bound T_{U} , the heating coils turns OFF. When taking showers or washing dishes, the hot water is drawn and cool water flows in, causing the tank water temperature to drop. After the lower temperature limit is reached, heating coils are turned on to heat the water until the upper temperature limit is reached.

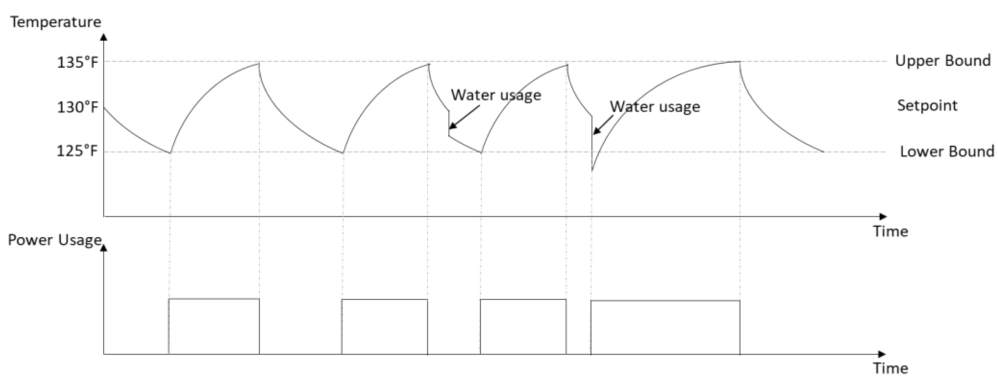


Figure 4.39 A typical thermal characteristic curve of an electric water heater load

Based on the equivalent thermal parameter (ETP) approach introduced in [105], the thermal dynamic of the TCA can be modeled as Eq. 4.1:

$$T_{\text{TCA},n+1} = T_{\text{out},n} + u_{\text{TCA},n} \cdot Q \cdot R - (T_{\text{out},n} + u_{\text{TCA},n} \cdot Q \cdot R - T_{\text{TCA},n}) \cdot \exp(-\Delta t / R \cdot C) \qquad (4.1)$$

where $T_{\mathrm{TCA},n}$ (°F) is the TCA controlled temperature, $T_{\mathrm{out},n}$ (°F) is the ambient temperature at time n, $u_{\mathrm{TCA},n}$ is TCA status, Q is the appliance electric capacity (kW), R is the appliance thermal resistance (°F /kW), C is the appliance thermal capacitance (kWh/°F), and Δt is the time step. Note that for the EWH and HVAC heating mode, Q is a positive value. For the refrigerator and HVAC in its cooling mode, Q is a negative value.

In addition, the temperature changed by cool water inflow can be modeled as Eq. 4.2:

$$T'_{\mathrm{WH},n} = \frac{[T_{\mathrm{WH},n} \cdot (V - d_n) + \alpha \cdot T_{out,n} \cdot d_n]}{V} \tag{4.2}$$

where $T'_{\mathrm{WH},n}$ is the water temperature after hot water used, V is the mass of water in the full tank (gallon), d_n (gallon) is the demand of hot water drawn (or mass of water from cold water inlet) at time n, and α is ratio of inlet water temperature over ambient temperature.

For a heating unit, the TCA status can be described as Eq. 4.3:

$$u_{\mathrm{TCA},n} = \begin{cases} 1, & T_{\mathrm{TCA},n} \le T_{\mathrm{L}} \\ 0, & T_{\mathrm{TCA},n} \ge T_{\mathrm{U}} \\ u_{\mathrm{TCA},n-1}, & T_{\mathrm{L}} < T_{\mathrm{TCA},n} < T_{\mathrm{U}} \end{cases} \tag{4.3}$$

To formulate the TCA status linearly, Eq. 4.3 can be reformulated as Eq. 4.4 and 4.5:

$$u_{\mathrm{TCA},n} \ge \frac{T_{\mathrm{L}} - T_{\mathrm{TCA},n}}{M} \tag{4.4}$$

$$1 - u_{\mathrm{TCA},n} \ge \frac{T_{\mathrm{TCA},n} - T_{\mathrm{U}}}{M} \tag{4.5}$$

Where M is an arbitrary large positive value (e.g. 1000) that makes the right side of above inequalities between 0 and 1 when the temperature is outside the deadband [T_{L} , T_{U}].

For an HVAC unit, the model should consider the unit's minimum ON/OFF time limit. Before that, it needs to introduce the switch ON and switch OFF indicators: $z_{\mathrm{TCA},n}$ and $y_{\mathrm{TCA},n}$, as illustrated in Figure 4.2.

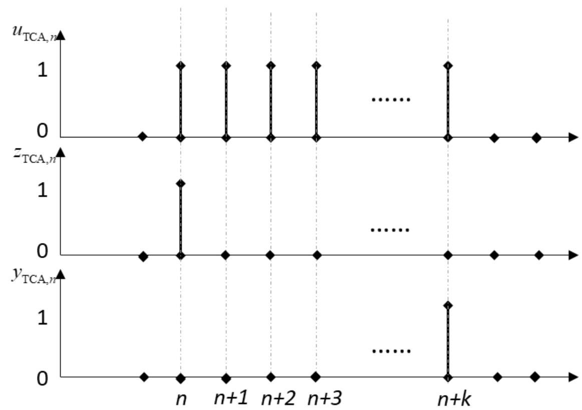


Figure 4.40 An example of the TCA status and switch on/off indicators

When the unit turns on at time n, $z_{\mathrm{TCA},n}$ is 1 and $u_{\mathrm{TCA},n}$ becomes 1. When the unit turns off at time n, $y_{\mathrm{TCA},n}$ is 1 and $u_{\mathrm{TCA},n}$ becomes 0. Such a relationship can be described by Eq. 4.6 – 4.8.

$$u_{\mathrm{TCA},n+1} - u_{\mathrm{TCA},n} = z_{\mathrm{TCA},n} - \mathrm{y}_{\mathrm{TCA},n} \tag{4.6}$$

$$z_{\mathrm{TCA},n} \le u_{\mathrm{TCA},n} \tag{4.7}$$

$$\mathrm{y}_{\mathrm{TCA},n} \le 1 - u_{\mathrm{TCA},n} \tag{4.8}$$

$$u_{\mathrm{TCA},n}, z_{\mathrm{TCA},n}, \mathrm{y}_{\mathrm{TCA},n} \in \{0,1\}$$

Thus, the minimum ON/OFF time limit can be modeled by Eq. 4.9 and 4.10.

$$\sum_{n'=\max(1,\, n-t_{on}+1)}^{n} z_{\mathrm{TCA},n'} \le u_{\mathrm{TCA},n} \tag{4.9}$$

$$\sum_{n'=\max(1,\, n-t_{off}+1)}^{n} y_{\mathrm{TCA},n'} \le 1 - u_{\mathrm{TCA},n} \tag{4.10}$$

Where t_{on} and t_{off} are the unit minimum ON time and OFF time, respectively.

4.2.2 TBA Modeling

The second type of controllable load is call Task based appliance (TBA). It includes dish washer, cloth washer, cloth dryer, and automatic irrigation system. A user assigns a task for a TBA and expects the task is completed before certain time. Also, for some TBA, the task can be separated into several sub-tasks, which allow interruption between two neighbor sub-tasks. For example, a cloth washer cycle can include soak, wash, rinse, and spin. Each task or sub-task is run sequentially and takes certain time to finish. Thus, TBA can be modeled as discontinuous load between the user-defined start time and must-finish time, with multiple consecutive subtasks.

Similar to the TCA modeling in Eq. 4.6 – 4.8, the TBA status and turn ON/OFF indicators can be modeled as in Eq. 4.11 – 4.13.

$$u^k_{\mathrm{TBA},n+1} - u^k_{\mathrm{TBA},n} = z^k_{\mathrm{TBA,n}} - \mathrm{y}^k_{\mathrm{TBA,n}} \tag{4.11}$$

$$z^k_{\mathrm{TBA,n}} \le u^k_{\mathrm{TBA},n} \tag{4.12}$$

$$y^k_{\mathrm{TBA,n}} \le 1 - u^k_{\mathrm{TBA},n} \tag{4.13}$$

$$u^k_{\mathrm{TBA},n}, z^k_{\mathrm{TBA,n}}, \mathrm{y}^k_{\mathrm{TBA,n}} \in \{0,1\}$$

$u^k_{\mathrm{TBA},n}, z^k_{\mathrm{TBA,n}}, \mathrm{y}^k_{\mathrm{TBA,n}}$ are the TBA status (on/off), turn ON indicator, and turn OFF indicator of the kth (k=1,2,…K) sub-task at time n respectively.

In this study, it assumes that each task or sub-task is run once in an optimization/scheduling horizon. If a TBA runs more than twice in a scheduling horizon, this appliance will be modeled as two separate TBAs. For example, if there are two loading of cloth washer in a day, then there will be two separate cloth washer models in the HEMS scheduling. This fact is modeled in Eq. 4.13 and 4.14.

$$\sum_{n=1}^{N} z_{\mathrm{TBA,n}}^{k} = 1 \tag{4.13}$$

$$\sum_{n=1}^{N} y_{\mathrm{TBA,n}}^{k} = 1 \tag{4.14}$$

Each task or sub-task task needs certain time to finish. Eq. 4.15 represents that a TBA needs to run uninterruptedly to finish a sub-task k for a time period of $t_{\mathrm{TBA}}^{\mathrm{on},k}$. Also each sub-task runs in sequence as modeled in Eq. 4.16, meaning a sub-task starts only after the previous sub-task is finished.

$$\sum_{n'=\max(1,\, n-T_{\mathrm{TBA}}^{\mathrm{on},k}+1)}^{n} z_{\mathrm{TBA,n'}}^{k} = u_{\mathrm{TBA},n}^{k} \tag{4.15}$$

$$\sum_{n=1}^{N} n \cdot z_{\mathrm{TBA,n}}^{k} \geq \sum_{n=1}^{N} n \cdot y_{\mathrm{TBA,n}}^{k-1}, \quad k = 2,3,\ldots,K \tag{4.16}$$

Finally, Eq. 4.17 and 4.18 describe that a task should be completed between the user-defined start time point $t_{\mathrm{TBA},start}$ and end time point $t_{\mathrm{TBA},end}$.

$$\sum_{n=1}^{N} n \cdot z_{\mathrm{TBA,n}}^{k} \geq t_{\mathrm{TBA},start}, \quad k = 1 \tag{4.17}$$

$$\sum_{n=1}^{N} n \cdot y_{\mathrm{TBA,n}}^{k} \leq t_{\mathrm{TBA},end}, \quad k = K \tag{4.18}$$

4.2.3 EV Modeling

Similar to the TBA, an EV needs to be charged during some time of the day, but how long the charging time is depends on the initial and target status of the SoC (state of Charge) of the battery. Also, most of the EV manufactures offer multiple charging rates for the battery [106]. This should be considered in the EV modeling, since the HEMS can adjust the charging rate according to electricity price and remaining charging time.

Similar as the previous two controllable loads, the EV charging status and switch ON/OFF indicators are modeled in Eq. 4.18 – 4.20. In this study, we assume that there are two charging levels.

$$u_{\mathrm{EV1(2)},n+1} - u_{\mathrm{EV1(2)},n} = z_{\mathrm{EV1(2)},n} - y_{\mathrm{EV1(2)},n} \tag{4.18}$$

$$z_{\mathrm{EV1(2)},n} \le u_{\mathrm{EV1(2)},n} \tag{4.19}$$

$$y_{\mathrm{EV1(2)},n} \le 1 - u_{\mathrm{EV1(2)},n} \tag{4.20}$$

$$u_{\mathrm{EV1(2)},n}, z_{\mathrm{EV1(2)},n}, y_{\mathrm{EV1(2)},n} \in \{0,1\}$$

Where $u_{\mathrm{EV1(2)},n}, z_{\mathrm{EV1(2)},n}, y_{\mathrm{EV1(2)},n}$ are the two charging levels' (1 and 2) status, switch ON, and switch OFF indicator 2 respectively. Since EV can only be charging at one of the two levels, Eq. 4.21 shows this relationship.

$$u_{EV1,n} + u_{EV2,n} \le 1 \tag{4.21}$$

Assuming that the user defines the start time (plug-in time) $t_{\mathrm{EV,start}}$ and end time $t_{\mathrm{EV,end}}$ for charging the EV, Eq. 4.22 means that the EV starts charging no earlier than the start time. Eq. 4.23 means that the SoC should reach to target value, say 95%, at the end time. Please note that if the target SoC can't be reached even by using that fastest charging rate all the charging time, the HEMS will charge the EV as much as possible during when it is plug-in.

$$z_{\text{EV1(2)},n} = 0,\ n < t_{\text{EV,start}} \tag{4.22}$$

$$SoC_{n=t_{\text{EV,end}}} = 95\% \tag{4.23}$$

The change of SoC over time can be formulated in Eq. 4.24, in which P_{EV1} and P_{EV2} are the charging rate, and Cap is the battery total capacity (kWh).

$$SoC_{n+1} = SoC_n + \frac{(u_{\text{EV1},n} \cdot p_{\text{EV1}} + u_{EV2,n} \cdot p_{\text{EV2}}) \cdot \Delta t}{Cap} \tag{4.24}$$

4.3 Control Strategy

The main objective of the proposed HEMS is to maximize user's cost benefit and to level the household electricity demand profile. This objective can be formulated in Eq. 4.25 – 4.28.

$$p_{\text{total},n} = p_{\text{base}} + \sum_{a=1}^{A} u_{a,n} \cdot p_a + \sum_{b=1}^{B} \sum_{k=1}^{K_b} u_{b,n}^k \cdot p_b^k + \sum_{e=1}^{E} u_{e,n} \cdot p_e \tag{4.25}$$

$$c_1 = \sum_{n=1}^{N} p_{\text{total},n} \cdot \Delta t \cdot r_n \tag{4.26}$$

$$\overline{p} = \frac{1}{N} \sum_{n=1}^{N} p_{\text{total},n} \tag{4.27}$$

$$c_2 = \frac{1}{N} \sum_{n=1}^{N} \left| p_{\text{total},n} - \overline{p} \right| \tag{4.28}$$

The HEMS scheduler consider all the appliances, including base load, TCA, TBA (with sub-tasks), and EV, as shown in Eq. 4.25. r_n is the electricity price at time n. In this study, it focuses on TOU pricing scheme with demand charge. A demand charge is a charge to the monthly maximum power, usually in 15 minute resolution, during peak hours [106, 107].

The objective above, together with constraints (4.1) — (4.24) (except 4.3), can be formulated as a Mix Integer Linear Programming (MILP) problem, and solved by available optimization software. However, such an optimization problem for day-ahead scheduling can be computationally expensive and is intangible for the HEMS computer. Moreover, the MILP problem requires precise load forecast for scheduling, thus, it may not be able to achieve optimal in reality and may lead to higher electricity cost. In this study, while using the MILP model as benchmark, it proposes a heuristic approach for the HEMS with an objective to achieve better cost saving and reduce demand peak. Such a control strategy is computational economic for HEMS control unit and robust to household energy demand forecast. It schedules the load according to load forecast (in Chapter 3), time varying price, user comfort setting and controllable load types. Also it extends the load elasticity by quantifying user's cost saving expectation in return for reducing comfort level. In addition, a power cap control algorithm is developed to reschedule some energy use to avoid high demand charge. The following subsections present the control strategy and algorithm of the heuristic approach for each type of controllable appliance.

4.3.1 TCA Control Strategy

In general, the HEMS aims to use TCAs' thermal capacity to store the heat/cool at low price or low load period, such that reduce the consumption during high price or high load period. So there are two key questions needs to answer for managing TCAs: 1) when to start pre-heating/pre-cooling; 2) how much is the temperature change of setpoint. The control strategy can be summarized in two steps.

The HEMS changes the TCA setpoint to pre-heat/pre-cool the air or water before the price increases. Based on the DA demand forecast (discussed in Chapter 3), the HEMS selects the lowest load time slot within 1 hour before price increases to start the pre-heat/pre-cool, such that it can avoid creating a high demand in this period.

Outside the pre-heat/pre-cool period, the HEMS keeps the highest setpoint for cooling mode or lowest setpoint for heating mode according to user's comfort preference. However, the HEMS can extend the setpoint outside comfort zone in order to achieve high cost saving that exceeds the user-defined penalty of uncomfortableness. Figure 4.3 illustrates such a mechanism.

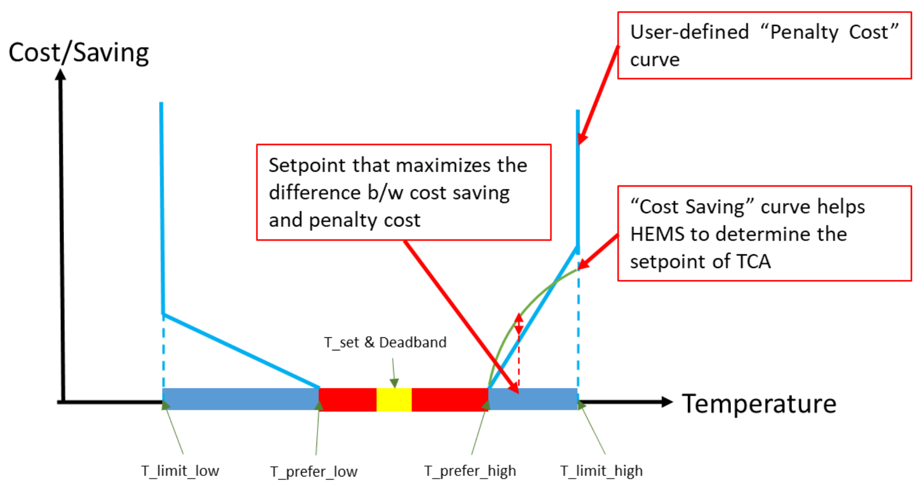


Figure 4.41 A mechanism for HEMS to extend the setpoint according to user's cost saving expectation

In Figure 4.3, the yellow bar is TCA's setpoint and deadband, when operated, a TCA's temperature varies between the deadband lower and upper bound. The red bar is the user-defined temperature preference zone, within which user feels comfortable. For air conditioning, people usually set it around 70 – 74°F. Outside the preference zone, the user-defined "penalty cost" increases by the distance away from preferred temperature. It means that user expects certain amount of dollar is compensated by one degree Fahrenheit temperature higher/lower than the highest/lowest bound of preference temperature zone. The penalty cost curve can be linear, step-wise or even quadratic. By the meantime, the HEMS provides the “cost saving” curve along different temperature setpoint, as shown as the green curve, based on the TCA ETP model. Then the HEMS determines the setpoint that can maximize the difference between cost saving and penalty.

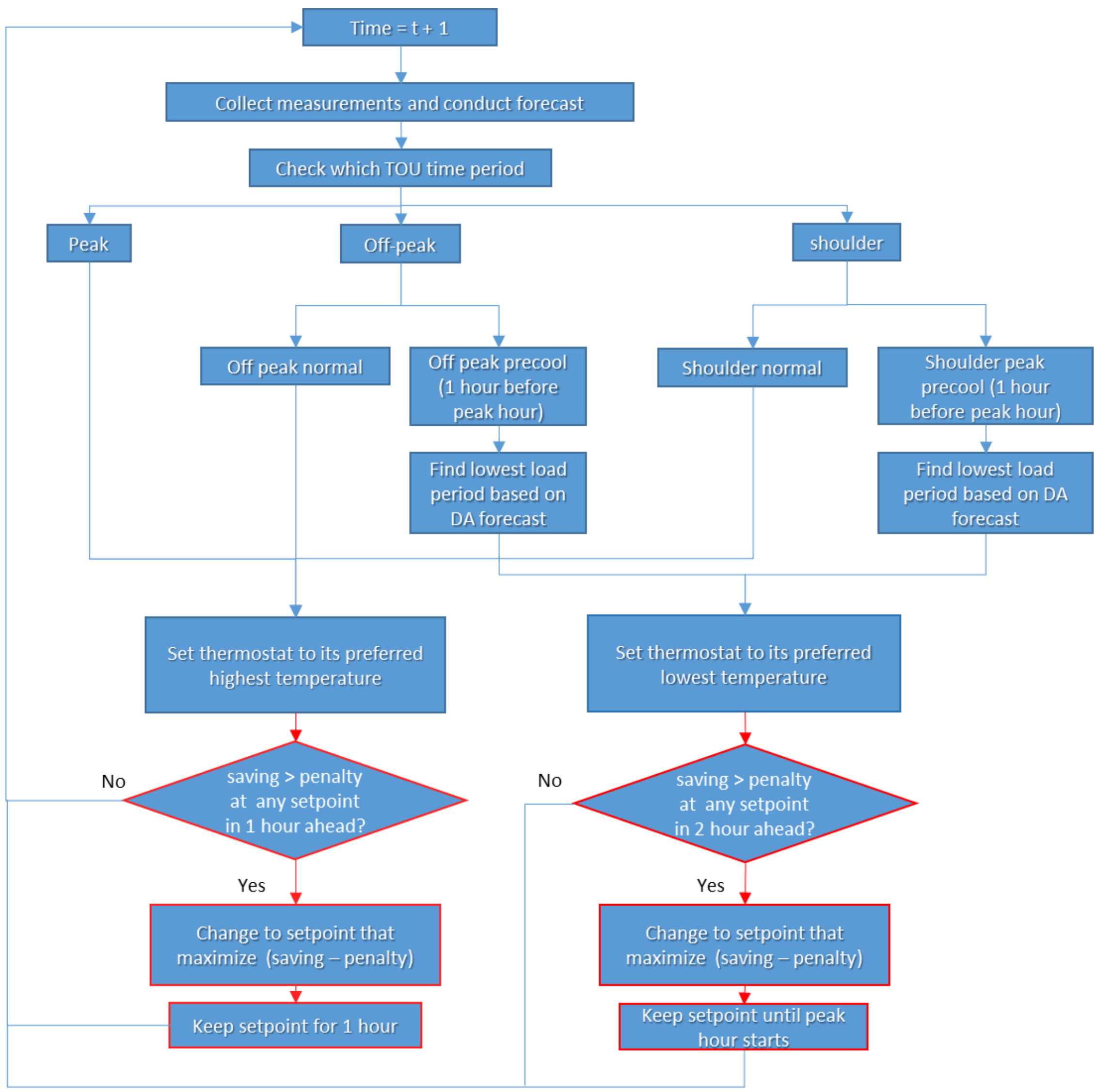


Figure 4.42 Algorithm flowchart of HEMS TCA control strategy (cooling mode)

Figure 4.4 shows the flowchart of TCA control algorithm with considering user’s cost saving expectation. At each time step, the HEMS measure the current TCA energy consumption and retrieve DA energy forecast of next two hours. If there is an upcoming price increase (either peak hour or shoulder peak hour), HEMS finds the lowest load time period to start pre-cooling/pre-heating process. In other time (no price increase in next hour), HEMS tries to find a setpoint that can maximize user's cost benefit (saving - penalty) by comparing costs with different the setpoint outside preferred zone. This process is highlighted in red. Note that the cost benefit considered here is in one hour time length, meaning the amount of money costed/save in one hour ahead with certain setpoint setting. If such a setpoint is found, it will be kept for one hour. But in a pre-cooling/pre-heating process, the cost benefit should be foreseen in two hour ahead, in order to fully evaluate the thermal energy stored. If the setpoint is extended outside preference zone to achieve better cost benefit, it will return to normal when the price changes.

4.3.2 TBA Control Strategy

The TBA scheduling is triggered when a task is assigned on the appliance. User defines the end time before when the task assignment should be finished. HEMS can quickly checks if there is enough time to finish the job. The control strategy can be summarized in two steps.

1) HEMS greedily searches a time slot with lowest cost of finishing the task, lowest DA demand forecast, and closest to start time.
2) Similar to TCA, TBA also applies the mechanism shown in Figure 4.5 to delay some tasks in order to further maximize users' cost benefit.

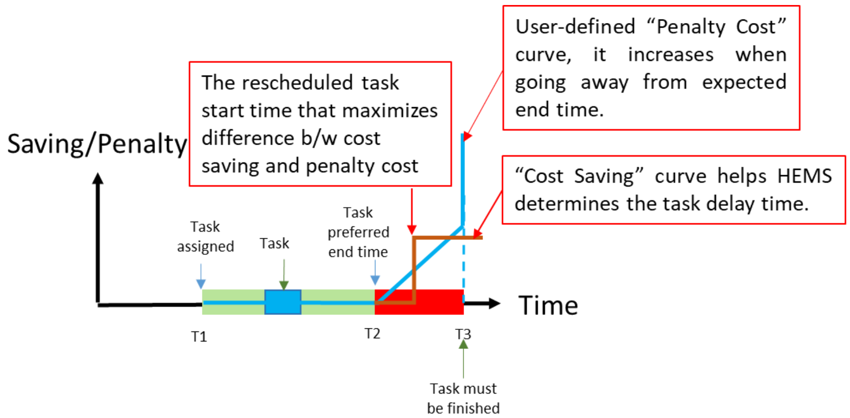


Figure 4.43 A mechanism for HEMS to delay TBA task according to user's cost saving expectation

Figure 4.5 shows the task assigned time, task duration, task end time, and task must-finish time on the timeline. The HEMS tries to delay the task within must-finish time and reschedules a start time that maximize user's cost benefit (saving – penalty).

Figure 4.6 shows the flowchart of TBA control algorithm. When a TBA task is assigned with preferred end time and must-finish time, HEMS firstly checked if there is enough time to finish this job within the given time period. Then, it starts to greedily search time slots within preferred end time that can finish the task with lowest cost. It records all the low cost time slots in a set {Ta}. Also, HEMS further searches time slots between preferred end time and must-finish time and records the low cost time slots in a set $\{T_b\}$. Note that the cost with delay needs to include the penalty cost. This process is highlighted in read. Then, HEMS compare the cost of time slots in Ta and Tb, and determine the lowest cost time slot. If there are multiple time slots with same cost, HEMS selects the one with lowest DA demand forecast as start time. If there are some time slots with same cost and same demand forecast, HESM selects the one closest to task assigned time, meaning to start the task as soon as possible. When a task is upcoming, HEMS adjusts its start time by finding the lowest RT load forecast in next 30 minute, and starts the task at that time in order to help flatten the demand curve. By using such a heuristic control strategy, HEMS doesn't need to compute complex optimization problem and can be more robust to forecast error.

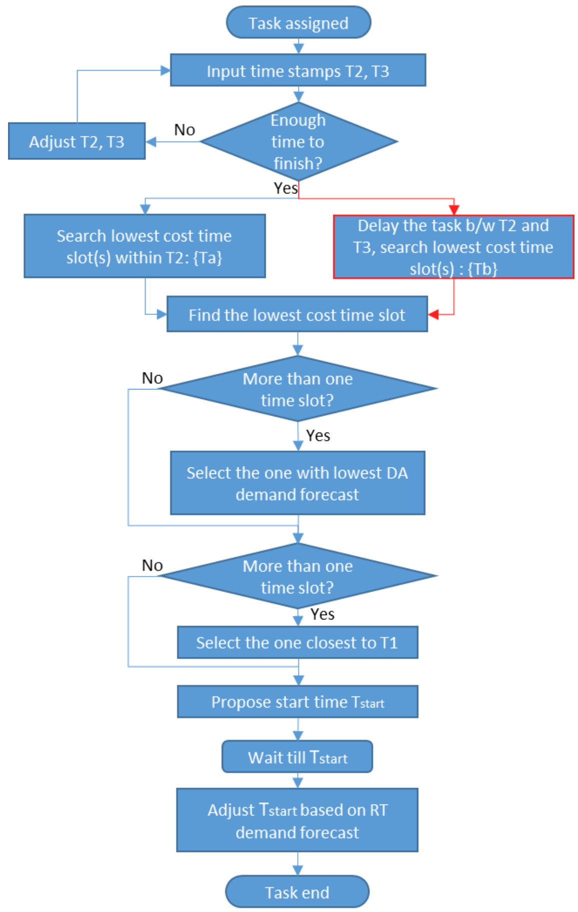


Figure 4.44 Algorithm flowchart of HEMS TBA control strategy

4.3.3 EV Control Strategy

When the EV is plugged-in for charging, HEMS is triggered to determine when to start the charging and what is the charging rate (fast or normal rate). The total charging time depends on the initial SoC, end SoC, and leaving time of the EV. Thus, HEMS firstly needs to check if the EV charging target can be finished before it leaves. Figure 4.7 shows four situations in charging EV. The first situation is that there is enough time between the plug-in and leave time, so that the EV can be charged during low price period using normal rate. The second situation is that there is still sufficient time for charging the EV during low price period, but it needs to use fast charging rate in order to reach expected SoC. The third situation is that, the EV is plugged in during high price period, so the charging is delayed to low price period. But it can finish the charging with normal or fast or combined charge rate. The last situation is that the EV has to be charged during some time of the high price period after charging all the time during low price period.

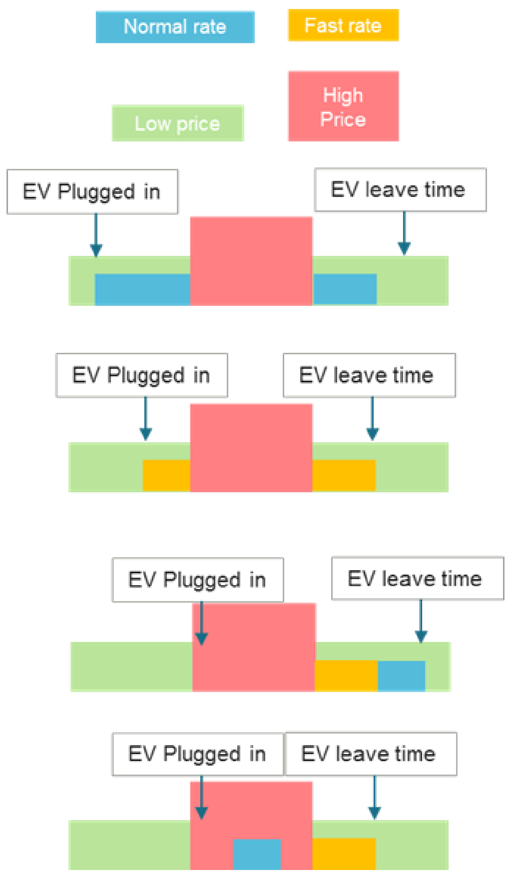


Figure 4.45 EV charging time and charge rates based on price and available time

In general, HEMS schedules EV charging time and charging rate by considering available time (arrive and leave time) and electricity price. In order to avoid creating high demand on system, EV should be charged with normal rate instead of fast rate if possible. Then, the demand forecast is also considered for locating some fast charging time. The EV control strategy can be summarized in three steps.

1) Sufficient time in low price period: charge EV with normal rate in low price period. If fast rate is needed to reach SoC target, fast charge at time slots with low DA demand forecast.
2) Need to charge some time during high price: charge as much as possible during low price period, then select low demand forecast time slots in high price period to charge EV with normal rate.
3) Similar to previous two types of controllable load in balancing comfort setting and cost saving, users can adjust the target SoC in return of better cost with the mechanism shown in Figure 4.8.

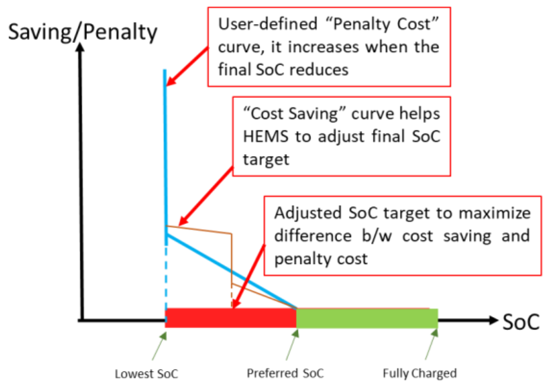


Figure 4.46 A mechanism for HEMS to adjust SoC target according to user's cost saving expectation

Figure 4.8 shows the penalty cost is zero beyond preferred SoC. If the final SoC is lower than preferred setting, user defines the penalty cost and expect a cost saving in return. The lowest SoC point indicates that the final SoC must research to such a level no matter how much cost saving is offered. If there is a SoC point that can maximize user's cost benefit (saving – penalty), HEMS will adjust the SoC target.

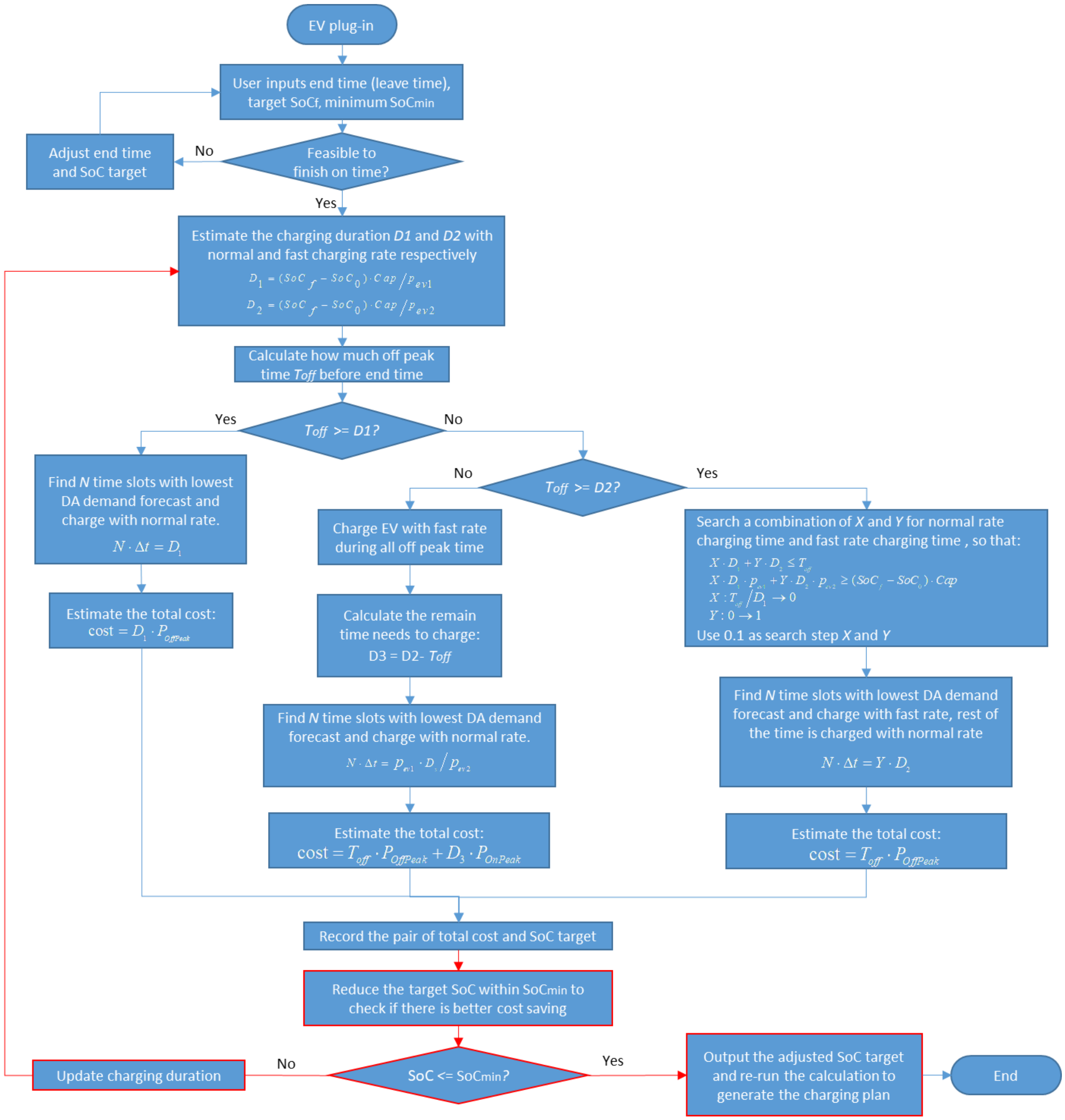


Figure 4.47 Algorithm flowchart of HEMS EV charging control strategy

The EV charging control algorithm flowchart is shown in Figure 4.9. When an EV is plugged in with user-define end time (leave time), target SoC and minimum SoC requirement, HEMS starts the EV charging scheduling process. It firstly needs to check if the charging task can be finish before end time. If not, HEMS advise the user to adjust the SoC target. Then, it estimate the charging duration with normal and fast charging rate based on the SoC target.

Secondly, HEMS calculates the remaining off peak time before end time, based on which HEMS determine the charging plan. There are three situations. When there are sufficient off peak time (toff > D1), the EV will be charged with normal rate at the time slots with lowest DA demand forecast. When there are sufficient off peak time but EV needs to charge with fast rate some time (D2 < toff < D1), HEMS search the combination of normal and fast charging rate time. It uses as much as possible time to charge with normal charging rate, while using low DA demand forecast time slots to charge with fast charging rate. The last situation is that EV has to be charged some time in high price period (toff < D2). EV will be charged with fast rate during all the off peak time, then be charged with normal rate at low DA demand forecast time slots during on peak time. After HEMS gets the base case cost and SoC pair, it reduces the target SoC in order to seek better cost benefit (saving – penalty). This sub-process is highlighted in read. HEMS finally determines the adjusted SoC target and provides the charging plan.

4.3.4 Power-Cap Control Strategy

The previous control strategies help HEMS to schedule the demand in advance. In real time, HEMS monitors the actual demand and tries to maintain the total power demand below a certain cap defined by the user, in order to avoid a high demand charge. Such a power-cap control will delay or turn off some controllable appliances. The power-cap control strategy can be summarized in three steps.

The user defines a power cap based on HEMS advice. The selection of power cap will be discussed in section IV.

If a controllable appliance is about to turn on, and the HEMS sees the total power will exceed the power cap, then the controllable appliance will be delayed until the foreseeing demand reduces below the cap.

If the total power exceeds the cap at a moment, HEMS will turn off one or more available controllable appliances to bring back to total power below the power cap, and turn on again after certain time.

There are three ways to select an appliance to turn off:

1) Select an appliance that uses the most power at each time, such that minimum number of appliance(s) will be curtailed.

2) Select a combination of appliance(s) with minimum power usage while it still meets the cap requirement.

3) Select the appliance on the top of a rolling priority list until the total power is lower than the cap. There are two conditions for the appliance on the list: the minimum on time t1 and minimum time between two adjacent turn off. HEMS selects an appliance from the top of the list with both conditions are satisfied. Once the appliance is turned off, it goes to the bottom of the list. Figure 4.10 illustrates the rolling priority list method.

App.	t_1	t_2
HVAC	✗	✗
Water heater	✓	
Ventilation	✓	✓
...	...	...
EV	✗	✗

App.	t_1	t_2
HVAC	✓	
Water heater	✓	✓
...	...	...
EV	✓	✗
Ventilation	✗	✗

Figure 4.48 A rolling priority list for selecting appliance to turn off

The power-cap control algorithm flowchart is shown in Figure 4.11. The power cap level is defined or updated by users and HEMS. In real time, when a controllable appliance is about to turn on, HEMS checks if the forecast in next step is over the power cap, then determines whether this appliance should be delay. HEMS keeps monitoring the total power, if power is higher than the cap, then HEMS turns off the first available appliance on top of the priority list until the total power is lower than the cap. Once the appliance is forcibly turned off, it will be moved to the bottom of the priority list.

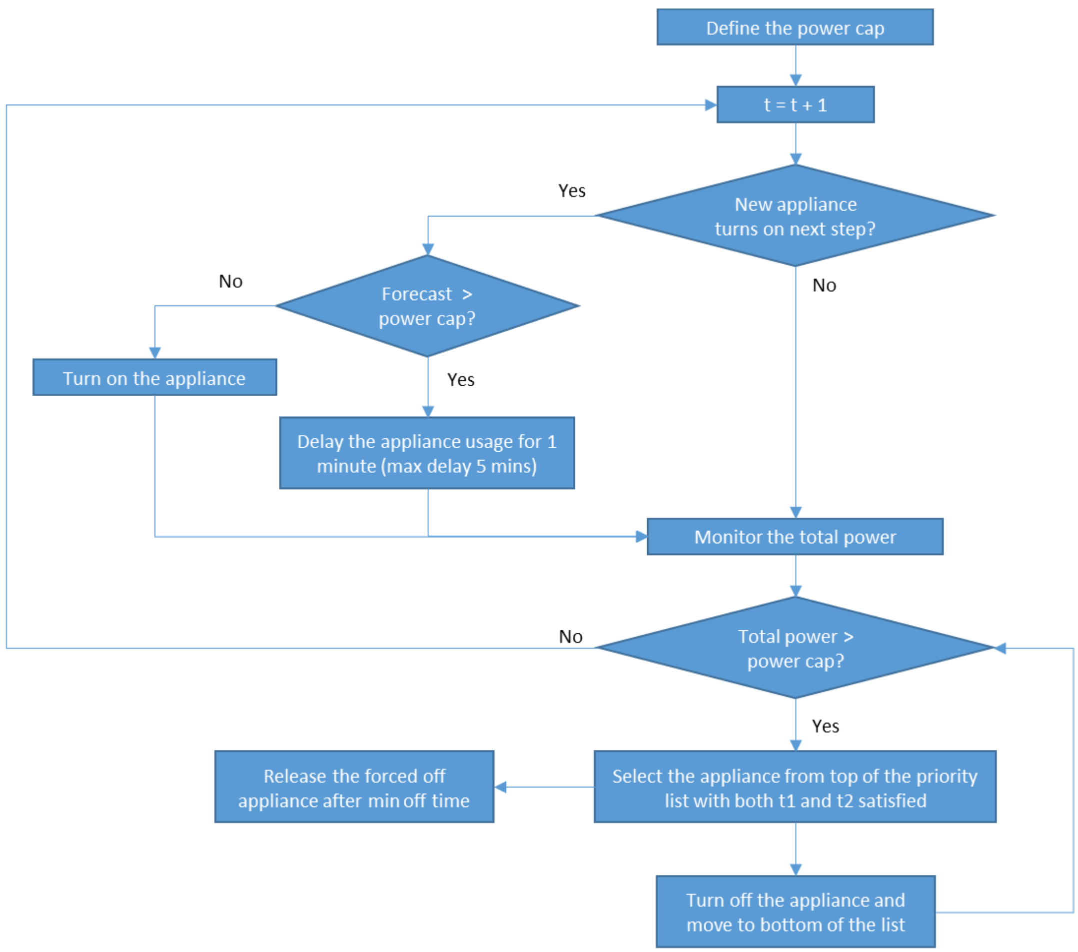


Figure 4.49 Algorithm flowchart of HEMS power cap control strategy

4.4 Case study

4.4.1 Case description

A summer case is studied to evaluate the effectiveness of the proposed HEMS control strategy. To show the rescheduling of some appliances, the case study simulates a 36-hour time window with a 1-minute time step, from midnight to noon time next day. The outdoor temperature and price profile is shown in Figure 4.12. The outdoor temperature goes high as 95°F around H15, and low as 75°F in the early morning second day. The TOU price has high price of ¢6.961/kWh from 11AM to 10 PM with a demand charge of $4.88/kW, the rest of the time is off peak time [12].

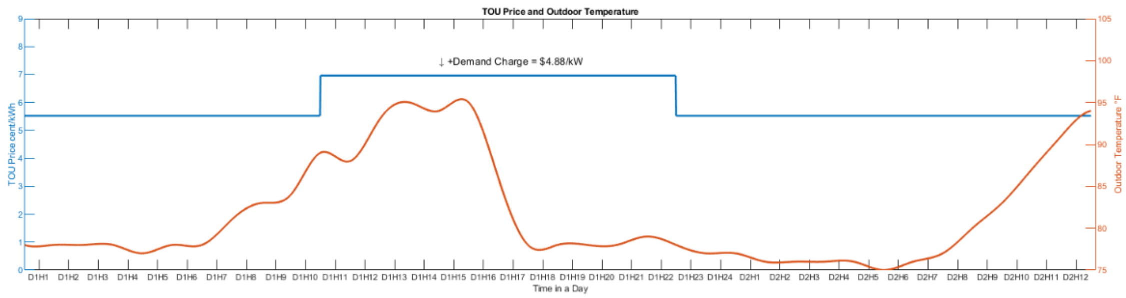


Figure 4.50 TOU price and outdoor temperature used in the case study

Table 4.4 Controllable appliances setting

Controllable Appliance	Power rating	Setting	Minimum on/off time
Air conditioner	3.2kW	Setpoint: 70°F Comfortable temperature range: 67°F - 74°F	Min on: 5 min Min off: 5 min
Electric water heater	4.5kW	Setpoint:145°F Comfortable temperature range: 130°F – 155°F	Min on: 5 min Min off 5 min
Dish washer	1.5kW	Assign at 7 PM Finish no later than 7AM next day	Min on: every sub-task Min off: 5 min
Washing machine	500W	Assign at 8PM Finish no later than 7AM next day	Min on: every sub-task Min off: 1 min
Clothes dryer	4kW	Assign within 1 hour after washing machine is done. Finish no later than 7AM next day	Min on: every sub-task Min off: 5 min
Electric Vehicle	Fast rate: 6.6kW Normal rate: 3.3kW Capacity: 40kWh	Arrive at 6:30PM with 55% SoC Leave at 7:30AM next day with a SoC no lower than 95%	Min on: 5 min Min off: 5 min

The household load profile consists of base load (uncontrollable load) and controllable load (TCA, TBA, and EV). By excluding the TBA, TCA and EV load, a realistic household load from Pecan Street [91] is used as the base load. The controllable load is simulated by the model shown in section II of this chapter. In this study, HEMS controls the household air conditioner, electric water heater, dish washer, clothes washer and dryer, and EV. Table 4.1 shows the controllable appliances' setting and user's preference.

The household electric demand forecast is provided both in day-ahead (DA) and real-time (RT) as discussed in Chapter 3. The DA forecast is published at midnight with 36 hours ahead, since there may be some appliances reschedule to overnight. The RT forecast is updated every 5 minutes for 1 hour ahead with a 5-minute resolution. Figure 4.13 shows the DA probabilistic load forecast, based on which HEMS schedules controllable load usage.

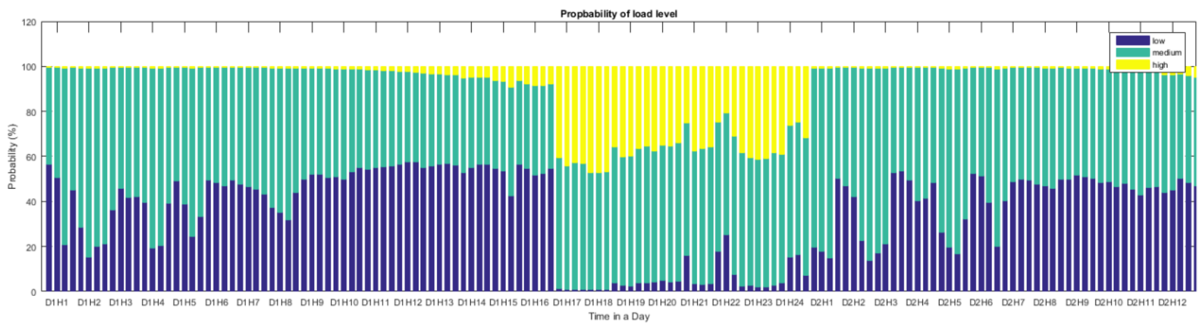


Figure 4.51 DA probabilistic load forecast in the case study

4.4.2 Results

The simulation results are shown in Figure 4.14 – 4.18, comparing the total household load, TCA temperature, TBA usage, EV charging and SoC, under the power cap of 8kW during peak hours.

Figure 4.14 compares the total household power consumption before and after HEMS scheduling. One can see that HEMS reduces the energy consumption in the high price period and moves some energy usage to low price period, so that it can save some energy cost. Meanwhile, the maximum demand has been significantly reduced by HEMS, the total demand charge is much lower than the one without HEMS, from 16.3kW down to 7.3kW on a 15-minute average.

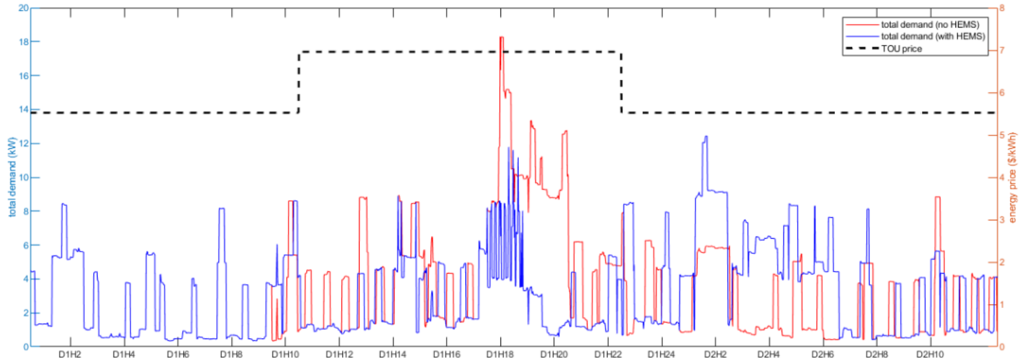


Figure 4.52 Household total energy usage comparison with and without HEMS

In Figure 4.15, it shows that HEMS adjusts the air conditioner (AC) temperature setpoint according to price change and user's temperature preferred zone. Before the peak hours, HEMS selects a low load period based on DA probabilistic forecast to start pre-cool the room temperature by changing the air conditioner setpoint to 67°F and forcing the air conditioner to turn on. Then, it changes setpoint to highest comfort level, 74°F, during peak hours. It notices that air conditioner is on/off more frequently in some period, that is because HEMS tries to cap the power below 8kW during peak hours. After peak hours, HEMS changes setpoint back to normal.

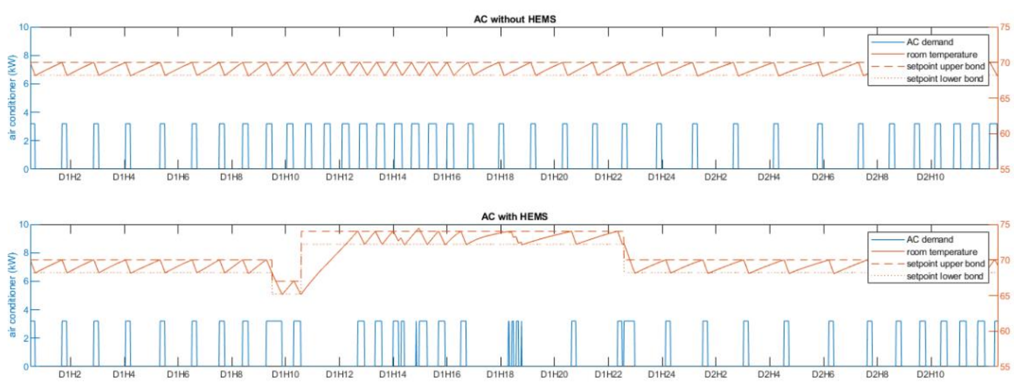


Figure 4.53 Air conditioner energy usage and temperature comparison with and without HEMS

Similar to AC, the electric water heater (EWH) is turned on before peak hours to preheat the water and set to lowest temperature setpoint during peak hours, as shown in Figure 4.16. The big temperature drops represent hot water usage. In hour 18, EWH is on/off more often to avoid high demand.

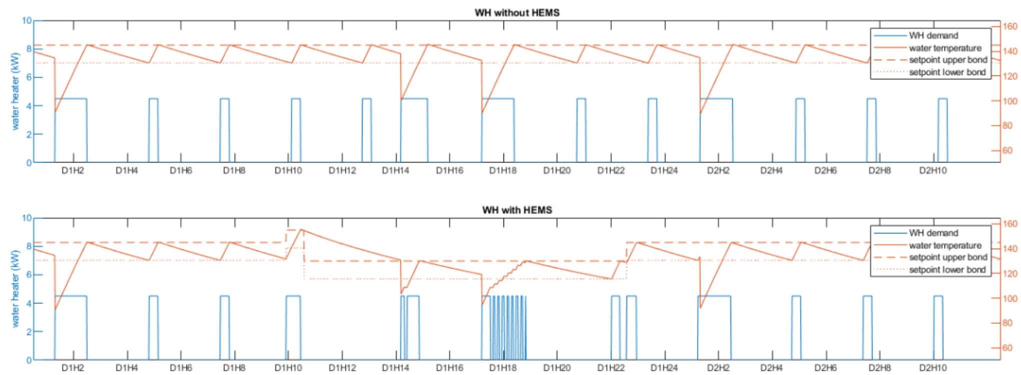


Figure 4.54 Water heater energy usage and temperature comparison with and without HEMS

In Figure 4.17, TBAs are shifted to low price period based on the DA load forecast and task time requirements. The dish washer and clothes washer are all rescheduled to almost the same time, because the DA forecast indicates it is a low load period.

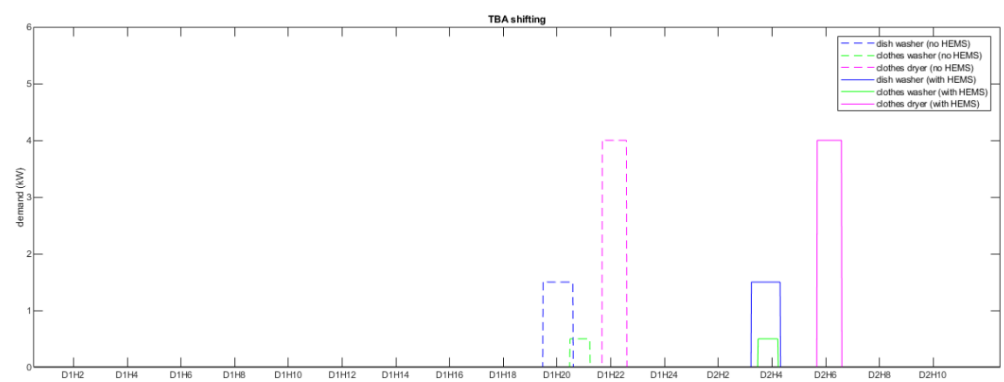


Figure 4.55 TBAs energy usage comparison with and without HEMS

The EV charging rate and SoC are shown in Figure 4.18. Without HEMS, EV is charged immediately when it is plugged-in, and charged with fast rate, which creates a high demand in high price period. Thus, HEMS finds low load period before EV leaves the next day and charges it with normal rate.

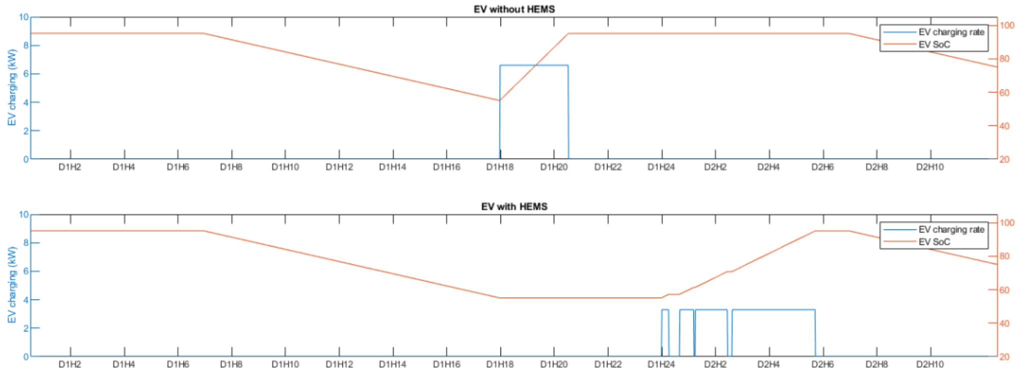


Figure 4.56 EV charging and SoC comparison with and without HEMS

4.4.3 Discussion

This section summarizes the effectiveness of proposed HEMS control strategies and discusses its performance under different power cap levels. In Table 4.2, it compares the cost and comfortableness before and after HEMS control in the simulation above.

Table 4.5 Scheduling algorithm simulation results summary

Criteria	**Without HEMS**	**With HEMS**
Energy Usage	122.1kWh	115.7kWh
Energy Cost	\$7.68	\$6.88
Peak Demand (15min average)	16.3kW	7.3kW
Demand Charge (\$4.88/kW)	\$79.5	\$35.6
Peak to Average Ratio	5.4	3.7
Room Temperature Uncomfortableness	0	0.7°F, 9.7mins, 3times
AC Switching Times	36 times	36 times
Water Temperature Uncomfortableness	19.5°F, 48mins, 4times	10.3°F, 29.3mins, 6times
EWH Switching Times	13 times	21 times
Dish Washer Delay	0	463 mins
Clothes Washer Daley	0	420 mins
Clothes Dryer Daley	0	480 mins
EV Charging Delay	0	551 mins

Cost: It shows that, in the simulation period of 36 hours, the energy cost is reduced over 10% from \$7.68 to \$6.88, even though the energy usage are similar before and after HEMS control. This is because HEMS shifts major appliance usage to off peak hours. The peak demand (in peak hours) is also significantly reduced from 16.3kW to 7.3kW. Assuming they are the peak demand of the month, HEMS can greatly save a demand charge from $79.5 to $35.6, over 50% reduction. Considering both energy cost and demand charge, HEMS can help the household to save about 25% of their electricity bill monthly. Meanwhile, HEMS can improve the Peak-to-Average-Ratio of energy usage as shown in Table 4.2, resulting in improving energy efficiency and deferring facility upgrade.

Comfortableness: For AC, user will experience some room temperature out of the prefer comfort zone. That is because HEMS turns off the unit to avoid high demand at some period. In this simulation, there are 3 times that room temperature exceeds the temperature setting, with an average of 0.7°F and last for 9.7minutes. Another criteria for AC is the switching times. An increasing number of switching times will shorten the unit's life. A higher setpoint can reduce the switching times, but the power cap control can increase the switching time. In this simulation, the total switching time after HEMS control is 36 times in 36 hours, which is the same as the one before HEMS control, though HEMS turns on/off more often during some period of time. In general, HEMS doesn't impact the room temperature comfortableness.

For EWH, the main temperature drops are caused by hot water usage. Before HEMS control, there are 4 temperature drops with an average 19.5°F lower than temperature setpoint, and the EWH uses 48 minutes to heat up the water to setpoint. When using HEMS, it has more times that temperature is lower than setpoint, however, the temperature drops are smaller with an average of 10.3°F, and EWH uses shorter time to heat the water. That is mainly due to pre-heat process before peak hours and the lower setpoint during peak hours. One can notice that HEMS will increase the EWH on/off times from 13 to 21 times.

For dish washer, clothes washer and dryer, HEMS shifts their usage to later low price period. Comparing to finish time without HEMS control, the tasks are finished about 7 to 8 hours later. Please note that the delay time highly depends on the task assign time and expected finish time.

For EV, HEMS starts the charging much later and finishes it over 9 hours later than the original finish time. Meanwhile, it uses a lower charging rate and stops several times in order to charge at low load time slots.

There is a trade-off between the selected power cap and user's comfortableness. A too high power cap level may not help to avoid high power demand, while a too low power cap level can impact users' comfort level and may not be achieved by HEMS when all the controllable resources are exhausted. In Table 4.3, it provides the power cap level impact on user's comfortableness. Note that the "No Cap" scenario still has HEMS control but no power cap limit in peak hours. One can see that if the cap is 12kW, it doesn't make any impact on the demand, so it is the same as the one of "No Cap". When the cap is reduced to 10kW, the maximum demand can be capped to 8.2kW, but both AC and EWH switching times increase with more temperature violation. When the cap is 8kW, HEMS can still achieve the cap goal. However, when the cap is set to 6kW, HEMS can't reduce the maximum demand below 6.8kW. If an even lower cap of 4kW is selected, though the maximum demand can be reduced, it dramatically increase the appliance switching on/off times and users experience more temperature violation. Therefore, in this simulation, a power cap selection of 8kW can be suitable to balance the maximum demand and user's comfortableness.

Table 4.6 Power cap level impact on user's comfortableness

Power Cap Leve	Maximum Demand	AC Switching times	Room Temperature Uncomfortableness	EWH Switching times	Water Temperature Uncomfortableness
No Cap	10.2kW	31	1.2°F, 14mins, 2times	12	11.2°F, 26.3mins, 6times
12kW	10.2kW	31	1.2°F, 14mins, 2times	12	11.2°F, 26.3mins, 6times
10kW	8.2kW	33	0.9°F, 8.1mins, 2times	15	10.9°F, 25.3mins, 6times
8kW	7.3kW	36	0.7°F, 9.7mins, 3times	21	10.3°F, 29.3mins, 6times
6kW	6.8kW	38	0.8°F, 10.3mins, 3times	23	10.7°F, 34.8mins, 5times
4kW	6.2kW	57	0.4°F, 5.8mins, 8times	34	11.9°F, 39.5mins, 6times

4.5 Summary

For scheduling purpose, HEMS should consider different types of controllable appliances. In this chapter, three types of appliances are modeled: TCA, TBA and EV. Each model considers the appliance physical characteristics (thermal dynamic, minimum running time, etc.) and user settings (temperature setpoint, expected finish time, etc.). Using the model set, a heuristic approach is proposed to minimize the energy cost under a "TOU plus demand charge" pricing scheme, when considering user's comfort preference and cost saving expectation.

The control strategies are developed for each type of controllable load with a cost-saving setting mechanism that allows users to input their cost saving expectation in return of comfort sacrifice. For TCA, HEMS conducts pre-cooling/heating process to store as much as possible thermal energy before the peak hours. The cost-saving setting mechanism allows users to go beyond the temperature comfortable zone in order to achieve more cost saving. For TBA, HEMS searches the lowest cost and lowest load time period to finish the task before expected finish time, the cost-saving mechanism allows users to delay a little bit task finish time in return for better cost. Finally, for EV, the control strategy aims to charge the EV at low price and low load time slots with a normal charging rate if possible. Users can reduce the target SoC to find a possible cost saving. In addition, a priority list method is applied to delay some energy usage to avoid high demand charge. When a high demand is foreseen, HEMS turn off the top list appliance that satisfies operational timing constraints.

The proposed HEMS scheduling approach can be easily implemented and is computational economic for local HEMS micro-processor. Also, the optimization process is robust to demand forecast, since it uses a probabilistic forecast in DA and uses an hour-ahead demand forecast to adjust the schedule in real time. Most important, the proposed approach allows user’s involvement regarding cost saving. Such a mechanism can be beneficial for both end users and the LSE, because user can be educated about energy saving expectation and LSE can has better understand about users’ demand elasticity. Based on such a design, LSE can use the price signal to perform demand side management.

The simulation results show the effectiveness of the proposed HEMS scheduling approach. It reduces the total energy cost and demand charge by about 25%, while maintaining user’s comfortableness. The sensitivity study of power cap level selection shows the trade-off between cap level and impact on comfortable. A suitable power cap can be the sum of one controllable appliance power rating and the third percentile of sorted controllable load.

CHAPTER 5 AGGREGATE STUDY OF HOME ENERGY MANAGEMENT

This chapter studies the aggregate impact of HEMS on system level, including distribution system and transmission system. It shows that a high HEM penetration may lead to loss of load diversity and create new peak demand right after electricity price changes from high to low. A mechanism is proposed for HEM to mitigate this issue. In addition, it investigates how the proposed HEMS helps residential energy consumers to provide demand response in wholesale energy market.

5.1 Introduction

The previous chapters focus on development and implantation of HEM in an individual home. The proposed control strategy can help individual customer to save money under the dynamic electricity price. However, a high penetration of HEMS in a system can create new stress on the distribution system, such as loss of load diversity and unintended peak demand in some local areas. For example, if all the HEM on a distribution feeder tends to pre-cool the houses before high price, it will not only create sudden a load surge in short period of time, but also synchronize most of the air conditioner units for a certain length of time after the pre-cool event. Under TOU pricing scheme particular, HEMSs shift their energy consumption to low price period. When the price changes from high to low, all the load are connected back in a short period of time, which is called the “rebound effect”. In [108 -111], they show some pilot project experience of TOU price implementation, indicating key factors on effectiveness of TOU pricing. Some publications focus on TOU pricing design in order to maximize total system welfare [112 - 114] or improve system load profile [115, 116], while some publications focus on design load control strategy under TOU pricing [117-119]. However, these designs either need a large amount of data to model consumers’ behaviors under time-varying pricing, or require a plenty of communication and computational resource to find the optimal solution for load control.

In this chapter, I proposed three control strategies to mitigate the issue of “loss of load diversity” based on the proposed HEMS in previous chapters. The first one is that each HEMS sets a random connection time within one hour after peak time, so that different HEMSs change energy consumption to normal mode at different time. The second control strategy is based on a “priority list”, on which controllable load has high priority when it is close to comfort limit or is exceed the comfort limit. For example, an air conditioner is close to its upper temperature bound, it will be placed on the top of priority list to turn on. The third control strategy is a combination of the previous two, it introduces randomness and consider priority, so that it avoid some possible comfort violation or unfairness in the first two control strategies.

HEMS can not only improves the system operation conditions, but also bring economic benefit for the system. In this chapter, it shows how to use aggregated HEMS to provide demand response in wholesale energy market. A variety of publications have discussed demand response participation in wholesale market of energy, ancillary service and capacity reserve [120-122], but discussion of detail end-user level implementation is limited, especially for HEMS with user’s involvement. With the proposed HEMS model in Chapter 4, the residential demand elasticity can be quantified and model as a virtual power plan in the system. An example of three bus system is used to demonstrate the effectiveness of HEMS in reducing total system cost.

The rest of the chapter is organized as following. Section 5.2 shows the problems of high HEMS penetration and proposes the control strategy to mitigate the “rebound effect” from HEMS. Section 5.3 models HEMS as virtual power plan in wholesale market and uses simple three-bus example to illustrate its effectiveness. Section 54. Summarizes this chapter.

5.2 High HEMS Penetration on Distribution Feeder: Problem and Mitigation

5.2.1 Problem of High HEMS Penetration

Houses with HEMS sometimes have similar load pattern, because they are scheduled based on electricity price. When HEMS penetration goes high, the distribution system may results in loss of load diversity. Some appliances, such as HVAC, may even be intentionally synchronized for certain time period.

To simulation the aggregation effect of HEM, a residential load profile of 900 houses is generated for case study. As the house model in Chapter 4, each house load consists of base load (non-controllable load) and controllable load managed by HEMS. The base load is from Pecan Street [91] database, and controllable load is simulated by the load model in Chapter 4. Figure 5.1 shows a total load profile of 900 houses with increasing HEMS penetration in the system. One can see that the total load has higher peak when HEMS penetration is higher, indicating the HEMS houses are synchronized and reduce the load diversity.

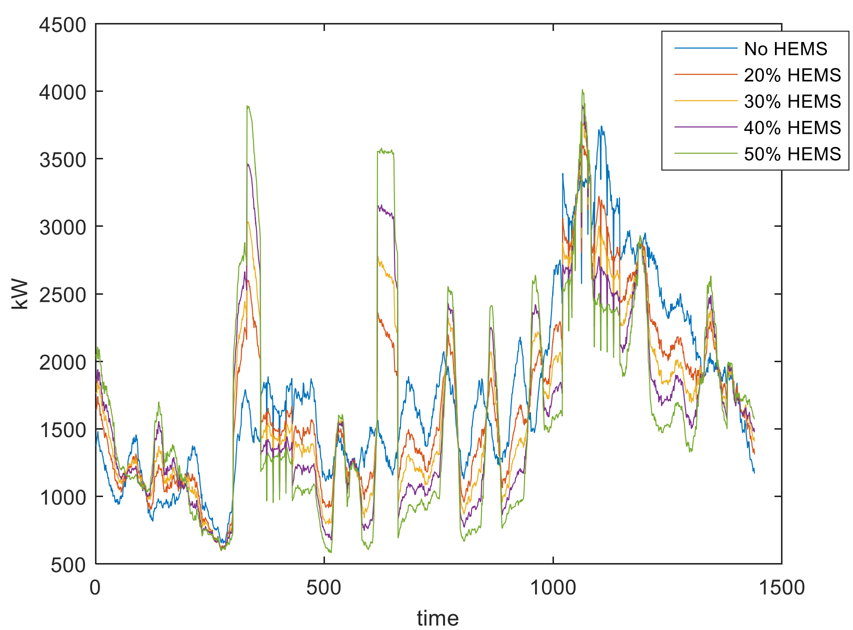


Figure 5.57 Substation level load profiles under different HEMS penetrations

This issue caused by high HEMS penetration can impact system reliability and efficiency. To evaluate the impact, I apply the above load profiles nn an IEEE 123 node test feeder system [123] and the topology is shown in Figure 5.2. There are 91 load nodes in the system, so the first step is to allocate the 900 houses to different nodes. In [124], Xiangqi proposes a bottom-up approach to determine the number of houses to assign to different nodes, based on an idea that aggregated load profile should match the load profile at the feeder top.

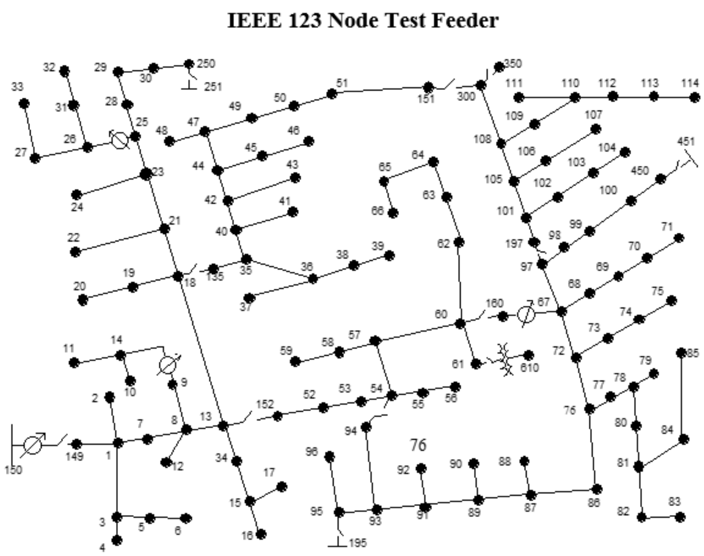


Figure 5.58 IEEE 123-node test feeder used in the HEMS aggregate study

Figure 5.3 shows the voltage violation at serval nodes in a day, and the system losses are shown in Table 5.1. They show that a higher HEMS penetration can increase local voltage violation and the system losses. Therefore, it is necessary to develop a control strategy to mitigate the loss of load diversity raised by high HEMS penetration.

Table 5.7 System average daily loss

HEMS Penetration	P (kW)	Q (kVar)
0%	11.9	23.4
20%	13.9	27.5
30%	15.3	30.2
40%	16.1	31.8
50%	17.9	35.3

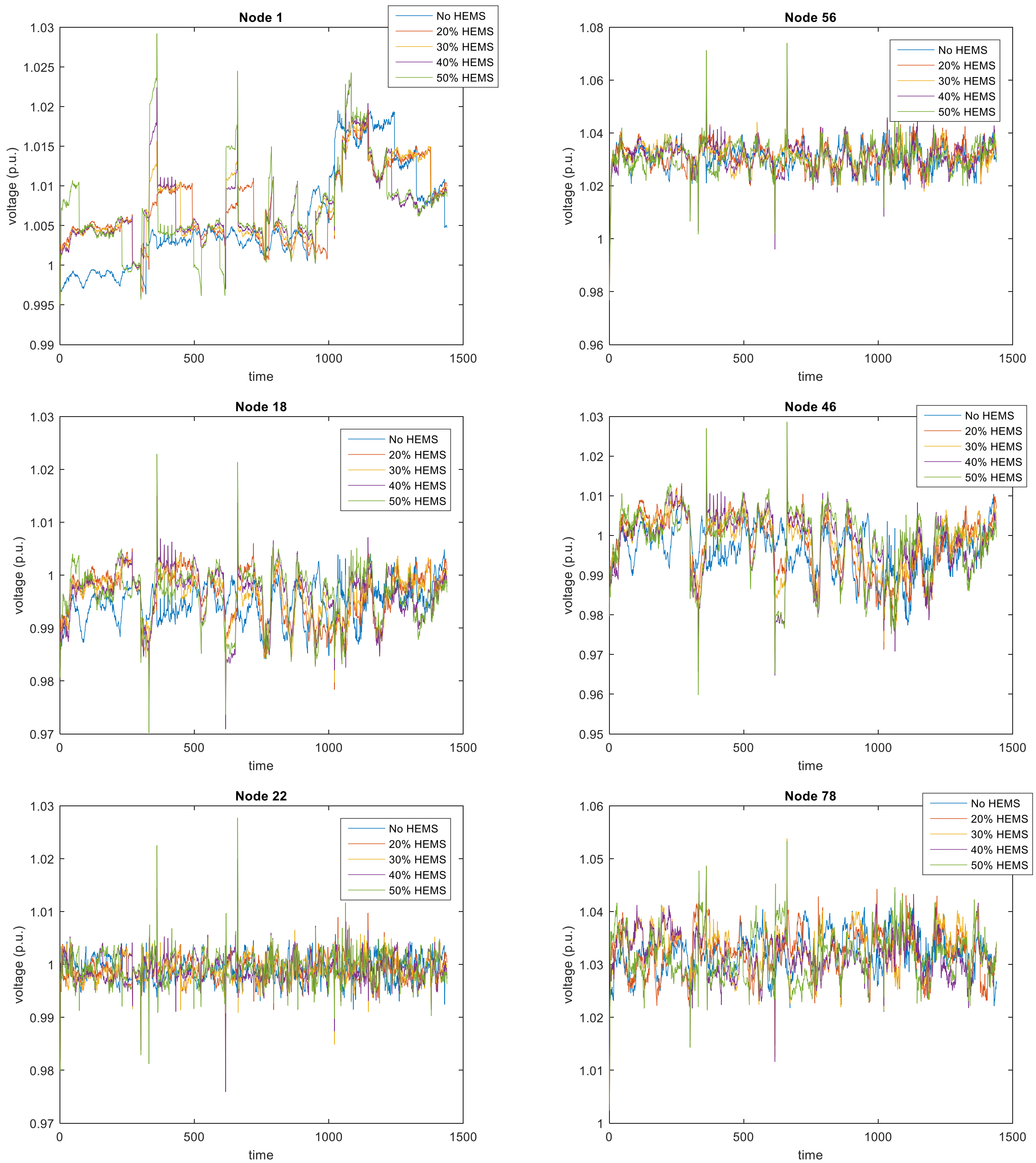


Figure 5.59 Voltage profiles at some selected nodes

5.2.2 Control Strategy of Mitigating "Loss of Load"

In order to mitigate the "loss of load" issue, the direct way is to introduce new randomness back to the energy consumption. In this section, we propose three control strategies to address this problem.

The first control strategy is called "random off-peak start time". As illustrated in Figure 5.4, individual HEMS randomly select a time within one hour after peak hour to be its real off-peak start time. After this selected time, HEMS can set the appliance back to low price condition or start running shifted load. The random number is uniformly distributed within peak hour ending, so each HEMS in the system has fair opportunity to start its normal mode as soon as possible without the need to communicate with other HEMS. However, this control strategy may make some consumers to experience inconvenience or uncomfortableness of energy usage, such as TCA temperature violation, longer waiting time for TBA.

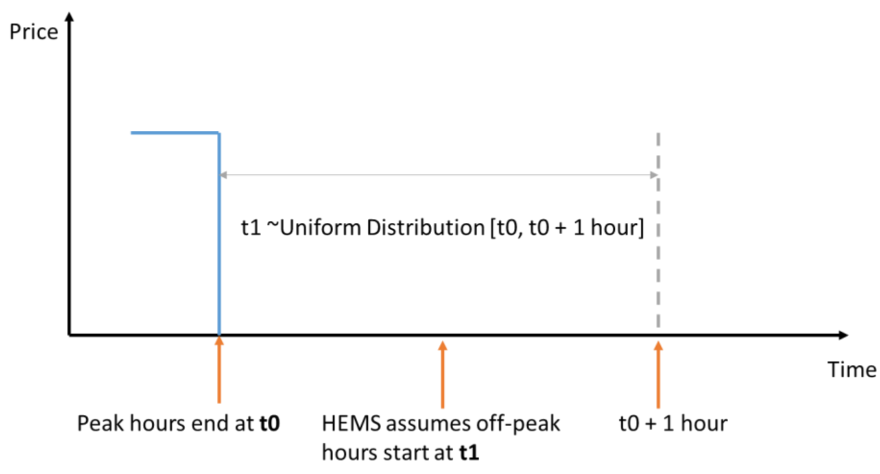


Figure 5.60 An illustration of "random off-peak start time"

The second control strategy is called "priority list" approach. In this control strategy, all the HEMs are coordinated and appliances are ranged by their comfort condition. A lower comfort condition, the high an appliance has to be turn on after peak hours, For example, if the room temperature is close to setpoint upper bound, then the air conditioner unit has high priority to turn on. Such a control strategy minimize the uncomfortableness for consumers. However, it requires a lot of two-way communication between individual HEMS to HEM aggregator. Also, it may not be fair to each HEMS/consumers, because the priority highly depends on the comfort setting by users. For example, an HEMS with narrow comfort zone settings can make it always be reconnected earlier than the one with wide comfort zone settings.

The third control strategy is the combination of the previous two. It selects the "random off-peak start time" based on appliance comfort condition. The less comfort, the higher probability for the appliance to be turn on earlier. Figure 5.5 illustrates the concept with air conditioner as example. When the room temperature is increasing, the closer the temperature to upper bound, the shorter time period from which t1 is selected. Such a control strategy has the same advantage as the one of "random off-peak start time", and also give higher priority for appliances with low comfort conditions.

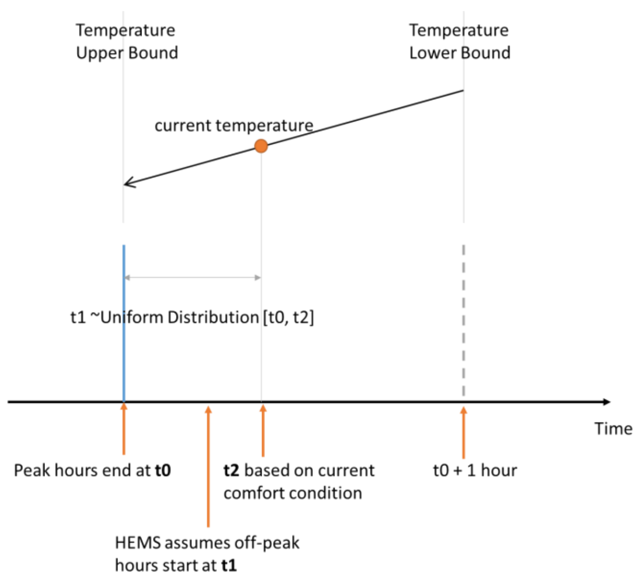


Figure 5.61 An illustration of "random off-peak start time" based on comfort condition priority

The total load profiles of three control strategies are compared under a 50% HEMS penetration scenario in Figure 5.6. It can be seen that the proposed control strategies can mitigate the “loss of load diversity” issue, showing less load synchronization and less “rebound effect”. Consider the third mitigation strategy is more efficient and fair to all HEMSs, its mitigated load profile is tested in the IEEE 123-node feeder system.

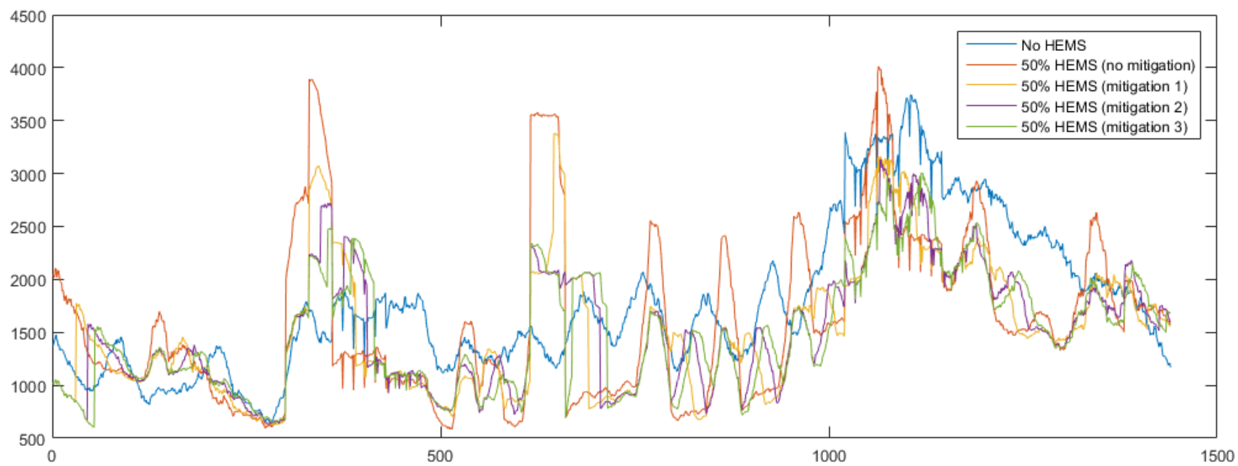


Figure 5.62 Comparison of total load profiles with three mitigation strategies for “loss of load diversity” issue

As shown in Figure 5.7, the voltage violation is less than the one without mitigation. Table 5.2 shows a less system losses after “loss of load diversity” mitigation.

Table 5.8 System average daily loss with/without “loss of load diversity” mitigation

HEMS Penetration	P (kW)	Q (kVar)
0%	11.9	23.4
50% without mitigation control	17.9	35.3
50% with mitigation control	12.2	24.6

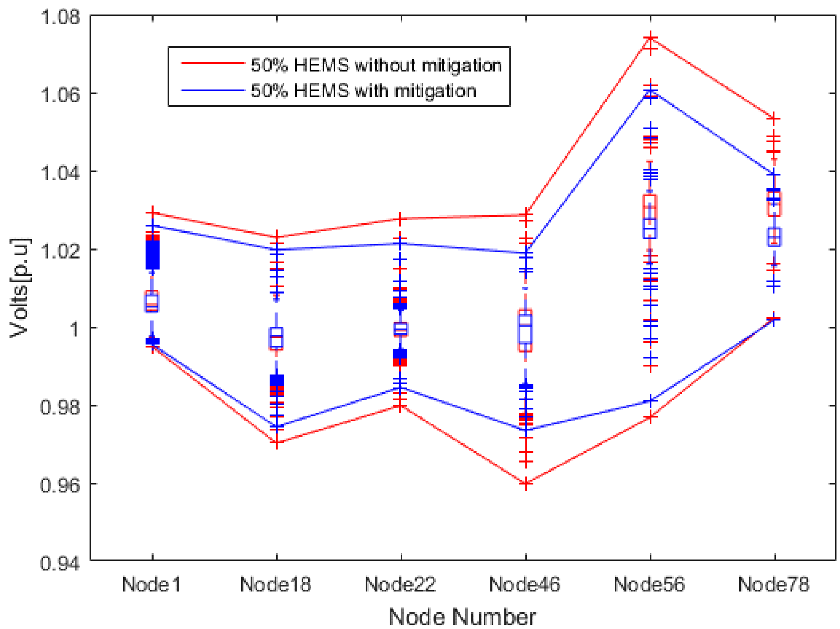


Figure 5.63 Voltage profile at some selected nodes before and after “loss of load diversity” mitigation

5.3 HEM Demand Response in Wholesale Market

5.3.1 Mapping End-user Comfort Setting to DR Bidding

In chapter 4, a mechanism is developed for users to quantify their cost saving expectation in return of comfort sacrifice for each type of load, as shown in Figure 4.3, 4.5 and 4.8. For TCA, the penalty cost (or cost saving expectation) is a function of temperature setpoint, meaning certain amount of cost saving is expected by the user if the temperature setpoint is outside comfort zone. It can be represented as Eq. 5.1.

$$F_{TCA} = f_{TCA}(Temperature) \tag{5.1}$$

Where F_{TCA} is the penalty cost, *Temperature* is the temperature setpoint and $Temperature \subset [T_1, T_2]$.

Assuming 1°F setpoint increasing can save *m* kWh energy in an hour, the TCA penalty cost can be linked to an energy reduction as shown in Eq. 5.2.

$$F_{TCA} = g_{TCA}(Power)\text{, Power} \subset [\mathrm{P}_1, \mathrm{P}_2] \tag{5.2}$$

Here gives a numerical example. First, the user wants to get \$0.5 saving when setpoint is 1°F higher that comfort zone for an hour. Second, the user needs to get \$1 every time the temperature setpoint is outside comfort zone. Third, 1°F setpoint increasing can save 0.5 kWh energy in an hour, but no more than 2 kWh can be saved. Then, the cost function in term of power reduction is: $F_{TCA} = 1(\$) + 0.5(\$/°\text{F}\times\text{h}) * 0.5(°\text{F}\times\text{h/kWh}) * p(\text{kWh}) = 1 + 0.25 * p$, $p \le 2\text{kW}$.

Similarly, for TBA, the penalty cost is a function of task delay time, meaning certain amount of cost saving is expected by the user if the task is finished after the expected time. It can be represented as Eq. 5.3.

$$F_{TBA} = f_{TBA}(end\_time) \tag{5.3}$$

Where F_{TBA} is the penalty cost, *end_time* is the task finished time and $end\_time \subset [t_1, t_2]$.

Assuming 1 hour task delay can save *m* kWh energy in an hour, the TBA penalty cost can be linked to an energy reduction as shown in Eq. 5.4.

$$F_{TBA} = g_{TBA}(Power) \text{, Power} \subset [\text{P}_1, \text{P}_2] \tag{5.4}$$

For EV, the penalty cost is a function of final SoC, meaning certain amount of cost saving is expected by the user if the final SoC is lower than the original SoC target. It can be represented as Eq. 5.5.

$$F_{EV} = f_{EV}(SoC) \tag{5.5}$$

Where F_{EV} is the penalty cost, *SoC* is the final SoC and $SoC \subset [s_1, s_2]$.

Assuming 1% SoC lower can save *m* kWh energy in an hour, the EV penalty cost can be linked to an energy reduction as shown in Eq. 5.6.

$$F_{EV} = g_{EV}(Power) \text{, Power} \subset [\text{P}_1, \text{P}_2] \tag{5.6}$$

With Eq. 5.2, 5.4 and 5.6, the household cost saving expectation (or penalty cost) is formulated as a function of power reduction. In other words, the HEMS demand response is modeled as a virtual power plant with a cost function and operation limit (P_{min} and P_{max}).

When aggregated, HEMSs can be modeled as a virtual power plant with a piecewise cost function (assuming all the users' cost saving expectation is linear to the comfort setting violation). The following section uses a three-bus system example to show how the aggregated HEM DR can relieve transmission congestion and reduce system cost.

5.3.2 Example: A Three-bus System with HEMS DR

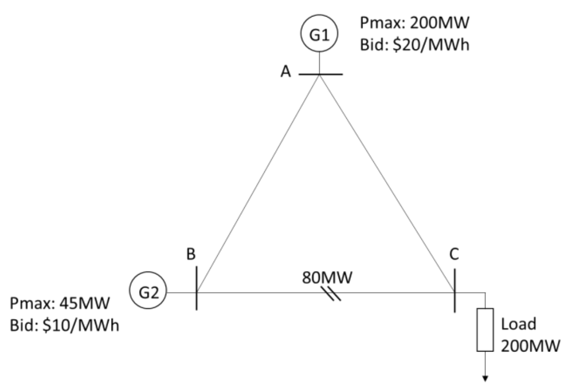


Figure 5.64 Three-bus system example

The three-bus system example is shown in Figure 5.8. Generation 1 at bus A has 200MW P_{max}, it is offering $20/MWh. Generation 2 at bus B has 45MW P_{max}, it is offering $10/MWh. There is a 200MW load at bus C. The three transmission lines are identical (same reactance), but only Line B-C has a capacity limit of 80MW.

Based on optimal power flow (OPF) calculation, we can get the locational marginal price (LMP) at each bus and generation optimal dispatch shown in Figure 5.9. The transmission Line B-C is binding with a shadow price of -$30/MW.

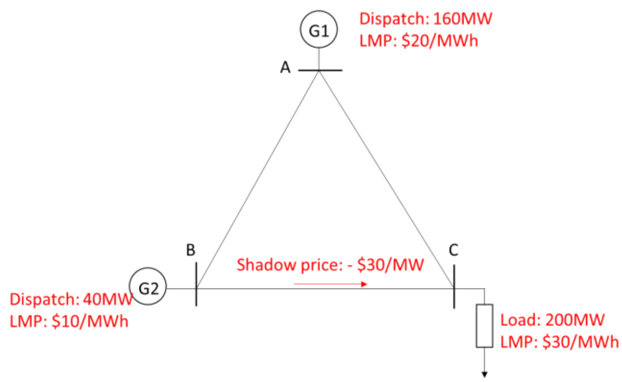


Figure 5.65 LMP and dispatch results with Line B-C congested

Now let's assume there is an aggregate HEMS DR at bus C. There are 4000 houses with HEMS. At this hour, there are 2500 HVAC, 2000 Cloth Washer and 1000 EV are submitting their bid (cost saving expectation). For simplification, let's assume each HVAC, cloth washer and EV can reduce 1kWh, 0.5kWh and 4.5kWh respectively in an hour, and assume their cost expectation are the same as $0.015/kWh. So the cost function of HEMS DR virtual power plan is:

$$F(p) = 5.5 + 15 * p, \ \ p \le 8\text{MW}$$

With such a DR virtual power plant, the transmission congestion on Line B-C is relieved. Total load cost is reduced by $400, since the system increases the dispatch of G2, the cheaper unit, and reduces the dispatch of G1, the more expensive unit. Figure 5.10 shows the LMP and generation dispatch.

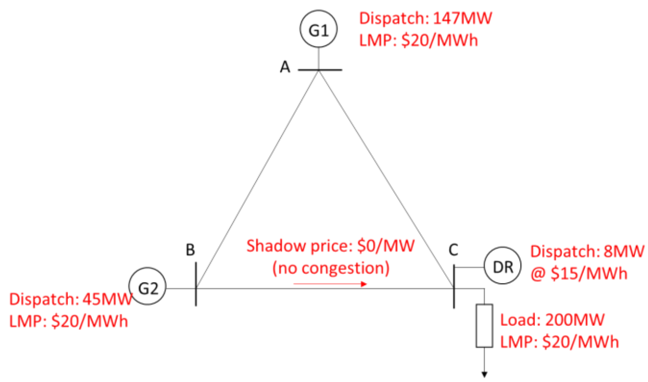


Figure 5.66 LMP and dispatch results with HEMS DR

5.4 Summary

In this chapter, the aggregate impact of HEMS is discussed. With increasing HEMS penetration, the distribution system is facing an issue of "loss of load diversity". Tested by an IEEE 123-node feeder system, high penetration HEMS will lead to voltage violation and more system loss. A control strategy is proposed to mitigate this issue by introducing a randomness in HEM control. The control strategy selects the a random time for HEMS to switch back to normal time while considering the priority of appliance based on its close to comfort limit. The case study shows the effectiveness of the control strategy to reduce the load synchronization and "rebound effect".

In addition, with the model of user's cost saving expectation, the HEMS DR can be formulated as a virtual power plant. Users quantify their cost saving expectation in return of comfort sacrifice. Such a model can map the residential users in retail side to wholesale energy market. A three-bus system example shows the aggregate HEMS DR can "provide" energy to relieve system congestion and reduce total cost.

CHAPTER 6 CONCLUSION

With the rapid change of power system on both supply and demand side, home energy management attracts increasing attentions from both system operators and residential energy users. In this research, a cost effective and computational economic HEMS is developed. The prototype of software and hardware design are presented. A physical HEMS test system is developed and implemented, allowing researchers to evaluate their HEM designs, such as control algorithm and pricing schemes.

In chapter 3, a forecast approach is proposed to predict the household level electricity demand in both day-ahead and hour-ahead. Due to the high volatility of household load, the proposed forecaster predicts the load level instead of exact value in day ahead, while it provides short-term forecast in hour ahead. In this way, HEMS can schedule tasks with less impact of demand uncertainty in day ahead, then fine tune schedule in real-time with the HA forecast results. The DA forecast includes two steps: (1) similar day clustering with k-mean algorithm and (2) probabilistic forecast of load levels with multinomial logistic regression. The HA forecast uses a state-space model updated with Kalman filter algorithm. Case study with a realistic dataset of 20 houses in both summer and winter is used to verify the proposed forecasting approach. The results shows a 57% of accuracy improvement compared to naïve method in day ahead, while the HA forecast has AMAPE of 35% and 26% in summer time and winter time respectively.

For scheduling purpose, HEMS should consider different types of controllable appliances. In this chapter, three types of appliances are modeled: TCA, TBA and EV. Each model considers the appliance physical characteristics (thermal dynamic, minimum running time, etc.) and user settings (temperature setpoint, expected finish time, etc.). Using the model set, a heuristic approach is proposed to minimize the energy cost under a “TOU plus demand charge” pricing scheme, when considering user’s comfort preference and cost saving expectation. The control strategies are developed for each type of controllable load with a cost-saving setting mechanism that allows users to input their cost saving expectation in return of comfort sacrifice. The simulation results show the proposed HEMS scheduling approach can reduces the peak demand significantly and reduce the total electricity cost (energy cost and demand charge) by about 25%, while maintaining user’s comfortableness. The sensitivity study of power cap level selection shows the trade-off between cap level and impact on comfortable. A suitable power cap can be the sum of one controllable appliance power rating and the third percentile of sorted controllable load.

Chapter 5 extends the HEM study to aggregation level. With increasing HEMS penetration, the distribution system is facing an issue of “loss of load diversity”, since the HEMSs tends to schedule controllable load to a similar usage pattern. A high penetration of HEMS may lead to local voltage violation and more system losses. A control strategy is proposed to mitigate this issue by introducing a randomness in HEM control that considers user comfort, fairness and system communication requirement. The control strategy can reduce the load synchronization and “rebound effect”. In addition, with the model of user’s cost saving expectation, the HEMS DR can be formulated as a virtual power plant. Users quantify their cost saving expectation in return of comfort sacrifice, so that DR aggregators can know how much does it cost to fulfill certain amount of energy reduction. Such a model can map the residential users in retail side to wholesale energy market price signal. A three-bus system example shows the aggregate HEMS DR can “provide” energy to relieve system congestion and reduce system cost.

In the near future, HEM will be one of the important technologies in the power industry with the present of time varying electricity price, reducing cost of two-way communication and home automation, increasing adaption of electricity vehicle and distributed energy resource, as well as the emerging market for demand response. An HEM design should consider cost efficiency, robustness to load/user behaviors uncertainty, users' preference and ease-of-use, as well as its cooperation with system operation. An extension of this research would be to study the cooperation among HEMSs and to investigate HEM on power system operation [125, 126].

REFERENCES

[1] Wiser, Ryan H., Andrew Mills, Joachim Seel, Todd Levin, and Audun Botterud. *Impacts of Variable Renewable Energy on Bulk Power System Assets, Pricing, and Costs*. No. LBNL-2001082. Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), 2017.

[2] U.S. Energy Information Administration, Electric Power Monthly with Data for October 2017, Table 1.2.E. Net Generation by Energy Source: Residential Sector, 2014-October 2017.

[3] International Energy Agency, "*Global EV outlook 2017: Two million and counting*." OECD/IEA, 2017.

[4] California independent System Operator. "*What the duck curve tells us about managing a green grid*." https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf (accessed October, 2013).

[5] Sun, Yongjun, Shengwei Wang, Fu Xiao, and Diance Gao. " Peak load shifting control using different cold thermal energy storage facilities in commercial buildings: a review." *Energy conversion and management* 71 (2013): 101-114.

[6] Caprino, Davide, Marco L. Della Vedova, and Tullio Facchinetti. "Peak shaving through real-time scheduling of household appliances." *Energy and Buildings* 75 (2014): 133-148.

[7] Mathieu, Johanna L., and Duncan S. Callaway. "State estimation and control of heterogeneous thermostatically controlled loads for load following." In *System Science (HICSS), 2012 45th Hawaii International Conference on*, pp. 2002-2011. IEEE, 2012.

[8] Ke, Xinda, Di Wu, and Ning Lu. "A Real-Time Greedy-Index Dispatching Policy for using PEVs to Provide Frequency Regulation Service." *IEEE Transactions on Smart Grid* (2017).

[9] Watson, David S. "Fast automated demand response to enable the integration of renewable resources." (2012).

[10] Palensky, Peter, and Dietmar Dietrich. "Demand side management: Demand response, intelligent energy systems, and smart loads." *IEEE transactions on industrial informatics* 7, no. 3 (2011): 381-388.

[11] U.S. Energy Information Administration, Electric Power Annual 2016, Table 2.2. Sales and Direct Use of Electricity to Ultimate Customers.

[12] Iwakuma, Yoshiaki, and Kiyoshi Toguchi. "Domestic load management system using power line carrier." In *Consumer Electronics, 1991 IEEE International Conference on*, pp. 146-147. IEEE, 1991.

[13] Wacks, Kenneth P. "Utility load management using home automation." *IEEE Transactions on Consumer Electronics* 37, no. 2 (1991): 168-174.

[14] Gustafson, M. W., J. S. Baylor, and Gary Epstein. "Direct water heater load control-estimating program effectiveness using an engineering model." *IEEE Transactions on Power systems* 8, no. 1 (1993): 137-143.

[15] Colak, Ilhami, Seref Sagiroglu, Gianluca Fulli, Mehmet Yesilbudak, and Catalin-Felix Covrig. "A survey on the critical issues in smart grid technologies." *Renewable and Sustainable Energy Reviews* 54 (2016): 396-405.

[16] Nest Lab. Nest learning thermostat efficiency simulation: Update using data from first three months. http://downloads.nest.com/efficiency_simulation_whitepaper.pdf (accessed Apr.2012).

[17] Ecobee Thermostat Overview. Available online: https://www.ecobee.com/ecobee4

[18] Joskow, Paul L., and Catherine D. Wolfram. "Dynamic pricing of electricity." *The American Economic Review* 102, no. 3 (2012): 381-385.

[19] Sexton, Richard J., Nancy Brown Johnson, and Akira Konakayama. "Consumer response to continuous-display electricity-use monitors in a time-of-use pricing experiment." *Journal of Consumer Research* (1987): 55-62.

[20] Caves, Douglas W., and Laurits R. Christensen. "Econometric analysis of residential time-of-use electricity pricing experiments." *Journal of Econometrics* 14, no. 3 (1980): 287-306.

[21] Mohsenian-Rad, Amir-Hamed, and Alberto Leon-Garcia. "Optimal residential load control with price prediction in real-time electricity pricing environments." *IEEE transactions on Smart Grid* 1, no. 2 (2010): 120-133.

[22] Patrick, Robert H., and Frank A. Wolak. *Estimating the customer-level demand for electricity under real-time market prices*. No. w8213. National Bureau of Economic Research, 2001.

[23] Herter, Karen. "Residential implementation of critical-peak pricing of electricity." *Energy Policy* 35, no. 4 (2007): 2121-2130.

[24] Taylor, Thomas N., and Peter M. Schwarz. "A residential demand charge: evidence from the Duke Power Time-of-Day pricing experiment." *The Energy Journal* 7, no. 2 (1986): 135-151.

[25] Zipperer, Adam, Patricia A. Aloise-Young, Siddharth Suryanarayanan, Robin Roche, Lieko Earle, Dane Christensen, Pablo Bauleo, and Daniel Zimmerle. "Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior." *Proceedings of the IEEE* 101, no. 11 (2013): 2397-2408.

[26] Inoue, Masahiro, Toshiyasu Higuma, Yoshiaki Ito, Noriyuki Kushiro, and Hitoshi Kubota. "Network architecture for home energy management system." *IEEE Transactions on Consumer Electronics* 49, no. 3 (2003): 606-613.

[27] Hammerstrom, Donald J., Jerry Brous, David P. Chassin, Gale R. Horst, Robert Kajfasz, Preston Michie, Terry V. Oliver et al. *Pacific northwest gridwise™ testbed demonstration projects; part ii. grid friendly™ appliance project*. No. PNNL-17079. Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2007.

[28] JordA, C. E. P., B. Asare-Bediako, G. M. A. Vanalme, and W. L. Kling. "Overview and comparison of leading communication standard technologies for smart home area networks enabling energy management systems." *In Universities' Power Engineering Conference (UPEC), Proceedings of 2011 46th International*, pp. 1-6. VDE, 2011.

[29] McCary, Eric, and Yang Xiao. "Home area network accountability with varying consumption devices in smart grid." *Security and Communication Networks* 9, no. 10 (2016): 977-995.

[30] Zhu, Xiangqi, Jiahong Yan, Lining Dong, and Ning Lu. "A Matlab-based home energy management algorithm development toolbox." In *Power and Energy Society General Meeting (PESGM), 2016*, pp. 1-5. IEEE, 2016.

[31] Ramchurn, Sarvapali D., Perukrishnen Vytelingum, Alex Rogers, and Nicholas R. Jennings. "Agent-based homeostatic control for green energy in the smart grid." ACM *Transactions on Intelligent Systems and Technology (TIST)* 2, no. 4 (2011): 35.

[32] Lu, Ning, and Yu Zhang. "Design considerations of a centralized load controller using thermostatically controlled appliances for continuous regulation reserves." *IEEE Transactions on Smart Grid* 4, no. 2 (2013): 914-921.

[33] Vytelingum, Perukrishnen, Thomas D. Voice, Sarvapali D. Ramchurn, Alex Rogers, and Nicholas R. Jennings. "Theoretical and practical foundations of large-scale agent-based micro-storage in the smart grid." *Journal of Artificial Intelligence Research* 42 (2011): 765-813.

[34] Li, Na, Lijun Chen, and Steven H. Low. "Optimal demand response based on utility maximization in power networks." In *Power and Energy Society General Meeting, 2011 IEEE*, pp. 1-8. IEEE, 2011.

[35] Deng, Ruilong, Zaiyue Yang, Jiming Chen, and Mo-Yuen Chow. "Load scheduling with price uncertainty and temporally-coupled constraints in smart grids." *IEEE Transactions on Power Systems* 29, no. 6 (2014): 2823-2834.

[36] Chen, Zhi, Lei Wu, and Yong Fu. "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization." *IEEE Transactions on Smart Grid* 3, no. 4 (2012): 1822-1831.

[37] Oldewurtel, Frauke, Andreas Ulbig, Alessandra Parisio, Göran Andersson, and Manfred Morari. "Reducing peak electricity demand in building climate control using real-time pricing and model predictive control." In *Decision and Control (CDC), 2010 49th IEEE Conference on*, pp. 1927-1932. IEEE, 2010.

[38] Široký, Jan, Frauke Oldewurtel, Jiří Cigler, and Samuel Prívara. "Experimental analysis of model predictive control for an energy efficient building heating system." *Applied energy* 88, no. 9 (2011): 3079-3087.

[39] De Angelis, Francesco, Matteo Boaro, Danilo Fuselli, Stefano Squartini, Francesco Piazza, and Qinglai Wei. "Optimal home energy management under dynamic electrical and thermal constraints." *IEEE Transactions on Industrial Informatics* 9, no. 3 (2013): 1518-1527.

[40] Shi, Wenbo, Na Li, Xiaorong Xie, Chi-Cheng Chu, and Rajit Gadh. "Optimal residential demand response in distribution networks." *IEEE journal on selected areas in communications*32, no. 7 (2014): 1441-1450.

[41] Baharlouei, Zahra, Massoud Hashemi, Hamed Narimani, and Hamed Mohsenian-Rad. "Achieving optimality and fairness in autonomous demand response: Benchmarks and billing mechanisms." *IEEE Transactions on Smart Grid* 4, no. 2 (2013): 968-975.

[42] Lopes, JA Pecas, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins. "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities." *Electric power systems research* 77, no. 9 (2007): 1189-1203.

[43] U.S. Energy Information Administration, 2015 RESIDENTIAL ENERGY CONSUMPTION SURVEY (RECS).

[44] Huang, Alex Q., Mariesa L. Crow, Gerald Thomas Heydt, Jim P. Zheng, and Steiner J. Dale. "The future renewable electric energy delivery and management (FREEDM) system: the energy internet." *Proceedings of the IEEE* 99, no. 1 (2011): 133-148.

[45] Yan, Jiahong, Xiangqi Zhu, and Ning Lu. "Smart hybrid house test systems in a solid-state transformer supplied microgrid." In *Power & Energy Society General Meeting, 2015 IEEE*, pp. 1-5. IEEE, 2015.

[46] Han, Dae-Man, and Jae-Hyun Lim. "Design and implementation of smart home energy management systems based on zigbee." *IEEE Transactions on Consumer Electronics* 56, no. 3 (2010).

[47] Han, Jinsoo, Chang-Sic Choi, and Ilwoo Lee. "More efficient home energy management system based on ZigBee communication and infrared remote controls." *IEEE Transactions on Consumer Electronics* 57, no. 1 (2011).

[48] Hu, Qinran, and Fangxing Li. "Hardware design of smart home energy management system with dynamic price response." *IEEE Transactions on Smart grid* 4, no. 4 (2013): 1878-1887.

[49] Li, Jian, Jae Yoon Chung, Jin Xiao, James Won-Ki Hong, and Raouf Boutaba. "On the design and implementation of a home energy management system." In *Wireless and Pervasive Computing (ISWPC), 2011 6th International Symposium on*, pp. 1-6. IEEE, 2011.

[50] Kurucz, C. N., D. Brandt, and S. Sim. "A linear programming model for reducing system peak through customer load control programs." *IEEE Transactions on Power Systems* 11, no. 4 (1996): 1817-1824.

[51] Zhu, Xiangqi, Gonzague Henri, Jiahong Yan, and Ning Lu. "A cost-benefit study of sizing residential PV and ES systems based on synthesized load profiles." In *Power & Energy Society General Meeting, 2017 IEEE*, pp. 1-5. IEEE, 2017.

[52] Logenthiran, Thillainathan, Dipti Srinivasan, and Tan Zong Shun. "Demand side management in smart grid using heuristic optimization." *IEEE transactions on smart grid* 3, no. 3 (2012): 1244-1252.

[53] Hafen, Ryan P., Nader Samaan, Yuri V. Makarov, Ruisheng Diao, and Ning Lu. "Joint seasonal ARMA approach for modeling of load forecast errors in planning studies." *In T&D Conference and Exposition, 2014 IEEE PES*, pp. 1-5. IEEE, 2014.

[54] Nguyen, Duong Tung, and Long Bao Le. "Risk-constrained profit maximization for microgrid aggregators with demand response." *IEEE Transactions on smart grid* 6, no. 1 (2015): 135-146.

[55] Negash, Ahlmahz I., Tobias W. Haring, and Daniel S. Kirschen. "Allocating the cost of demand response compensation in wholesale energy markets." *IEEE Transactions on Power Systems* 30, no. 3 (2015): 1528-1535.

[56] Negash, Ahlmahz I., and Daniel S. Kirschen. "Combined optimal retail rate restructuring and value of solar tariff." In *Power & Energy Society General Meeting, 2015 IEEE*, pp. 1-5. IEEE, 2015.

[57] Zhong, Haiwang, Le Xie, and Qing Xia. "Coupon incentive-based demand response: Theory and case study." *IEEE Transactions on Power Systems* 28, no. 2 (2013): 1266-1276.

[58] Faruqui, Ahmad, and Sanem Sergici. "Household response to dynamic pricing of electricity: a survey of 15 experiments." *Journal of regulatory Economics* 38, no. 2 (2010): 193-225..

[59] Hu, Qinran, Xin Fang, Fangxing Li, Xiaojing Xu, Chien-fei Chen, and Haolu Hu. "An approach to assess the responsive residential demand to financial incentives." In *Power & Energy Society General Meeting, 2015 IEEE*, pp. 1-5. IEEE, 2015.

[60] Ke, Xinda. "Solution Methods of Large-Scale Power System Resource Scheduling and Dispatch Problems." (2016).

[61] Melton, Ron. Pacific Northwest Smart Grid Demonstration Project Technology Performance Report Volume 1: Technology Performance. No. PNW-SGDP-TPR-Vol. 1-Rev. 1.0; PNWD-4438, Volume 1. Pacific Northwest National Laboratory (PNNL), Richland, WA (United States), 2015.

[62] Yu, Zhe, Liyan Jia, Mary C. Murphy-Hoye, Annabelle Pratt, and Lang Tong. "Modeling and stochastic control for home energy management." *IEEE Transactions on Smart Grid* 4, no. 4 (2013): 2244-2255.

[63] Schneider Electric Home Energy Monitoring System, https://www.schneider- electric.us/ explore/wiser-energy

[64] Philips Hue Bulbs, https://www.usa.philips.com/c-m-li/home-lighting-innovations

[65] Samsung Smart Home SmartThings, https://www.samsung.com/us/smart-home

[66] Wang, Zhenpo, and Shuo Wang. "Grid power peak shaving and valley filling using vehicle-to-grid systems." *IEEE Transactions on power delivery* 28, no. 3 (2013): 1822-1829.

[67] Morais, Hugo, Péter Kádár, Pedro Faria, Zita A. Vale, and H. M. Khodr. "Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming." *Renewable Energy* 35, no. 1 (2010): 151-156.

[68] Kamgarpour, Maryam, Christian Ellen, Sadegh Esmaeil Zadeh Soudjani, Sebastian Gerwinn, Johanna L. Mathieu, Nils Müllner, Alessandro Abate, Duncan S. Callaway, Martin Fränzle, and John Lygeros. "Modeling options for demand side participation of thermostatically controlled loads." In *Bulk Power System Dynamics and Control-IX Optimization, Security and Control of the Emerging Power Grid (IREP), 2013 IREP Symposium*, pp. 1-15. IEEE, 2013.

[69] Newsham, Guy R., and Brent G. Bowker. "The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review." Energy policy 38, no. 7 (2010): 3289-3296.

[70] Zhu, Xiangqi, Jiahong Yan, and Ning Lu. "A probabilistic-based pv and energy storage sizing tool for residential loads." In *Transmission and Distribution Conference and Exposition (T&D), 2016 IEEE/PES*, pp. 1-5. IEEE, 2016.

[71] Ke, Xinda, Anjie Jiang, and Ning Lu. "Load profile analysis and short-term building load forecast for a university campus." In *Power and Energy Society General Meeting (PESGM), 2016*, pp. 1-5. IEEE, 2016.

[72] Papalexopoulos, Alex D., and Timothy C. Hesterberg. "A regression-based approach to short-term system load forecasting." *IEEE Transactions on Power Systems* 5, no. 4 (1990): 1535-1547.

[73] Amral, N., C. S. Ozveren, and D. King. "Short term load forecasting using multiple linear regression." In *Universities Power Engineering Conference, 2007. UPEC 2007. 42nd International*, pp. 1192-1198. IEEE, 2007.

[74] Yan, Jiahong, Hui Zheng, and Ning Lu. "Temperature-load sensitivity study for adjusting MISO day-ahead load forecast." In *Power and Energy Society General Meeting (PESGM), 2016*, pp. 1-5. IEEE, 2016.

[75] Rahman, Saifur, and Ossama Hazim. "A generalized knowledge-based short-term load-forecasting technique." IEEE Transactions on power systems 8, no. 2 (1993): 508-514.

[76] He, Yu-Jun, You-Chan Zhu, Jian-Cheng Gu, and Cheng-Qun Yin. "Similar day selecting based neural network model and its application in short-term load forecasting." In *Machine Learning and Cybernetics, 2005. Proceedings of 2005 International Conference on*, vol. 8, pp. 4760-4763. IEEE, 2005.

[77] Park, Dong C., M. A. El-Sharkawi, R. J. Marks, L. E. Atlas, and M. J. Damborg. "Electric load forecasting using an artificial neural network." *IEEE transactions on Power Systems* 6, no. 2 (1991): 442-449.

[78] Hippert, Henrique Steinherz, Carlos Eduardo Pedreira, and Reinaldo Castro Souza. "Neural networks for short-term load forecasting: A review and evaluation." *IEEE Transactions on power systems* 16, no. 1 (2001): 44-55.

[79] Senjyu, Tomonobu, Hitoshi Takara, Katsumi Uezato, and Toshihisa Funabashi. "One-hour-ahead load forecasting using neural network." *IEEE Transactions on power systems* 17, no. 1 (2002): 113-118.

[80] Pai, Ping-Feng, and Wei-Chiang Hong. "Forecasting regional electricity load based on recurrent support vector machines with genetic algorithms." *Electric Power Systems Research* 74, no. 3 (2005): 417-425.

[81] Hong, Wei-Chiang. "Electric load forecasting by support vector model." *Applied Mathematical Modelling* 33, no. 5 (2009): 2444-2454.

[82] Li, Qiong, Qinglin Meng, Jiejin Cai, Hiroshi Yoshino, and Akashi Mochida. "Applying support vector machine to predict hourly cooling load in the building." *Applied Energy* 86, no. 10 (2009): 2249-2256.

[83] McLoughlin, Fintan, Aidan Duffy, and Michael Conlon. "A clustering approach to domestic electricity load profile characterisation using smart metering data." *Applied Energy* 141 (2015): 190-199.

[84] Anderson, Ben, Sharon Lin, Andy Newing, AbuBakr Bahaj, and Patrick James. "Electricity consumption and household characteristics: Implications for census-taking in a smart metered future." *Computers, Environment and Urban Systems* 63 (2017): 58-67.

[85] Kwac, Jungsuk, June Flora, and Ram Rajagopal. "Household energy consumption segmentation using hourly data." *IEEE Transactions on Smart Grid* 5, no. 1 (2014): 420-430.

[86] Gajowniczek, Krzysztof, and Tomasz Ząbkowski. "Short term electricity forecasting using individual smart meter data." *Procedia Computer Science* 35 (2014): 589-597.

[87] Berges, Mario, Ethan Goldman, H. Scott Matthews, Lucio Soibelman, and Kyle Anderson. "User-centered nonintrusive electricity load monitoring for residential buildings." *Journal of computing in civil engineering* 25, no. 6 (2011): 471-480.

[88] Davies, David L., and Donald W. Bouldin. "A cluster separation measure." *IEEE transactions on pattern analysis and machine intelligence* 2 (1979): 224-227.

[89] Menard, Scott. *Applied logistic regression analysis*. Vol. 106. Sage, 2002.

[90] Kalman, Rudolph Emil. "A new approach to linear filtering and prediction problems." *Journal of basic Engineering* 82, no. 1 (1960): 35-45.

[91] PECAN STREET INC, Available online: http://www.pecanstreet.org/

[92] Available online: https://weatherspark.com/y/8004/Average-Weather-in-Austin-Texas-United-States-Year-Round

[93] Zhao, Zhuang, Won Cheol Lee, Yoan Shin, and Kyung-Bin Song. "An optimal power scheduling method for demand response in home energy management system." *IEEE Transactions on Smart Grid 4*, no. 3 (2013): 1391-1400.

[94] Ng, K-H., and Gerald B. Sheble. "Direct load control-A profit-based load management using linear programming." *IEEE Transactions on Power Systems* 13, no. 2 (1998): 688-694.

[95] Shinwari, Merwais, Amr Youssef, and Walaa Hamouda. "A water-filling based scheduling algorithm for the smart grid." *IEEE Transactions on Smart Grid* 3, no. 2 (2012): 710-719.

[96] Pipattanasomporn, Manisa, Murat Kuzlu, and Saifur Rahman. "An algorithm for intelligent home energy management and demand response analysis." *IEEE Transactions on Smart Grid* 3, no. 4 (2012): 2166-2173.

[97] Ke, Xinda, Di Wu, Ning Lu, and Michael Kintner-Meyer. "A modified priority list-based MILP method for solving large-scale unit commitment problems." In *Power & Energy Society General Meeting, 2015 IEEE*, pp. 1-5. IEEE, 2015.

[98] Zhu, Xiangqi, Jiyu Wang, David Lubkeman, Ning Lu, Nader Samaan, and Renke Huang. "Voltage-Load Sensitivity Matrix Based Demand Response for Voltage Control in High Solar Penetration Distribution Feeders." In *Power and Energy Society General Meeting (PESGM)*. 2017.

[99] Xiong, Gang, Chen Chen, Shalinee Kishore, and Aylin Yener. "Smart (in-home) power scheduling for demand response on the smart grid." In *Innovative smart grid technologies (ISGT), 2011 IEEE PES*, pp. 1-7. IEEE, 2011.

[100] Muratori, Matteo, Matthew C. Roberts, Ramteen Sioshansi, Vincenzo Marano, and Giorgio Rizzoni. "A highly resolved modeling technique to simulate residential power demand." *Applied Energy* 107 (2013): 465-473.

[101] Guttromson, R. T., D. P. Chassin, and S. E. Widergren. "Residential energy resource models for distribution feeder simulation." In *Power Engineering Society General Meeting, 2003, IEEE*, vol. 1, pp. 108-113. IEEE, 2003.

[102] Shao, Shengnan, Manisa Pipattanasomporn, and Saifur Rahman. "Development of physical-based demand response-enabled residential load models." *IEEE Transactions on power systems* 28, no. 2 (2013): 607-614.

[103] Chavali, Phani, Peng Yang, and Arye Nehorai. "A distributed algorithm of appliance scheduling for home energy management system." *IEEE Transactions on Smart Grid* 5, no. 1 (2014): 282-290.

[104] Anvari-Moghaddam, Amjad, Hassan Monsef, and Ashkan Rahimi-Kian. "Optimal smart home energy management considering energy saving and a comfortable lifestyle." *IEEE Transactions on Smart Grid* 6, no. 1 (2015): 324-332.

[105] Sonderegger, Robert C. "Dynamic models of house heating based on equivalent thermal parameters." (1978).

[106] Residential Service Time-of-Use/R-TOUD, https://www.duke-energy.com/media/pdfs /for-your-home/rates/electric-nc/r2ncschedulertouddep.pdf?la=en

[107] A closer look at commercial electricity demand charges, and how to lower them, http://businessfeed.sunpower.com/articles/commercial-electricity-demand-charges

[108] Abrahamse, Wokje, Linda Steg, Charles Vlek, and Talib Rothengatter. "A review of intervention studies aimed at household energy conservation." *Journal of environmental psychology* 25, no. 3 (2005): 273-291.

[109] Qian, Li Ping, Ying Jun Angela Zhang, Jianwei Huang, and Yuan Wu. "Demand response management via real-time electricity price control in smart grids." *IEEE Journal on Selected areas in Communications* 31, no. 7 (2013): 1268-1280.

[110] Ito, Koichiro. "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing." *American Economic Review* 104, no. 2 (2014): 537-63.

[111] Henley, Andrew, and John Peirson. "Time-of-use electricity pricing: evidence from a British experiment." *Economics Letters* 45, no. 3 (1994): 421-426.

[112] Faruqui, Ahmad, and J. Robert Malko. "The residential demand for electricity by time-of-use: a survey of twelve experiments with peak load pricing." *Energy* 8, no. 10 (1983): 781-795.

[113] Yang, Peng, Gongguo Tang, and Arye Nehorai. "A game-theoretic approach for optimal time-of-use electricity pricing." *IEEE Transactions on Power Systems* 28, no. 2 (2013): 884-892.

[114] Fang, Xi, Satyajayant Misra, Guoliang Xue, and Dejun Yang. "Smart grid—The new and improved power grid: A survey." *IEEE communications surveys & tutorials* 14, no. 4 (2012): 944-980.

[115] Herter, Karen, Patrick McAuliffe, and Arthur Rosenfeld. "An exploratory analysis of California residential customer response to critical peak pricing of electricity." *Energy* 32, no. 1 (2007): 25-34.

[116] Matsukawa, Isamu, Hiroshi Asano, and Hitoshi Kakimoto. "Household response to incentive payments for load shifting: A Japanese time-of-day electricity pricing experiment." *The Energy Journal* (2000): 73-86.

[117] Ozturk, Yusuf, Datchanamoorthy Senthilkumar, Sunil Kumar, and Gordon Lee. "An intelligent home energy management system to improve demand response." *IEEE Transactions on Smart Grid* 4, no. 2 (2013): 694-701.

[118] N. Samaan, M. Elizondo, B. Vyakaranam, M. Vallem, X. Ke, R. Huang, J. Holzer, S. Sridhar, Q. Quan, Y. Makarov, and X. Zhu. Combined transmission and distribution test system to study high penetration of distributed solar generation. In *2018 IEEE PES T&D Conference*, pages 1–5, April 2018.

[119] Tan, Zhao, Peng Yang, and Arye Nehorai. "An optimal and distributed demand response strategy with electric vehicles in the smart grid." *IEEE Transactions on Smart Grid* 5, no. 2 (2014): 861-869.

[120] CAISO capacity procurement mechanism replacement, http://www.caiso.com/informed/Pages/StakeholderProcesses/CompletedClosedStakeholderInitiatives/CapacityProcurementMechanismReplacement.aspx

[121] PJM Capacity Market (RPM), http://www.pjm.com/markets-and-operations/rpm.aspx

[122] MISO Resource Adequacy, https://www.misoenergy.org/planning/resource-adequacy

[123] IEEE 123-bus Feeder, available online: https://ewh.ieee.org/soc/pes/dsacom/testfeeders/

[124] Zhu, Xiangqi. "DSM-Based Methodology Development for Addressing Problems of High PV Penetrated Distribution System." (2017).

[125] Wang, Jiyu, Xiangqi Zhu, David Lubkeman, Ning Lu, and Nader Samaan. "Continuation power flow analysis for PV integration studies at distribution feeders." In *Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), 2017 IEEE*, pp. 1-5. IEEE, 2017.

[126] Ke, Xinda, Di Wu, Jennie Rice, Michael Kintner-Meyer, and Ning Lu. "Quantifying impacts of heat waves on power grid operation." *Applied Energy* 183 (2016): 504-512.