An Approach to Demand Response for Alleviating Power System Stress Conditions due to Electric Vehicle Penetration

By

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(Abstract)

Along with the growth of electricity demand and the penetration of intermittent renewable energy sources, electric power distribution networks will face more and more stress conditions, especially as electric vehicles (EVs) take a greater share in the personal automobile market. This may cause potential transformer overloads, feeder congestions, and undue circuit failures.

Demand response (DR) is gaining attention as it can potentially relieve system stress conditions through load management. DR can possibly defer or avoid construction of large-scale power generation and transmission infrastructures by improving the electric utility load factor. This dissertation proposes to develop a planning tool for electric utilities that can provide an insight into the implementation of demand response at the end-user level. The proposed planning tool comprises control algorithms and a simulation platform that are designed to intelligently manage end-use loads to make the EV penetration transparent to an electric power distribution network. The proposed planning tool computes the demand response amount necessary at the circuit/substation level to alleviate the stress condition due to the penetration of EVs. Then, the demand response amount is allocated to the end-user as a basis for appliance scheduling and control.

To accomplish the dissertation objective, electrical loads of both residential and commercial customers, as well as EV fleets, are modeled, validated, and aggregated with their control algorithms proposed at the appliance level.

A multi-layer demand response model is developed that takes into account both concerns from utilities for load reduction and concerns from consumers for convenience and privacy. An analytic hierarchy process (AHP)-based approach is put forward taking into consideration opinions from all stakeholders in order to determine the priority and importance of various consumer groups.

The proposed demand response strategy takes into consideration dynamic priorities of the load based on the consumers' real-time needs. Consumer comfort indices are introduced to measure the impact of demand response on consumers' life style. The proposed indices can provide electric utilities a better estimation of the customer acceptance of a DR program, and the capability of a distribution circuit to accommodate EV penetration.

Research findings from this work indicate that the proposed demand response strategy can fulfill the task of peak demand reduction with different EV penetration levels while maintaining consumer comfort levels. The study shows that the higher number of EVs in the distribution circuit will result in the higher DR impacts on consumers' comfort. This indicates that when EV numbers exceed a certain threshold in an area, other measures besides demand response will have to be taken into account to tackle the peak demand growth.

The proposed planning tool is expected to provide an insight into the implementation of demand response at the end-user level. It can be used to estimate demand response potentials and the benefit of implementing demand response at different DR penetration levels within a distribution circuit. The planning tool can be used by a utility to design proper incentives and encourage consumers to participate in DR programs. At the same time, the simulation results will give a better understanding of the DR impact on scheduling of electric appliances.

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1. Introduction

1.1. Background

The advent of the smart grid has brought about many challenges and opportunities that allow the operation of traditional electric power systems to be more secure, reliable and efficient. The smart grid is a vision that makes this possible – at the transmission and distribution levels – the integration of various distributed energy sources, smart sensors and frequency monitoring devices, intelligent substation and distribution equipment, as well as – at the customer level – the use of smart appliances at home.

With the smart grid, it is possible to perform load control using innovative demand response algorithms. This in turn helps alleviate power system stress conditions. Although the term ‘demand side management’ has been widely used since the 1980’s, the term ‘demand response’ has recently been introduced together with the smart grid concept. Demand response is a customer action to control loads to meet certain peak reduction and energy savings targets. With demand response, the customer chooses what loads to be controlled and for how long. This is different from Demand Side Management (DSM) where loads are controlled by the electric utility and customers have no control beyond the initial consent.

Recently, demand response has gained tremendous attention as it can potentially benefit power systems by relieving system stress conditions and possibly deferring or avoiding construction of large-scale power generation and transmission infrastructures. Federal Energy Regulatory Commission (FERC) has published a national action plan on demand response in 2010 that is designed to identify: “(a) requirements for technical assistance to States to allow them to maximize the amount of demand response resources that can be developed and deployed; (b) requirements for implementation of a national communication program; and (c) analytical tools, information, model regulatory, model contracts and other support for all stakeholders”.[1] In the FERC’s national action plan on demand response, several technical research issues have been identified as knowledge gaps. These issues include for example:

- Better understanding of the optimal amount of consumer versus demand response provider control of appliances.
- A study of how long demand response resources can be expected to provide resource adequacy and reliability benefits compared with other resources, such as generation, transmission, and storage.
- A study of how demand response resources can be dispatched to support and balance variable generation from renewable energy.

According to a thorough literature search, there are still many knowledge gaps in the area of demand response. This dissertation puts an emphasis on the design of the demand response strategy that takes into consideration consumer's comfort, convenience and privacy at a power distribution level.

1.2. Objectives and Scope of the Dissertation

The objective of the dissertation is to propose a planning tool for electric utilities that can provide an insight into the implementation of demand response at an end-use level. The proposed planning tool comprises control algorithms and a simulation platform that are designed to intelligently manage end-use loads and make the EV penetration transparent to an electric power distribution network. An analytic hierarchy process (AHP) based model is adopted to take into consideration opinions from multiple stakeholders. This is in order to determine the priority and importance of various demand categories, e.g. residential homes, office buildings, restaurants, and schools. The proposed demand response strategy also includes the control algorithms at the appliance level, considering their dynamic priorities based on the consumers' real-time needs. The uniqueness of this work is the design of the multi-layer demand response strategy that takes into account consumers' comfort and convenience, as well as respecting consumers' privacy.

To accomplish the dissertation objective, electrical loads of both residential and commercial customers are modeled, and their control algorithms are proposed at the appliance level. Controllable loads of interest include space heating/cooling (for both residential and commercial customers), as well as water heating, and clothes-drying loads (for residential customers). Electric Vehicles (EVs) are included as one load type that can be controlled as well. The proposed planning tool can be used to estimate demand response potentials and the benefit of implementing demand response at different DR penetration levels within a distribution circuit. The planning tool can be used by a utility to design proper incentives and encourage consumers to participate in DR programs. At the same time, the simulation results will give a better understanding of the DR impact on scheduling of electric appliances.

The proposed work includes the following tasks:

Task 1: Create a load profile for a distribution circuit that comprises both residential and small commercial customers. Industry and large commercial customers are not in the scope of this study. Specifically, the subtasks include:

a) Develop simulation models of residential controllable loads, including space heating/space cooling, water heater, and clothes dryer, and validate the developed models.
b) Develop simulation models of small commercial controllable loads, which are of the space heating/cooling type, and validate the developed models.
c) Create non-controllable load profiles from the historical industry-accepted

database.

d) Create a single house/single commercial load profile and diversify the inputs to obtain the distribution network load profile. This is the aggregation of the residential and commercial loads at the distribution level.

Task 2: Develop EV models and EV fleet load profiles that represent EV penetration into a distribution power system. Specifically, the subtasks include:

a) Develop EV models that represent the charge characteristics of EVs available in the U.S. market today, including GM Chevy Volt, Nissan Leaf and Tesla Roadster.
b) Diversify the inputs (e.g. driving patterns, which determines EVs' charge stages after driving, charging start time, and charging rate) and develop the load profile of the EV fleet at the distribution level.

Task 3: Develop an approach for multi-layer demand response. Specifically, the subtasks include:

a) Define a multi-layer demand response structure.
b) Calculate load-shedding allocation at the distribution circuit level. This includes the determination of load shedding allocation for different consumer groups using AHP; and the determination of load shedding allocation for each consumer unit within the same consumer groups.
c) Design a demand response strategy at the appliance level.

Task 4: Perform simulations to show the applicability of the proposed planning tool to study the impact of demand response on load shape changes and consumer comfort.

1.3. Contributions

1.3.1. Modeling of Distribution Network Loads

This dissertation proposes the detailed load models at the appliance level with 1-minute time interval for both residential and commercial buildings. The load models are validated against real data from different sources. The aggregated load profiles are created based on randomization of individual building data (e.g. house structure, hot water usage…), which is not available in the existing literature. The contribution in this part is the validated load models that are useful as a building block for demand response-related simulations and analyses in a distribution network.

1.3.2. Modeling of EV Penetration

This dissertation proposes EV models with 5-minute time interval and aggregated to create a fleet charge profile based on different driving patterns and randomized charge starting times. The contribution in this part is the development of the EV fleet charge profile to create realistic situations for load shape change with EV penetration. This work will be used to study the impact of EV penetration on a distribution network.

1.3.3. Design of Demand Response (DR) Strategy

This dissertation proposes a multi-layer demand response strategy, which has advantages over existing DR strategies that are mainly arbitrary, e.g. direct load control (DLC), which do not guarantee the desired load shape changes.

From the utility side, the proposed approach keeps the utility informed of the demand as well as provides the confidence in load reduction when there is a demand limit. From the consumer side, the demand response is performed within buildings, leaving the customers with freedom to decide their load priorities and convenience preferences, which also helps to maintain customer privacy.

Simulations of the demand response strategy will provide a basis for studying how demand-side resources can be controlled to support a demand limit request.

1.3.4. DR Potential Analysis

For all demand response programs, consumer comfort is always a concern since people don't want their lifestyles to be disturbed. To expand demand response to a larger scale, consumer comfort must be highlighted to encourage their participation, especially from the residential sector. Generally speaking, the price-based demand response leaves consumers with many options to decide their response strategies. However, some of the incentive-based demand response may be arbitrary, providing no room for consumers to manage their own load based on their preferences.

This dissertation proposes a method to analyze the demand response impact on the consumer comfort level. This approach is unique, and will provide a better understanding of the demand response potential in a distribution network. In other words, this can provide an estimate of how much demand response can be performed to accommodate EV penetration or tackle other power system stress conditions without violating a preset consumer comfort range.

The analysis can benefit utilities by helping design proper incentives to encourage consumers to participate in DR programs; and provide consumers better understandings of trade-offs to enroll in a DR program so that they can manage their electricity usage accordingly.

2. Literature Search

This chapter summarizes the literature search into two categories: the background information and the in-depth information. The background information section provides the basic information about smart grid, demand response (DR), electric vehicles (EVs) and analytic hierarchy process (AHP). The in-depth information section covers the research done in areas of demand response strategies and EV penetration into electric power systems. The knowledge gaps are identified in the last section.

2.1. Background Information

2.1.1. Smart Grid

Over the past 50 years, social and economic developments have resulted in the increase in several requirements and challenges to the electricity network. These include the needs for more reliable electric power services, the integration of digitally controlled devices and renewable energy as well as the needs for mitigating the increased cyber security threats. As most of the implementations in the power industry today are still based on the traditional technology available 120 years ago, the power grid is inevitably facing the modern challenges with a traditional system.

In response to the worldwide challenges in the power industry, smart grid is increasingly recognized as a perfect way to improve the energy efficiency of producing and using electricity in homes, businesses, and public institutions. Many believe that a smart grid is a critical foundation for reducing greenhouse gas emissions and transitioning to a low-carbon economy. Smart grid is also considered as a platform that allows an easier integration and higher penetration of renewable energy.

As stated by the DOE's general report 'The Smart Grid: An Introduction', a smart grid 'uses digital technology to improve reliability, security, and efficiency of the electric system: from large generation and delivery systems to electricity consumers and a growing number of distributed-generation and storage resources' [2].

The smart grid definition is based upon the descriptions found in the Energy Independence and Security Act of 2007. The term "Smart Grid" refers to a modernization of the electricity delivery system so it monitors, protects and automatically optimizes the operation of its interconnected elements – from the central and distributed generator through the high-voltage network and distribution system, to industrial users and building automation systems, to energy storage installations and to end-use consumers and their thermostats, electric vehicles, appliances and other household devices. [3]

The National Energy Technology Laboratory (NETL) provides the framework for the smart grid – 'A System View of Modern Grid', which is also widely accepted as the concept and guideline for other participants in the field of smart grid.

A. Characteristics of Smart Grid

According to NETL [4], a smart or modern grid should have the following seven principle characteristics:

1) *Self-healing*. The smart grid should be able to monitor its operation, detect, analyze and solve the problems and identify the potential problems to prevent the system collapse. When needed, it should be able to restore the services to its loads. The self-healing grid will minimize the disruption of service.
2) *Consumer participation*. In a modern smart grid, the consumers could be well informed of the prices and the load situations by the intelligent components. Therefore the consumers are able to balance between their demands and the electricity system's needs. The demand management, decision making, real time pricing will be needed to realize this function in the smart grid.
3) *Attack resisting*. The smart grid shall allow the power system to be more resilient, minimizing the consequence of an attack and restoring the system as soon as possible.
4) *High power quality for 21st century needs*. The smart grid shall minimize the harmonics, distortion, imbalance, sags and spikes during the power delivery. The feature will require more advanced components such as Flexible AC Transmission Systems (FACTS), Dynamic Voltage Restorers (DVR) and Static VAR Compensator (SVC).
5) *Accommodation of all generation and storage options*. The smart grid shall enable the integration of renewable energies like solar and wind, which are cleaner but might be more fluctuated. This will reduce the dependence on the fossil fuels and allow the system to be more environmental friendly.
6) *Market enabling*. The smart grid shall bring in more participants and options to make the system more efficient. It requires but is not limited to the technologies of distributed generations, real time pricing and customer responses. The planning and support system are also critical to make the market work.
7) *Optimizes assets and operates efficiently*. This is to realize the functions of the modern grid at minimum cost. It requires network and component assessment, optimization algorithms and anticipatory decision making.

B. Key technologies

Modern technologies are needed to support the seven key features motioned above. The technologies involved in smart grid as stated in Title XIII of 2007 Energy Independence and Security Act (EISA) [5] could be roughly put into five key categories:

1) *Integrated Communications*, including high-speed, fully integrated, two-way communication technologies for real-time information and power exchange and an open architecture to create a plug-and-play environment that secure networks grid components to talk, listen and interact.

2) *Sensing and Measurement*, which will enhance power system measurements and enable the transformation of data into information in support of advanced protective relaying. They enable consumer choice and demand response, and help relieve congestion.
3) *Advanced Components* play an active role in determining the grid's behavior. Their applications will produce higher power densities, greater reliability and power quality, enhanced electrical efficiency producing major environmental gains and improved real-time diagnostics.
4) *Advanced Control Methods* will be applied to monitor essential components, enabling rapid diagnosis and timely, appropriate response to any event. They will also support market pricing and enhance asset management and efficient operations.
5) *Improved Interfaces and Decision Support* are wide, seamless, real-time use of applications and tools that enable grid operators and managers to make decisions quickly. Decision support with improved interfaces will amplify human decision making at all levels of the grid.

C. Prototypes of Smart Grid

There are evidences indicating that today's grid is efficient, smart, and intelligent at the transmission level. However, at the distribution and customer levels, there are needs for a "smart grid" which will provide opportunities for energy efficiency and better integration of distributed generation including renewables to reduce carbon emission [6]. Several researchers have been working on developing a smart distribution power system and many prototypes have been built for study.

In 2007, the Advanced Research Institute of Virginia Tech brought forward the concept of an Intelligent Distributed Autonomous Power System (IDAPS) [7], which emphasized coordinating "customer-owned" DER's (EV included) for residential and commercial consumers.

A prototype of a "Perfect Power" system has also been built in the campus of Illinois Institute of Technology upon the High Reliability Distribution System design developed by S&C Electric [8]. The system focuses on the redundancy of electricity supply and management of the campus electricity distribution and usage including coordination with ComEd and the PJM ISO to provide ancillary services and demand response.

Utilities also join forces to build the smart grids at distribution level, among which SmartGridCity™ of Xcel Energy is the nation's first fully integrated smart grid community and will boast the largest and densest concentration of the emerging technologies to date. [9]

Besides the projects mentioned above, there are many other project in process or under review. Some smart grid related demonstration projects taking hold following the Recovery and Reinvestment Act of 2009 have been listed in the Smart Grid Information Clearing House [10] built in Advanced Research Institute of Virginia Tech.

2.1.2. Demand Response (DR)

2.1.2.1. Demand Response Concept and Category

According to the definition by the U.S. Department of Energy (DOE) in its February 2006 report to Congress [11], "demand response" is:

"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."

The definition is also used by Federal Energy Regulatory Commission (FERC) in their "National Action Plan on Demand Response" [1]. In the above-mentioned report, DR falls into two basic categories. Fig. 2-1 shows the role of demand response in electric power system planning and operation:

1) Price-based demand response (also called Time-based DR):
   a) Real-time pricing (RTP);
   b) Critical-peak pricing (CPP);
   c) Time-of-use (TOU) tariffs.
2) Incentive-based demand response [12]:
   a) Direct Load Control (DLC);
   b) Interruptible/curtail able service (I/C);
   c) Demand Bidding/Buy Back;
   d) Emergency Demand Response Program (EDRP);
   e) Capacity Market Program (CAP);
   f) Ancillary Service Markets (A/S);

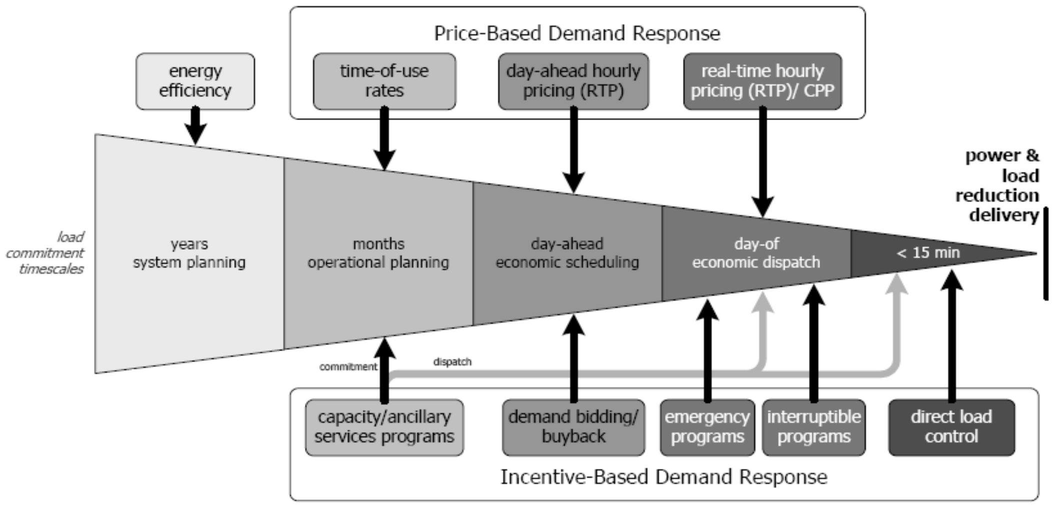


Fig. 2-1 Role of Demand Response in Electric System Planning and Operation

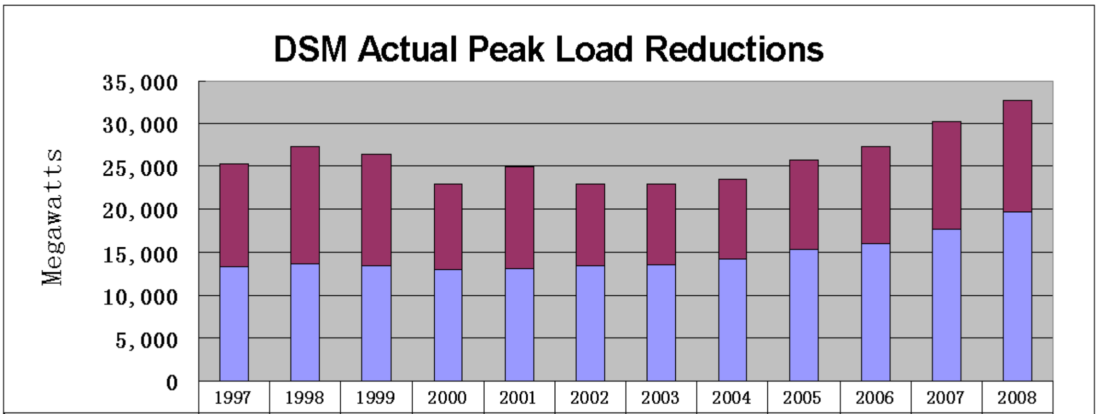
Utilities will provide different DR policies with regards to the specific situations in their serving areas and even for one utility multiple policies may be provided for customers to choose from. Generally speaking, both categories are considered “demand response” in a broad sense. In a narrow sense, the actions in the first category are from bottom up, initialized by consumers, which is typically referred to as “demand response” while the actions in the second category are from top down, initialized by utilities, which is typically referred to as “demand side management” (DSM).

2.1.2.2. Demand Response Development

The electric utility planning process has traditionally consisted of first forecasting the future demand for electricity, then determining the optimal supply-side options to meet the demand [13]. While this kind of demand driven planning became more and more difficult due to the increase of total demand and load variety, utilities started to consider managing load to match the supply several decades ago, which initiated the demand side management (DSM).

DSM is the utility activity that influences the customer load shape, which is performed in different ways to achieve different goals[14, 15, 16]. As larger consumers may bring more significant demand reduction results with low cost, DSM started with industry consumers and then gradually expanded to commercial and residential sectors. Of all the demand side management methods, the most straight-forward one is the direct load control (DLC), which is also the first one brought into use. Since the 1980s, DLC has been widely used by utilities for load shaping and it is still in use at many electric utilities in the US and abroad. Some of the early utility experiences have been reviewed in reference [17]. It is obvious that DLC can fulfill the task to reduce part of the demand when the supply is limited. However, DLC may bring significant customer inconvenience since it is a one direction command from utility to customer, thus it cannot take into consideration customers’ real-time situation when the program is performed.

The development of the DSM is not smooth. Data from Energy Information Administration (EIA) plotted in Fig. 2-2 DSM Actual Peak Load Reductions[18] shows that the DSM actual peak load reduction was high in the late 1990s and gradually dropped in the early 2000s, which may indicate that fewer DSM programs were offered and many utilities were turning away. There was a turning point after 2004 and the DSM peak load reduction grew fast both in load management and energy efficiency. Up until 2008, the peak load reduction was already over 30,000 MW, higher than 1998, which was the golden time for DSM before 2004.



	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Load Management	11,958	13,640	13,003	10,027	11,928	9,516	9,323	9,260	10,359	11,281	12,543	13,091
Energy Efficiency	13,327	13,591	13,452	12,873	13,027	13,420	13,581	14,272	15,351	15,959	17,710	19,650

Fig. 2-2 DSM Actual Peak Load Reductions

Apparently, a renewed interest is back on demand side management due to higher incentives such as the demand growth, technology development and nation wide recognition. According to a DOE report [11], a number of initiatives after 2004 indicated that federal and state policymakers, regional grid operators and utilities started putting efforts into strengthening DSM capability. Almost at the same time, a smart grid is also going from concept to practice, started with an advanced metering system, which provides better infrastructures, more options and a wider range for DSM, or generally called, demand response.

Recently, along with the development of the smart grid, demand response is also stepping into a fast growing stage. Many projects with various concerns and different DR program designs have been deployed, indicating that demand response is becoming more and more mature and practical.

2.1.2.3. Estimation of Demand Response Potential

In order to estimate the nationwide demand response potential in 5 and 10-year horizons, the FERC's National Assessment of Demand Response Potential [19] develops four scenarios of such potential to reflect different levels of demand response programs. These scenarios are:

1) Business-as-Usual (BAU): assuming the existing demand response programs (interruptible rates, curtailable loads and DLC) to be continued unchanged over the next ten years.
2) Expanded Business-as-Usual: assuming the BAU is expanded to all states with higher participation, partial deployed AMI and small percentage (5%) of dynamic pricing available.
3) Achievable Participation: assuming full scale AMI deployment by 2019 and dynamic pricing is default for more than 60% of consumers while other consumers will chose alternative demand response programs

4) Full Participation: assuming full scale AMI deployment, dynamic pricing and cost-effective technologies for all consumers

The results under the four scenarios illustrate how the demand response potential varies according to certain variables. Fig. 2-3 illustrates the differences in peak load starting with no demand response programs and then comparing the four scenarios. The peak demand without any demand response is estimated to grow at an annual average growth rate of 1.7 percent, reaching 810 gigawatts (GW) in 2009 and approximately 950 GW by 2019.

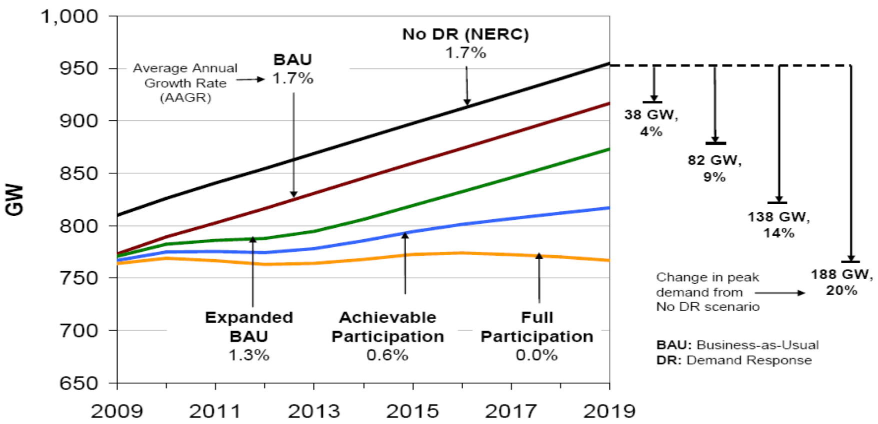


Fig. 2-3 Peak Demand Forecast by Scenario

It can be seen from the picture that the peak demand can be reduced by varying levels of demand response under the four scenarios. Under the highest level of demand response, it is estimated that from 2009 to 2019, the peak load will almost stay at the same level. Peak demand reduction can reach 20% percent. Therefore the amount of demand response potential that can be achieved increases as one moves from the Business-as-Usual scenario to the Full Participation scenario.

The Electric Power Research Institute (EPRI) has a similar but less aggressive estimation for demand response and energy efficiency potential. In EPRI's report [20], the base line is set according to EIA's 2008 Annual Energy Outlook. The annual energy usage will grow by 1.07% through 2008 to 2030 while the peak demand will grow by 1.5% each year.

Three types of potentials are defined and studied in EPRI's report:

1) Technical potential: assuming that all homes and businesses (100% customer acceptance) adopted the most efficient, commercially available technologies and measures, regardless of cost.
2) Economic potential: assuming that all homes and businesses (100% customer acceptance) adopted the most widely-proved cost-effective technologies.
3) Achievable potential: by refining the economic potential with various barriers for customer acceptance.
    a) Maximum achievable potential: applying a market acceptance rate on the economic potential estimation. Considering only the barriers with perfect

information like financial barriers.

b) Realistic achievable potential: considering existing market, financial, political, and regulatory barriers and recent utility experience and reported savings.

Fig. 2-4 shows the potential of peak demand saving by maximum and achievable potentials.

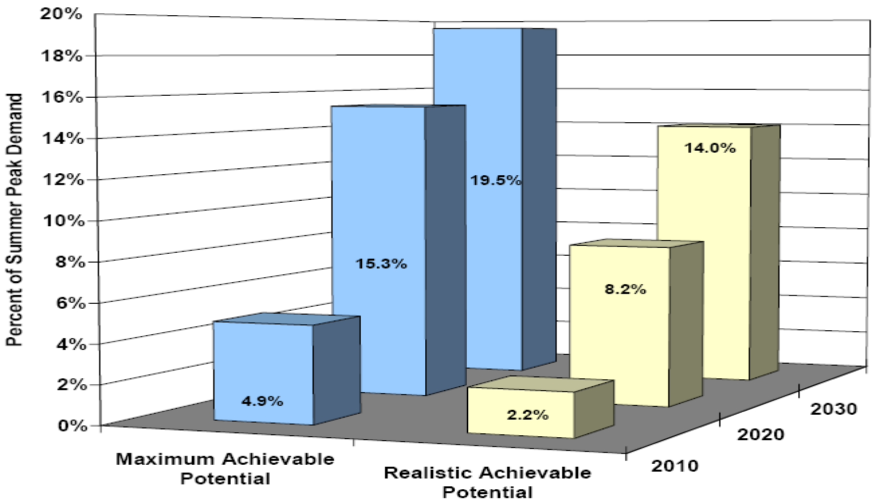


Fig. 2-4 Potential for Peak Demand Savings from Energy Efficiency and DR

Even though EPRI's estimation is less aggressive, the results still provide a hint that DR and energy efficiency will provide considerable peak demand savings, which may help delay or prevent new constructions for conventional power system infrastructure.

2.1.2.4. Demand Response Initiatives in the United States

There are hundreds of smart grid projects going on all over this country and more around the world, many of which are demand response related. The demand response initiatives are mainly led by the government and national laboratories, as well as the private sector (ISO/RTOs and utilities). As mentioned in the above section, demand response is developing through these studies and projects, from which DR goes from concept to practice.

1) Government and National Laboratories

   a) GridWise™ Testbed Demonstration – Pacific Northwest National Laboratory (PNNL)

   GridWise[21] is a term coined at PNNL referring to various smart grid management technologies based on real time electronic communication and intelligent devices that are expected to mature in the near future. With the help of these technologies and proper management, the new construction of conventional power grid infrastructure should be deferred or even prevented in step with the load growth anticipation.

The GridWise Testbed Group was formed in 2004 to facilitate a field demonstration of the GridWise technologies developed by PNNL. The demonstration is composed of two major projects: The *Olympic Peninsula Project* and the *Grid Friendly^{TM} Appliance Project*.

The *Olympic Peninsula Project* [22] is to demonstrate the economic dispatch of demand response and distributed energy resources with real-time two-way communications of cost information and end-use value of electrical services. The results showed that the distribution congestion was well managed. At the same time, the market based control through internet was tested and the peak loads could be reduced. Also the back up generations turned out to be valuable resources in the economic dispatch.

The *Grid Friendly^{TM} Appliance (GFA) Project* [23] is to demonstrate how well the GFA can help improve the grid frequency stability by shedding residential load for a short time during frequency drop (heavy loading time) without having obvious impacts on the end-users. The controllers and their appliances were installed and monitored for more than a year at residential sites at three locations in Washington and Oregon. The controllers and their appliances responded reliably to each shallow under-frequency event—an average of one event per day—and shed their loads for the durations of these events. Appliance owners reported that the appliance responses were unnoticed and caused little or no inconvenience for the homes' occupants.

b) PIER Demand Response Research Center (DRRC) [24] - Lawrence Berkeley National Laboratory (LBNL)

The main objective of the Center is to develop, prioritize, conduct, and disseminate multi-institutional research that develops broad knowledge to facilitate DR.

The research in the center on demand response includes:

- Load response for reliability purposes;
- Direct load control, partial or curtailable load reductions;
- Complete load interruptions;
- Price response by end-use customers;
- Dynamic pricing: real-time pricing (RTP), coincident peak pricing (CPP), time-of-use rates (TOU);
- Demand bidding or buyback programs;

The center is working on many demand response related projects and has published a series of important reports/papers on:

- Commercial building demand response
- Automated Facility Demand Response
- Demand Shifting with Thermal Mass
- Industrial Demand Response
- Programmable Communicating Thermostat (PCT) Reference
- Program and Tariff Analysis: Dynamic Electricity Pricing and Demand Response
- Demand Response Spinning Reserve Demonstration Project

2) State-level Demand Response Initiatives [1]

California is very aggressive in demand response, maintaining a leadership position for a long time. As early as 1978, TOU pricing was introduced for large commercial and industrial customers by California Energy Commission. In addition, regulations for appliance and building energy consumption have kept the per capita electricity use in California lower than the U.S. average level during the past three decades.

California's Energy Action Plan developed after the energy crisis in 2000~2001 specified a loading order of resources: first, energy efficiency; second, demand response; third, renewable energy sources; and finally, conventional generation options [25].

The Energy Action Plan also set a target reduction in peak demand of 5 percent for 2007. At the same time, the California Public Utilities Commission (CPUC) approved business cases for the deployment of advanced metering initiatives (AMI) by all three utilities [26] and then made dynamic pricing the default tariff for all nonresidential customers who were part of AMI.

The nation's first comprehensive test with dynamic pricing was carried out by California, known as the Statewide Pricing Pilot, which involved approximately 2,500 residential and small commercial and industrial customers, starting from 2003. The results of the Statewide Pricing Pilot provided information about the likely amount that customers would lower their peak demand at different price levels, both with and without enabling technologies. In addition, a large number of participants chose to stay with the experimental rates despite a new metering charge, indicating that participants were satisfied with the experimental rates. [27]

2.1.3. Electric Vehicle (EV)

2.1.3.1. EV Type and Concept

According to the National Renewable Energy Laboratory (NREL) [28], a plug-in hybrid-electric vehicle (PHEV) is a hybrid-electric vehicle (HEV) with the ability to recharge its electrochemical energy storage with electricity from an off-board source (such as the electric utility grid). Fig. 2-5 [29] shows the pictures of battery electric vehicle (BEV, i.e. EV), HEV and PHEV.

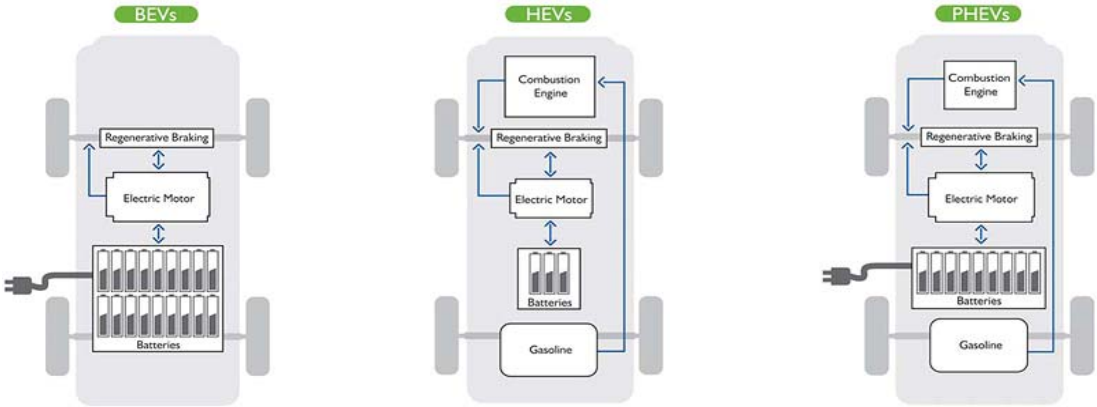


Fig. 2-5 BEV, HEV and PHEV

For a more detailed definition, the Institute of Electrical and Electronics Engineers (IEEE) defines a plug-in hybrid electric vehicle as any hybrid electric vehicle which contains at least: (1) A battery storage system of 4 kWh or more, used to power the motion of the vehicle; (2) A means of recharging that battery system from an external source of electricity; (3) An ability to drive at least ten miles (16 km) in all-electric mode, while consuming no gasoline.[30] Important PHEV related glossary definition can be found from Appendix B of Department of Energy's PHEV R&D plan. [31]

2.1.3.2. EV Working Mechanisms

Fig. 2-6 [32] shows two schematics of possible EV architectures: series and parallel. A series drive train architecture powers the vehicle only by an electric motor using electricity from a battery. The battery is charged from an electrical outlet, or by the gasoline engine via a generator. A parallel drive train adds a direct connection between the engine and the wheels, adding the potential to power the vehicle by electricity and gasoline simultaneously and by gasoline only.

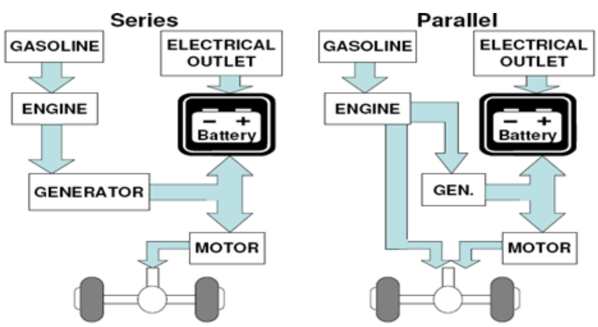


Fig. 2-6 Basic PHEV Drive-train – Series (EV) vs. Parallel Design

Toyota is developing a plug-in version of the Prius to be available in 2012, which will have a parallel drive train. General Motors's Chevy Volt comes with a series architecture, which is actually considered an electric vehicle (EV).

For any given architecture, an EV can operate in one of two modes: charge sustaining (CS) or charge depleting (CD), which are illustrated in Fig. 2-7. In practice, for the consideration of battery life and safety, the maximum state of charge (SOC) may not reach 100 percent, and the minimum SOC is kept higher than 0 percent. The difference between the maximum and minimum SOC is known as the usable depth of discharge (DOD), which varies across battery and vehicle designs.

In Fig. 2-7 [33], the battery is "fully" charged (from an electrical outlet) to 90 percent SOC at the beginning of the cycle. For a distance the EV is driven in CD mode, during which time the vehicle is powered by the energy stored in the battery and the battery's SOC is gradually getting lower. Once the battery is depleted to its minimum SOC (about 25% in this figure), the vehicle switches to CS mode. In CS mode the vehicle depends primarily on the gasoline engine and the SOC is kept around its minimum level. The battery and electric motor are used to increase the efficiency of the gasoline engine, like an HEV.

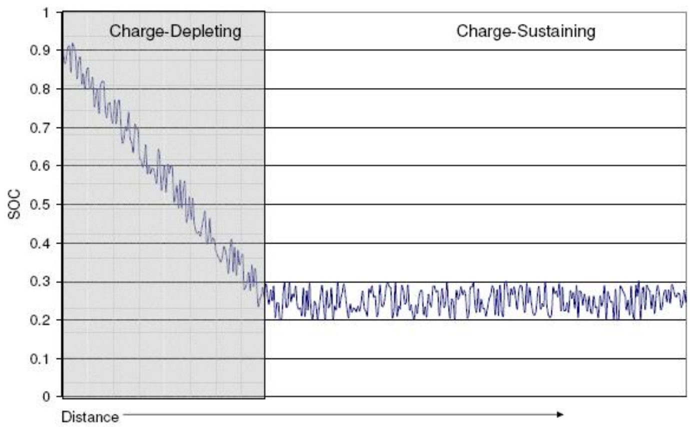


Fig. 2-7 Illustration of Typical EV Discharge Cycle

Small cycles, or "waves," can be seen in the SOC during the CS operation, where the battery takes on energy from the engine driven generator or from regenerative braking and uses the energy in the electric motor to improve the efficiency of engine operation. The vehicle remains in CS mode until the battery is plugged in again to recharge. The distance a fully charged EV can travel in CD mode before switching to CS mode is called CD range.

2.1.3.3. EV Market Trend

According to data from the Energy Information Administration (EIA) on petroleum in 2010 [34,35] about 62% of domestically used crude oil is refined into gasoline. High petroleum prices, high emissions from gasoline powered vehicles, and dependence on foreign oil, all contribute to a well known national problem [36].

Transportation accounts for two-thirds of the oil demand in the US, and this sector relies 97 percent reliant on oil [37]. Plug-in hybrid electric vehicles have recently emerged as a promising alternative that uses electricity to displace a significant fraction of fleet petroleum consumption [38]. Based on Tony Markel's analysis, petroleum reductions exceeding 45% per vehicle can be achieved by EVs equipped with electric range of 20 mile or more energy storage[39].

As shown from the EPRI/NRDC's report of Environmental Assessment of EV[40], annual and cumulative GHG emissions are reduced significantly across each of the nine scenario combinations projected in the report. EVs deliver the largest global warming reductions compared to other cars and trucks when they are charged with renewables, such as wind and solar, or power plants that capture and dispose of their global warming pollution.

From the economic point of view, at current average U.S. energy prices- that is, with the annual average cost of gasoline about $3/gallon [41] and national average electricity price about 10¢/kWh [42]- an EV runs on an equivalent of 50¢/gallon in its all-electric range with the reasonable assumption that the gas mileage is 25mile/gallon and electric mileage 5mile/kWh. Furthermore, the electric drive systems has a higher efficiency. The overall efficiency of EVs would be 22.5%~45% [43,44,45] as compared to the typical 20% for gasoline-powered vehicles.

As EVs move toward commercialization, they are expected to reach a high market share in several decades. In an analysis of the EV projected for 2020 and 2030 in 13 regions of the United States, ORNL researchers used a projection of 25% market penetration of hybrid vehicles by 2020 including a mixture of sedans and sport utility vehicles.[46] Fig. 2-8 shows the projected market share of PHEV from ORNL report.

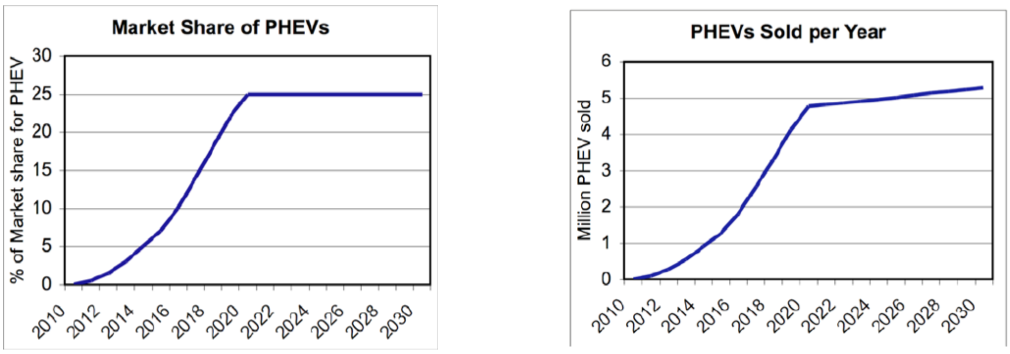


Fig. 2-8 Projected Market Share of PHEVs and Projected Number of PHEVs Sold per Year

Other research may provide less aggressive estimation, but still shows a promising EV market share. According to the data from the Electric Power Research Institute (EPRI) and the Natural Resources Defense Council (NRDC) [40], even the lowest EV penetration case shows 20% share of the 2050 New Vehicle Market. In the presentation provided by Argonne National Laboratory in EVS 22, they expected that in 2030 EV annual sales would reach 2.7 million and there will be 27 million EVs on the road, which meant 9% of the nearly 300 million vehicles.[47] For the nearer future, Morgan Stanley forecasts sales of

1.2 million hybrids by 2015 with 250,000 Plug-in hybrids [48], which is the most conservative estimation indicating only 1‰ market share of EVs according to the vehicle sales data from 2009 U.S. Transportation Energy Data Book [49]. However, the report still states that the introduction of EVs in 2010 will have the "potential to revolutionize the auto industry."

Virtually every major auto manufacturer in the world, along with several smaller outfits, is developing EVs and Plug-In America is tracking their progress. [50]

In December 2008, BYD Auto started selling the world's first mass-produced plug-in hybrid vehicle, the BYD F3DM, made for the domestic Chinese market [51]. Right now the Toyota Prius can be commercially converted to a plug-in hybrid by CalCars [52] and a number of third-party companies. The PHEV Toyota Prius is expected to be offered in 2012 [53]. The Prius PHEV version will be powered by lithium-ion batteries. Nikkei news reported that Toyota will start series production of the Prius PHEV version in 2012, and the estimated price is USD 48,000 [54]. General Motors started to sell Chevrolet Volt in December, 2010 [55].Volkswagen also staged the world debut of its XL1 diesel plug-in PHEV prototype at the Qatar Motor Show in early 2011. [56]. Volvo's diesel plug-in [57] and Ford's PHEV-30 Escape SUV, already being used in utility fleets, are scheduled to be available to the general public in 2012. On a smaller scale, EVs have been sold as commercial passenger vans, utility trucks, general and school buses [58], motorcycles [59], scooters [60], and military vehicles [61]. Table 2-1 [62] summarizes the EV characteristics and introduction dates released by major automobile manufacturers.

Table 2-1 PHEVs Announced by Major Automobile Manufacturers

Company	Vehicle Platform	Battery			Electric Range (km)	On-Road Evaluation (small fleets)	Planned Commercial Introduction
		Type	Power (kW)	Capacity (kWh)			
Ford	Escape	Li Ion	> 80	10	48	2009-11	?
General	Malibu/Volt	Li Ion	≥100	16	64	2010-11	2010/2011
Motors	Saturn Vue	Li Ion	60	5	16	2010-11	2010/2011
Toyota	Prius	NiMH; Li Ion	50	(3)	13	2009-11	?
VW	Golf	Li Ion	≥60	12	40-50	2010-12	?

2.1.3.4. Definition of PHEV-X and Battery Requirements

PHEV designs are commonly described according to CD range. The common notation is PHEV-X, where X is the distance in miles. According to California Air Resources Board's definition, X is the total miles that can be driven before the gasoline engine turns on for the first time, also known as all-electric range (or zero-emissions range) [63]. By this definition, a fully charged PHEV-10 could be driven for the first 10 miles without using any petroleum.

Another important point for PHEV design and notation is the assumed drive cycle schedule used to estimate CD operation and CD range. A drive cycle is a pattern of changing accelerations, speeds, and braking over time used to test fuel economy, as well as battery performance. A cycle usually repeats one or more schedules designed by the U.S. Environmental Protection Agency (EPA) [64]. The Urban Dynamometer Driving Schedule (UDDS) is most common, established by the EPA to simulate city driving conditions. This schedule includes many accelerations and decelerations over a 23-minute period, with an average speed of 20 miles per hour. The federal highway schedule (HWFET) is typically used to simulate highway driving conditions under 60 mph. The Federal Test Procedure (FTP) is composed of the UDDS followed by the first 505 seconds of the UDDS. It is often called the EPA75. California EPA Air Resources Board LA92 Dynamometer Driving Schedule, often called the Unified driving schedule, was developed as an emission inventory improvement tool. Compared to the FTP, the LA92 has a higher top speed, a higher average speed, less idle time, fewer stops per mile, and a higher maximum rate of acceleration. LA92 is recently considered to be more suitable to describe today's aggressive driving.

The USABC adopted the requirements proposed by the PHEV Battery Work Group and included them as goals in a request for proposals to developers of PHEV batteries [65]. Table 2-2 [66] is the final version of the PHEV battery requirements, targets, and goals as posted on the USABC Web site.

Table 2-2 USABC Requirements of End of Life Energy Storage Systems for PHEVs

Characteristics at EOL (End of Life)	**Units**	**High Power/Energy Ratio Battery**	**High Energy/Power Ratio Battery**
Reference Equivalent Electric Range	miles	10 (PHEV-10)	40 (PHEV-40)
Peak Pulse Discharge Power (10 sec)	kW	45	38
Peak Regeneration Pulse Power (10 sec)	kW	30	25
Available Energy for CD Mode, 10 kW Rate	kWh	3.4	11.6
Available Energy for CS Mode	kWh	0.5	0.3
Minimum Round-trip Energy Efficiency	%	90	90
CD Life / Discharge Throughput	Cycles/MWh	5,000 / 17	5,000 / 58
CS HEV Cycle Life, 50 Wh Profile	Cycles	300,000	300,000
Calendar Life, 40°C	year	15	15
Maximum System Weight	kg	60	120
Maximum System Volume	Liter	40	80
Maximum Operating Voltage	Vdc	400	400
Minimum Operating Voltage	Vdc	>0.55 x Vmax	>0.55 x Vmax
System Recharge Rate at 30°C	kW	1.4 (120V/15A)	1.4 (120V/15A)
Max. Current (10 sec pulse)	Amps	300	300

The above table has summarized four of the five main attributes considered by the USABC for PHEV batteries: power, energy capacity, life (calendar and cycle) and cost. Safety is another important factor because batteries store energy and contain chemicals that can be dangerous if discharged in an uncontrolled manner. The USABC’s battery goals do not include specific safety objectives, although safety is implied in goals of longevity and operation temperature.

2.1.4. Analytic Hierarchy Process

“The Analytic hierarchy Process (AHP) is a basic approach to decision making. It is designed to cope with both the rational and intuitive to select the best from a number of alternatives evaluated with respect to several criteria.” [67]. Fig. 2-9 shows a three level hierarchy.

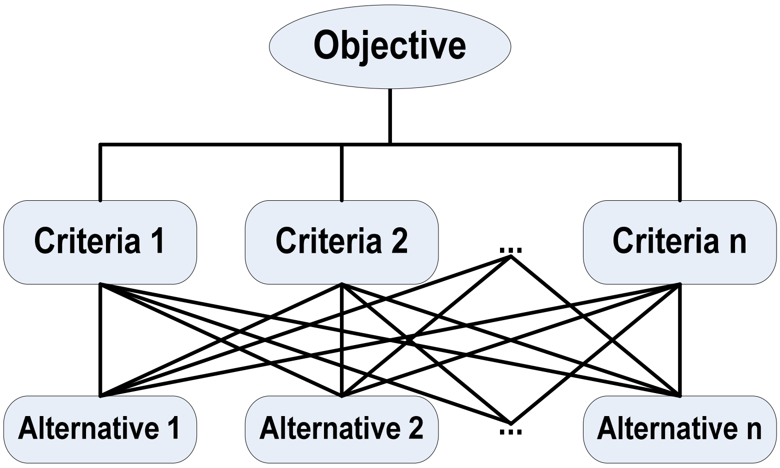


Fig. 2-9 A Three-level Hierarchy

In the decision making process, the simple pair wise comparisons are carried out to form a judgment matrix. The Eigen vector will be used to decide overall priorities for ranking the alternatives. [67]

AHP is being used in many areas for evaluation, resource allocation, forecasting, decision making and so on [68]. In this paper, AHP is adopted to decide the demand reduction allocations among different consumer groups when there is a demand limit.

2.2. In-depth Information

2.2.1. Research on Distribution Load Modeling

Load modeling has been attracting interest for several decades now. The scale ranges from appliance to large power grid. IEEE has provided a bibliography for load models for power flow and dynamic performance simulation, in which the methodologies are categorized by the model type (i.e. static, dynamic, others) [69]. This bibliography has covered almost all relevant load modeling works in late 20th century.

The classical load model defined “load” as functions of voltage and frequency, which has been referred to as “static” [70]. Then “dynamic” load models have been developed for transient studies. Simultaneously, some works were focusing on physically based load models, especially on heating, ventilation, and air conditioning (HVAC) loads [71] and water heating loads [72] for evaluation or analysis of the demand management strategies. A physically-based methodology for synthesizing the hourly residential HVAC load was developed in reference [71] and tested against utility data. The model captures the thermodynamic principles of the building structures and the diversification is created by random distribution functions when building the distribution network load profile. It should be noted that these kinds of load models have already started to take into account the customers’ behavior. [73]

References [74,75,76] presented models that are built from statistical data taken from of surveys and historical measurements, with which proper random functions are designed for aggregation diversity.

2.2.2. Research on Electric Vehicle

2.2.2.1. EV Charge and Discharge Profile

Before we look into the EVs impacts on the power system, it is very important to understand their grid-to-vehicle charge (G2V) and vehicle-to-grid discharge (V2G) characteristics. Many researchers have been seeking ways to model EVs penetration into the power system. As EV is much more flexible than household loads and they can perform as both loads and sources, it is not easy to get an accurate curve of an EV fleet charging and discharging, nor there is any historical data we can take as reference since EVs haven’t been widely received in the mass market. However, single EV G2V and V2G profiles can be acquired thus the fleet behavior can be modeled based on the “plug-in” time.

The power demand on the grid for charging EVs will be a function of the voltage and amperage of the connection to the grid. The capacity of the battery will then determine the length of time it will take to recharge the battery.

Dr. Mark S. Duvall’s presentation [77] at the DOE Plug-in Hybrid Electric Vehicles Workshop reviewed several characteristics for evaluating EV impacts on the grid. Duvall shows that there are many options for connecting vehicles to the grid. A comparison of times required for recharging is given in Table 2-3 [77]. It shows that large battery packs (for longer range) would increase the time required for charging.

Table 2-3 Charging Times Required for PHEV20 for 20% – 100% SOC

PHEV-20	Battery Size	Charge Circuit	Charging time
Compact Sedan	5.1 kWh	120VAC/15A	3.9-5.4 hrs
Mid-size Sedan	5.9 kWh	120VAC/15A	4.4-5.9 hrs
Mid-size SUV	7.7 kWh	120VAC/15A	5.4-7.1 hrs
Full-size SUV	9.3 kWh	120VAC/15A	6.3-8.2 hrs

On the other hand, higher voltage or amperage would reduce the charge time, which is usually called quick charge.

Timing of EV plug in is very critical. The optimum time for utilities is typically at night when demand is relatively low while consumers are likely to prefer the time as soon as they are within easy access to a plug. For the analysis in ORNL's report [46], they use the weighted average charging profile, which is a rough aggregation. For each region, the hourly demand from the curve is multiplied by the number of EVs on the road to get the hourly addition to the system electrical load. They assumed that for the evening charge half of the vehicles were plugged in at 5pm and half at 6pm. For the night charge half were plugged in at 10pm and half at 11pm. They then remained plugged in until fully charged. The resulting weighted average profile is shown in Fig. 2-10 [46].

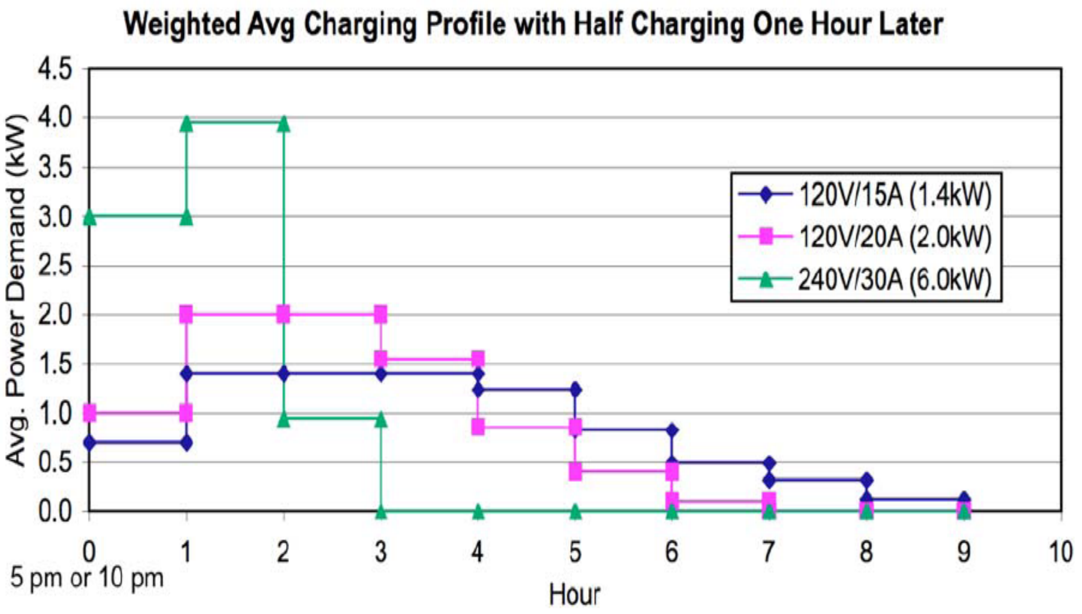


Fig. 2-10 Weighted Average Charging Profile

There are various ways for utilities to modify customer choices, including pricing schemes favoring night-time charging or mandatory regulation on vehicle charging with contract incentives. Technically, the intelligence could be in the charger and/or in the vehicle itself.

Other than conventional evening or night charge, consumers could also recharge at their places of work, giving them additional range. Utilities and businesses could even install the infrastructures like a "charging meter" to allow consumers to plug in anywhere and have the cost of purchased power added to their bills. NREL has brought forward four typical scenarios for EV fleet G2V charge with different daily charge strategies, shown in Fig. 2-11 [78]. The charging profiles are all for EV fleet charge and show a probability function for the charge start time with variance from a certain time point. The first one shows the scenario that people tend to charge their EVs as soon as they get home from work. The second one illustrates the central charge time delayed to 10 pm. The third one is the scenario for off-peak charge, which will vary according to different electricity rate schedules. The last one is showing an opportunity-charging scenario which means as long as EVs are parked, they may choose to charge.

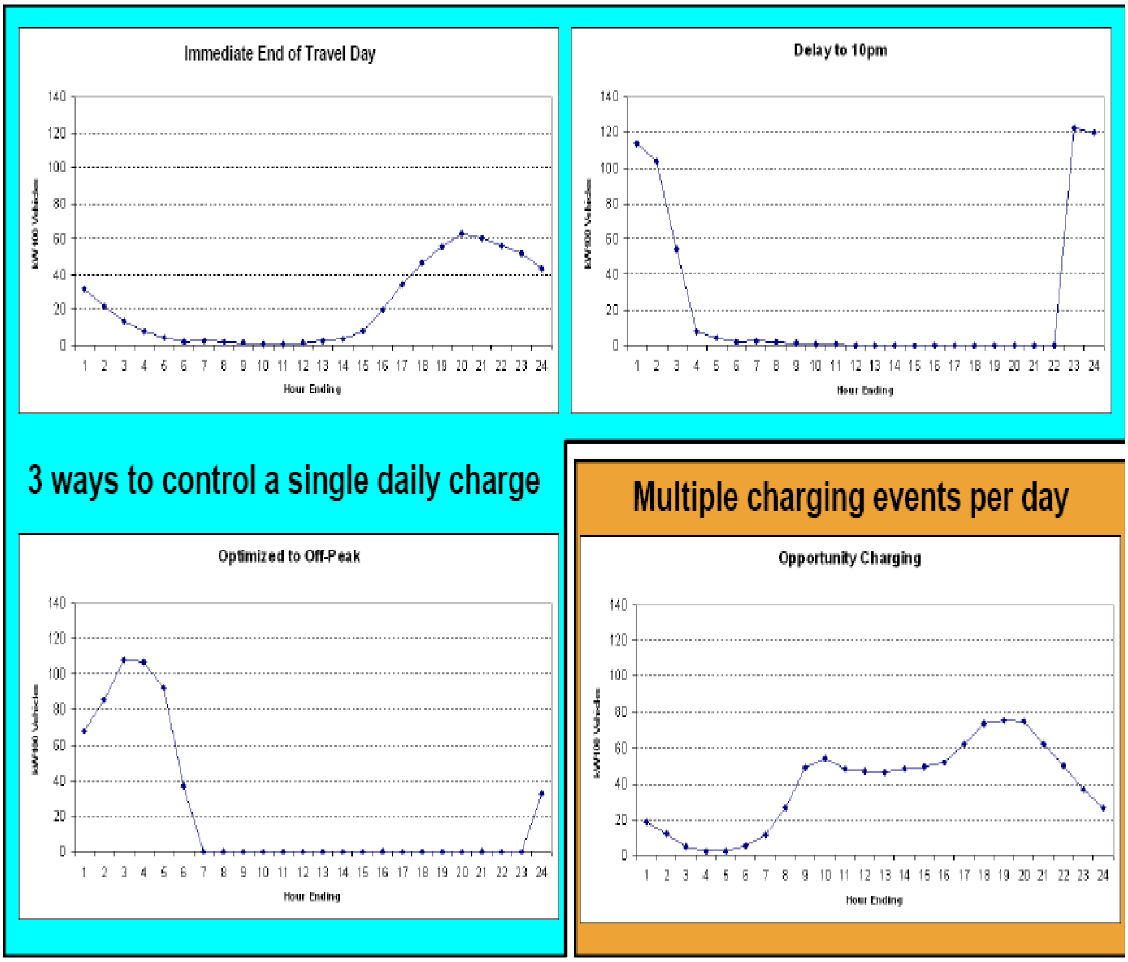


Fig. 2-11 Four Potential Daily Recharge Strategies

As cars are parked over 90% of time [79], the charging profiles can be very complicated considering all the scenarios mentioned above and multiple control strategies.

Unlike G2V, V2G is not a basic need of EVs. In contrast, V2G is a behavior called by control signals. Therefore the V2G discharge profiles are usually designed according to the need of the power grid within the battery capability boundaries, which explains why there is no previous work that models V2G discharge curve.

For fleet EV behavior, a paper by the University of Washington [80] uses four typical EV charge profiles for their analysis, listed as uniform, home-based, off-peak and V2G, which was shown as negative charge. Fig. 2-12 [80] illustrates the four profiles. Here V2G is considered as negative G2V charge.

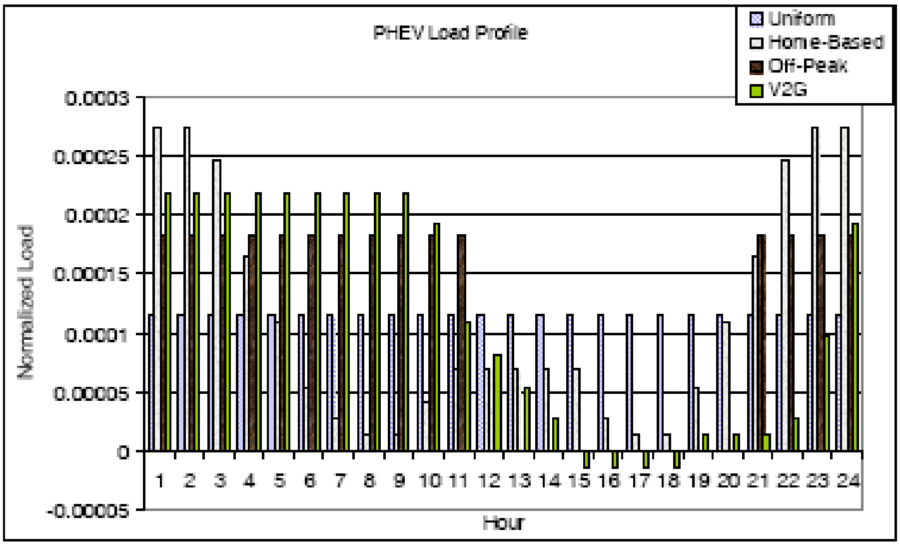


Fig. 2-12 Typical Daily Load Profiles of EV

All profiles are averaged to reflect a fleet behavior and normalized to make the total energy drawn from the power grid in one year equal to 1.0. The paper ranked these four load profiles from high to low of feasibility for people's everyday charging as: home-based > V2G > off-peak > uniform.

In practice, an EV battery will not be allowed to charge over its upper limit (about 80%) or discharge below its lower limit (about 30%) due to the concern of battery life. Therefore when the V2G is performed, the energy management system should take the battery constrains into consideration.

The deployment of EVs has the potential to have substantial positive impact on the electric power system from the aspects of increasing electric energy consumption to fill the demand valley, offsetting petroleum fuels with other energy sources, adding additional regulation capability, and assisting in emergency capacity (these last benefits will require specific additional capabilities of the grid/vehicle interface). This positive impact is mitigated with the fact that the existing electric power system infrastructure may not be ready to deal with the increased demand and new patterns of consumption and power flows in the power grid [**Error! Bookmark not defined.**].

2.2.2.2. Potential Threats

A lot of researchers have optimistically claimed that EVs will not increase the system peak much, instead, they will fill the load valley, which is good for system operation [81,**Error! Bookmark not defined.**,38,82]. The PNNL Report in 2007 indicated that, "The U.S. electric power infrastructure…could generate and deliver the necessary energy to fuel the majority of the U.S. light duty vehicle fleet.” [83]

According to the Electric Power Research Institute (EPRI), more than 40% of U.S. generating capacity operates overnight at a reduced load, and it is during these off-peak hours that most EVs could be recharged. Recent studies by EPRI [84] show that if EVs replace one-half of all vehicles on the road by 2050, only an 8% increase in electricity generation (4% increases in capacity) will be required.

However, a thorough simulation analysis of EV penetration into the regional power grid from ORNL [46] shows the situation may not be that optimistic. Without proper incentives, we cannot simply assume people will charge their cars during the period when utilities want them to charge. EV quick charge at evening can create much higher new peaks by 2030. In this case, all regions will need additional generation to serve the extra demand. Table 2-4 [46] shows the increase in the annual peak for each region using the evening quick charge scenario in 2020 and 2030. (The projected EV numbers can be found in Fig. 2-8).

Table 2-4 Increase in Annual Peak Demand with EV Charging at 6 kW in the Evening

	2020		**2030**	
	Peak Increase (GW)	**Peak Increase (%)**	**Peak Increase (GW)**	**Peak Increase (%)**
ECAR	5.2	4.2	19.3	14.7
ERCOT	3.5	4.5	10.9	12.7
MAAC	4.3	6	15.3	19.4
MAIN	6.4	10.1	16.9	24.4
MAPP	2.5	7.4	6.9	18.5
NPCC-NY	2.4	6.9	7.9	21.8
NPCC-NE	1.6	4.9	7.4	21.7
FRCC	3.3	5.3	10.2	13.7
SERC	6.4	3.1	25.9	10.8
SPP	0.6	1.2	2.7	4.9
WECC-NW	3.2	6.9	9.4	17.9
WECC-RMP/ANM	1.3	2.3	4.2	6.4
WECC-CA	5.6	9	20.7	27.9

In the scenarios in ORNL’s report [46], even though the total energy demand increase from EVs is in the range of 1~5%, the peak capacity demand can be as high as 28%. Although that is the worst case, still there is possibility it may happen, which will result in challenges to the nationwide power generation and transmission, including equipment investment, generation dispatch, human resource and many other aspects.

Other than the long-term problem of congestion and exceeding capacity, we also have short-term challenges to deal with. As the population is much larger in a metropolitan area than in a rural area, the EV adoption may also show a cluster effect [85]. Even though the generation and transmission may be fine with the increasing demand, the distribution networks serving areas with high population density still have to assume the burden of feeding the large number of EVs plugged in.

2.2.2.3. Potential Benefits

A. Economic Opportunities

Clearly, there are many potential benefits that EVs bring to the power system. The most straightforward one is that the higher adoption of EVs will bring higher revenues to most of the utilities. According to EIA's data, an average retail electricity price 11.36 ¢/kWh [86], a typical PHEV-20 with 6kWh battery capacity and daily charge will bring additional revenues of about $250 per annum for every single EV in service. This is 62.5 million dollars per year even with the most conservative estimation from Morgan Stanley's report of 1‰ EV penetration into the market in 2015.

Another opportunity for utilities in California to take advantage of is the recently released "Proposed Regulation to Implement the Low Carbon Fuel Standard (LCFS)" [87]. The power that a utility firm sells to refuel EVs may be considered a fuel, thereby allowing utilities to receive offset credits for each watt sold, which they can then sell to high emissions fuel makers at a profit.

A recent report from PJM pointed out that a centralized control of EV fleet charging can reduce the energy cost that would otherwise be incurred from adding EVs to the system. However, as a comparison, the report showed that a distributed intelligence platform with time-of-use (TOU) rate will not provide significant benefit. [88]

B. Regulation Opportunities

1) Valley Filling: EVs have the valuable characteristic of being a deferrable load. Daily EV recharging can be scheduled for "off-peak" time, which is called valley filling. Fig. 2-13 [83] shows a stylized load profile for one day during peak season together with generation dispatch profiles and total installed capacity. The shaded area is the under-utilized capacity available for charging EVs, which will in result better utilization of installed capacity.

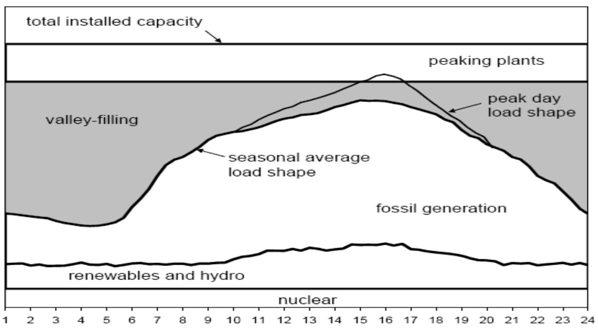


Fig. 2-13 Stylized Load Profile for a Typical Summer Day

The maximum potential to accommodate EVs varies by NERC regions, depending on the load profiles, the present capacity utilization and the mix of generation capacity. On average, the PNNL study [83] concludes that the existing U.S. electric system could accommodate 74% of the light-duty vehicle fleet for 24-hrs valley filling while 43% for night charge.

2) Compliance with Renewable Portfolio Standards: According to EPA, Renewable Portfolio Standard (RPS) provides states with a mechanism to increase renewable energy generation using a cost-effective, market-based approach that is administratively efficient. An RPS requires electric utilities and other retail electric providers to supply a specified minimum amount of customer load with electricity from eligible renewable energy sources.[89]

However, since the most used renewable sources are intermittent, meeting the RPS is a big problem for many utilities. EVs' flexibility thus provides a possible solution for utilities to comply with the RPS when regulated as "supply-driven" demand, which means when there is enough renewable energy supply, EVs can be recharged from the power grid, otherwise the charging need to cease to balance the demand with supply

2.2.2.4. EV for Ancillary Services

Electric-drive vehicles have within them the energy source and power electronics capable of producing the 60Hz AC electricity that powers our homes and offices. When connections are added to allow this electricity to flow from cars to power lines, we call it "vehicle to grid" power, or V2G [90].

There are many debates on V2G. The series publications from University of Delaware, Newark drew conclusions that Vehicle-to-grid power could provide a significant revenue stream that would improve the economics of grid-connected electric-drive vehicles and further encourage their adoption. It would also improve the stability of the electrical grid [91,92,93]. However, many of these papers ignore the downside of V2G operation; namely, reduced battery life, additional infrastructure cost, safety issues, etc.

In the evaluation report for V2G for PJM, the authors claimed that the most economic entry for V2G is the market for ancillary services (A/S), among which frequency regulation is of the highest value, of about $40/MW per hour. Another market of interest is spinning reserves, or synchronous reserves, with values in the range of $10/MW per hour, but much less frequent dispatch. The primary revenue in both of these markets is for capacity rather than energy, and both markets are well suited for batteries as a storage resource because they require quick response times yet low total energy demand. When there is large number of parked V2G EVs, they can provide support to a distribution system at the time of overloading or accommodation for intermittent renewable resources [94].

According to the estimations from CET of U.C. Berkeley, every percent of the Light Duty

Vehicle Fleet (LDVF) replaced by electric vehicles under a load aggregation and control system adds 1,040 MW of loads that can be regulated to reduce demand and avoid initiating ancillary services. At the average ancillary price this represents additional annual revenues of $364M per annum per 1% of the LDVF for an electric vehicle operator in a competitive power market or a comparable level of cost savings to a vertically integrated utility. However, they also believe that V2G will not become a reality in the short term due to the lack of the supporting standards and the smart grid infrastructures. Besides, the unjustified benefits for utilities and customers, the complexity of the V2G control and the concerns on battery life based on current battery technologies are also obstacles for the applications of V2G. [85]

2.2.2.5. V2G Control and Calculations

To provide ancillary services, the Vehicle to Grid (V2G) function has to be enabled by regulation policies, advanced power electronic technologies, and necessary infrastructures.

Up until now, there hasn't been much research on V2G control. An NREL paper focusing on the intersection of renewable electricity generation and electric vehicles has highlighted the limitations and opportunities for renewable energy resources to fuel electrified vehicles [95].

In the NREL paper, three promising fleet charge-control methods are proposed and demonstrated: 1) price-signal-based charging, 2) load-signal-based charging and 3) renewable-energy-based charging. The three control algorithms are compared with a baseline of 4.8kW opportunity charging. V2G has been discussed as a negative charge in the control strategies of 1) and 2) whenever the real-time electricity price is lower than an EV's offering price. In 3) EVs are charged according to the availability of renewable resources, V2G excluded. Three scenarios (12 sub-scenarios) with different EV adoption rates, different annual renewable energy percentages and different battery costs have been studied based on LA load data. The conclusions indicate that properly designed real-time pricing structure is sufficient to offset battery wear impacts when battery costs fall below $600/kWh when EVs are allowed to perform V2G.

2.2.3. Research on Demand Response

2.2.3.1. Demand Response Barriers and Benefits

1) Barriers

In the FERC demand response assessment [19], a number of barriers need to be overcome in order to achieve the estimated potential of demand response in the United States by 2019. The most significant ones are:

a) Regulatory Barriers:
   i. Lack of a direct connection between wholesale and retail prices.
   ii. Measurement and verification challenges.
   iii. Lack of real time information sharing.
   iv. Ineffective demand response program design.
   v. Disagreement on cost-effectiveness analysis of demand response.
b) Technological Barriers.
   i. Lack of advanced metering infrastructure.
   ii. High cost of some enabling technologies.
   iii. Lack of interoperability and open standards.
c) Other Barriers.
   i. Lack of customer awareness and education.
   ii. Concern over environmental impacts.

To overcome the barriers, encouraging this expansion of demand response programs and wide adoption of dynamic pricing, FERC staff recommends that efforts should be put on consumer education, utility collaboration, market coordination, program diversification, technology and standards development, financial incentives and dynamic tariff design.

2) Demand Response Benefits

According to the DOE report on demand response benefits analysis [11], the most important benefit of demand response is improved resource-efficiency of electricity production due to closer alignment between customers' electricity prices and the value they place on electricity. This increased efficiency creates a variety of benefits, which fall into four groups:

a) Participant financial benefits: bill savings and earned incentive payments.
b) Market-wide financial benefits: driving production costs and prices down for all wholesale electricity purchasers due to the use of the most cost-effective generation; reducing the costs of power supply in the long term and eventually passing some of the benefits to the consumer bill savings.
c) Reliability benefits: reduce the costs and inconvenience of consumers due to the improvement of system security and adequacy.
d) Market performance benefits: mitigating suppliers' market power of raising power prices significantly above production costs.

Similar to the suggestions made to over come demand response barriers described in FERC's assessment report, the DOE report offers recommendations to encourage demand response nation-wide, which includes a) the improvement of price and incentive based demand response by dynamic tariff design and program diversification; b) the adoption of new technologies; c) the integration of demand response into resource planning; and d) collaboration between utilities.

2.2.3.2. Price-Based Demand Response

Many of the existing and planned projects are fostering the price-based demand response therefore extensive studies have been conducted on tariff design, consumer strategies and load reshape analysis.

LBNL has been doing research on the price-based demand response in industrial, commercial and residential buildings. Reference [96] is an overview report on opportunities, barriers and Actions for industrial demand response in California including the previous auto-DR review, industry willingness study and practical analysis. References [97,98,99,100] and other related reports focus on demand response for different industries with detailed strategies and load shape analysis.

Reference [101] provides an overview of DR strategies in commercial buildings. Some detailed demand response strategies are provided for large and small non-residential customers in response to CPP in a series of technical reports [102,103,104,105]. In the reports, most focuses have been laid on Heating, Ventilating, and Air Conditioning (HVAC) and lighting systems, for which detailed shifting and shedding strategies are provided.

For residential demand response, reference [106] provides a scope study to summarize and evaluate the existing methods. The report recommends that the regression-based load comparison is a reasonable approach to accurately estimate demand response to dispatchable events, which leads to further use of the approach for residential demand response estimation based on load data collected from an experiment or on-going program.

In the GridWise Testbed *Olympic Peninsula Project* [22], the data was based on an experimental shadow market reflecting realistic wholesale costs and incentives to relieve the feeder congestion. Consumer groups are given a flat rate, a TOU rate a CPP rate and a RTP rate respectively for study purposes. As the project mainly involves residential HVAC and water heater loads, a programmable thermostat named "GoodWatt™" is used to receive the price signal and try to avoid a high pricing period. The most important saving tip for consumers is not to override the automatic control of the smart thermostat unless necessary.

Other than the pilot field studies being conducted in national laboratories, many other analytic studies are going on all over the world. Analysis on the impacts of TOU rates on load shape considering certain elasticity of electricity demand has been reported in [107]. [108,109,110,111] focus on benefit optimization for consumers and utilities while [112] works on designing reasonable DR strategies.

Critical peak pricing is another important type of tariff for demand response. Reference [113,114] both discussed the optimal decision in reply to critical peak pricing based on models of electricity demand elasticity.

While much of the research is focused on strategy design and tariff analysis, reference [115] brings forward the concerns of the potential problems that may be caused by large scale of DR implementation, in which the coincidence response have to be taken into consideration in further Research and pilot projects.

2.2.3.3. Incentive-Based Demand Response

According to the categorization from DOE, incentive based demand response includes many kinds of programs: DLC, Interruptible/curtail able service (I/C), Demand Bidding/Buy Back, EDRP, Capacity Market Program (CAP), Ancillary Service Markets (A/S). Generally speaking, the incentive based demand response can be considered as a program that request consumers to hand in the load control rights to utilities with some contracted limits and incentives. Some of the DR in this category has been conducted for decades, used to be referred to as demand side management (DSM), like DLC.

This category requires more effort from the utility side to take into consideration the system reliability, economic dispatch, consumer comfort and so on.

As a type of mature incentive-based demand response, DLC has been thoroughly studied. Reference [116] used the Monte Carlo Method to build a dynamic model for DLC and generations with which the simulations results show that DLC is a very effective form of load management method. Many control methods have been proposed based on different optimization objectives [117,118,119,120]. References [121,122,123] report studies on HVAC DLCs while [124,125] target water heater DLCs focusing on modeling and control strategies with consideration of consumer comfort zone.

Reference [126] presents the results from a two-year study of industrial and commercial response to interruptible/curtailable (I/C) rate programs. The analysis indicates that I/C can provide significant load relief and the consumer compliance is good. The paper suggests a sliding credit instead of fixed credit to consumers with different load factors.

Reference [127] performs assessment of demand bidding comprehensiveness and pointed out the problems that should be taken into consideration in a competitive electricity pool. After that, some research has been conducted on the design of demand bidding (DB) strategies [128, 129, 130]. Recent use of agent technologies and the advanced communications provide new DB opportunities in a dynamic way [131,132].

Emergency Demand Response Program (EDRP) is an incentive-based DR with a shorter time between the notification and the actual event, which means the "emergency". EDRP has been mainly used for congestion relief [133,134] and spinning reserve [135]. The research is mainly focused on the analysis of the system impact.

2.2.3.4. Demand Response for Ancillary Services

According to FERC definition, the ancillary services are those functions performed by the equipment and people that generate, control, and transmit electricity in support of the basic services of generating capacity, energy supply, and power delivery [136].

FERC specifically recognized six key ancillary services in its landmark Order 888 (FERC 1996): (1) Scheduling, System Control and Dispatch Service; (2) Reactive Supply and Voltage Control from Generation Sources Service; (3) Regulation and Frequency Response Service; (4) Energy Imbalance Service; (5) Operating Reserve – Spinning Reserve Service; and (6) Operating Reserve - Supplemental Reserve Service. [137]

Table 2-5 [137] lists the key real-power ancillary services, which the ISOs generally purchase in the competitive markets.

Table 2-5 Key Real-Power Ancillary Services

Service	**Service Description**		
	Response Speed	**Duration**	**Cycle Time**
Regulating Reserve	Online resources, on automatic generation control, that can respond rapidly to system operator requests for up and down movements; used to track the minute-to-minute fluctuations in system load and to correct for unintended fluctuations in generator output to comply with Control Performance Standards (CPSs) 1 and 2 of the North American Electric Reliability Council (NERC 2006)		
	~1 min	Minutes	Minutes
Spinning Reserve	Online generation, synchronized to the grid, that can increase output immediately in response to a major generator or transmission outage and can reach full output within 10 min to comply with NERC's Disturbance Control Standard (DCS)		
	Seconds to <10 min	10 to 120 min	Hours to Days

Ancillary services account for 5-10% of electricity cost, or $12 billion per year in the US, 80% of which is for regulation and spinning reserve. [94]

Theoretically, most short-term quick response DR can provide ancillary services as shown in Fig. 2-1. For real world implementation, PJM opened its Synchronized Reserves and Regulation Markets to demand response resources in 2006, in which EnerNOC was the first to bid. Reference [138] explains how demand resources are being integrated into the PJM ancillary service markets. Reference [139] provides a brief introduction of the EnerNOC demand response platform.

The GridWise Testbed *Grid Friendly™ Appliance (GFA) Project* [23] is another example of the ancillary services. Fifty residential electric water heaters and 150 new residential clothes dryers were modified to respond to signals received from under-frequency, load-shedding appliance controllers. Each controller monitored the power-grid voltage signal and requested that electrical load be shed by its appliance whenever electric power-grid frequency fell below 59.95 Hz.

2.2.3.5. Demand Response Strategy Design

Based on the previous discussion, demand response strategies have already been studied together with the tariff design and load impact analysis. Generally speaking, the strategies for price-based DR are trying to avoid the peak pricing period while the strategies for incentive-based DR are trying to meet certain system requirements by utility control. Strategies for both DR categories have to take into consideration the consumer comfort as well as the system adequacy and economic dispatch. Energy efficiency appliances will also help to reduce the demand. According EIA's data of DSM on industry, half of the saving comes from energy efficiency improvement.

According to the studies from LBNL, PNNL and other related papers, HVAC can be an excellent resource for load savings because they take a large share of load in commercial buildings and can be shut down for a short while without immediate impacts on the building occupants. For HVAC systems, the DR strategies include zone control, air distribution, and central plant, in order of recommended priority to achieve these goals: 1) Global Temperature Adjustment of Zones; 2) Systemic Adjustments to the Air Distribution and/or Cooling Systems.

The water heater is another type of "controllable loads", which has been studied and controlled since almost 20 years ago in the DLC programs. Considered as a thermal mass, water heater has a control strategy and effect similar to that of HVAC. Mainly the concerns on room air temperature are changed to concerns on the hot water temperature. The advantage of water heater control over HVAC is that the power consumption in kW of a water heater is usually higher than an air conditioner, which provides a higher potential of peak demand reduction.

The electric clothes dryer is a large load in a residential house. On average, the energy consumption in kWh is not very high. However, when it is in use, the demand in kW may even be higher than a water heater. At the same time, it also has the characteristic that short-term shut down may well go unnoticed. The GridWise Testbed *Grid Friendly™ Appliance (GFA) Project* takes clothes dryers as one of the responsive load for the frequency support and most consumers report no obvious impact. Therefore clothes dryer heating coil can be listed as one of the DR strategies.

Lighting DR strategies tend to be simple and provide constant, predictable demand savings. As the controls of lighting systems are more noticeable, they should be carried out selectively and carefully, considering the immediate impacts on occupants. For lighting systems, the DR strategies in increasing order of sophistication are listed as: zone switching; fixture switching, lamp switching, stepped dimming, continuous dimming. Another possible choice is to change the lights to CFLs or LEDs to reduce both the demand in kW and energy consumption in kWh, which may involve the cost-benefit analysis for the device changes and bill savings.

DR strategies targeting other devices such as refrigerators and ovens have also been studied though not widely accepted. Further study can be conducted on those areas. However, consumers' convenience has to be kept in mind always when designing the DR strategies no matter what the category.

2.2.3.6. Analysis Tools for Demand Response

1) eQuest [140]

eQuest is a sophisticated, yet easy-to-use building energy analysis tool. This tool is a combination of a building creation wizard, an energy efficiency measure (EEM) wizard, and a graphical reporting as well as a widely recognized and trusted DOE-2 simulation engine.

DOE-2 can predict the energy use and cost for all types of buildings. It uses a description of the building layout, constructions, operating schedules, conditioning systems (lighting, HVAC, etc.) and utility rates provided by the user, along with weather data, to perform an hourly simulation of the building energy consumption and to estimate utility bills.

2) EnergyPlus [141]

EnergyPlus is an energy analysis and thermal load simulation program. Based on a user's description of a building from the perspective of the building's physical make-up and associated mechanical and other systems, EnergyPlus calculates heating and cooling loads necessary to maintain thermal control set-points, conditions throughout a secondary HVAC system and coil loads, and the energy consumption of primary plant equipment.

Key capabilities:

- Integrated, simultaneous solution;
- Sub-hourly, user-definable time steps;
- ASCII text based weather, input, and output files;
- Heat balance based solution technique;
- Transient heat conduction;
- Improved ground heat transfer modeling;
- Combined heat and mass transfer;
- Thermal comfort models;
- Anisotropic sky model;
- Advanced fenestration calculations;
- Day lighting controls;
- Atmospheric pollution calculations.

3) GridLAB-D™ from PNNL [142]

GridLAB-D™ is a flexible simulation environment that can be integrated with a variety of third-party data management and analysis tools. The core of GridLAB-D™ has an advanced algorithm that simultaneously coordinates the state of millions of independent devices, each of which is described by multiple differential equations. The advantages of this algorithm over traditional finite difference-based simulators are: 1) it handles unusual situations much more accurately; 2) it handles widely disparate time scales, ranging from sub-seconds to many years; and 3) it is very easy to integrate with new modules and third-party systems.

At its simplest, GridLAB-D™ examines in detail the interplay of every part of a distribution system with every other. It becomes an essential tool that enables industry and government planners to design more effective and efficient programs to manage load growth and improve system reliability.

The residential end-use modeling details are described in reference [143] including water heater, lights, dish washer, microwave, refrigerator, internal heat gains and house (HVAC).

4) Demand Response Quick Assessment Tool (DRQAT) [144]

The demand reduction potential and cost saving with building DR vary tremendously with building type and location. This assessment tool will predict the energy and demand saving, the economic saving, and the thermal comfort impact for various demand response strategies based on the most popular feature and capabilities of EnergyPlus.

User inputs include: basic building information such as building type, square footage, building envelope, orientation, utility schedule, etc. The assessment tool will then use the prototypical simulation models to calculate the energy and demand reduction potential under certain demand response strategies, such as pre-cooling, zonal temperature set up, and chilled water loop and air loop set points adjustment.

5) Demand-Limiting Assessment Tool (DLAT) [145]

The Demand-Limiting Assessment Tool (DLAT) evaluates the peak demand reduction, utility cost savings, and comfort impacts associated with the use of building thermal mass for pre-cooling and demand limiting for a limited number of prototypical small commercial buildings. The program performs hourly calculations with fairly detailed models of the buildings and equipment. The user inputs include: building type and size; location; occupancy schedule; utility rates; equipment type and efficiency; demand-limiting control parameters.

With this simulation tool, relative demand reductions, cost savings, and comfort impacts associated with the alternative control strategies are expected be similar for similar building types.

2.2.4. Research on System Analysis and DR Evaluation

1) System Analysis

As demand response can perform load reshape, system analysis has been conducted by some previous research. Some of the research focus on the general assessment of DR benefits or barriers, which will cover part of the system analysis like DOE's and FERC's reports [11,19]. Others may be more specific, focusing on issues like reliability, adequacy, security and so on.

Reference [146] introduces a simplified framework for analyzing forms of demand-side management considering Incentive structures, methods of actuating demand-side response, and information exchange requirements. Reference [147] proposes a computationally efficient simulation approach to quantify the impacts of DR resources on market performance, generation dispatch, transmission usage, environment and other system variable effects.

More specifically, reference [148] concludes that the price-based DSM can improve the system security by congestion relief. Reference [135] analyzes system reliability considering expected energy not served (EENS) and spinning reserve cost with EDRP as a source of ancillary service.

2) DR Evaluation

As consumers' participation is very critical to the implementation of demand response programs, a lot effort has been put on the consumer encouragement. From the consumer side, demand response programs have been studied, evaluated or analyzed based on consumers' comfort level [149]. Reference [150] points out that the consumer comfort zone (thermal comfort and air quality) should not be affected during a DR program. Some DR strategies are also designed with consideration of consumers' comfort [151,152,153].

2.3. Conclusions and Knowledge Gaps

This chapter summarizes the literature search and identifies the knowledge gaps from four aspects: load modeling, EV penetration, demand response strategies and system analysis with demand response.

2.3.1. Load Modeling

Much work has been done on load modeling at different levels in different time scales. Models that provide daily, monthly or annual load curves for a large service area are good for the study of electric power grids at the transmission level. As the number of consumers grows, the fluctuations in each consumer can be canceled when aggregated with other consumers. These top-down models represent average load curves of a specific area, which are impossible to study the impact of demand response when appliance-level loads cannot be controlled.

For loads to be controllable to evaluate the demand response strategies, the bottom-up models should be developed that are based on characteristics of each loads, and of short-time interval, e.g. minutes. The previous work has covered some of this area and provides valuable references. However, there is a need for more realistic usage profiles and methodologies for aggregation.

Demand response analysis tools have been discussed in the literature review already presented. The building energy simulations tools, like DOE-2 and EnergyPlus, only provide the building energy consumption estimation. This will not help in simulations and analysis of real-time demand response. DLAT is an hourly based simulation tool, which is too rough for many types of loads such as HVAC, water heater, etc. However, there is something to learn from the analysis methodology in the tool.

Detailed load models at the appliance level or building level are typically used for control of a specific type of load, (e.g. air conditioner). The time intervals are usually shorter, depending on the input data. With a dynamic model, the control is realizable. However, these models are usually limited to the building level, like DRQAT, which cannot provide utilities with a general idea of the loading level of the distribution networks in their service areas.

For the study of a distribution network, a detailed load model which starts from the appliance level and aggregates to the feeder level or substation level will be more beneficial. As many appliances are only run for several minutes, hourly data is too rough for appliance control, therefore the model should be of short time interval (1~10 minutes).

GridLAB-D is the closest option to address the problem. It provides detailed load models for each appliance, and load aggregation of a distribution network. Based on the PNNL description, the load modeling methodologies are also very similar to the work in this dissertation. However, GridLAB-D doesn't provide the external data such as building structures and hot water usage profiles. Therefore it requires data input for the models to run realistically. (Default data for one type of load and for one building are provided but will not have diversity without different inputs.)

For subsequent studies on demand response, a set of detailed load models by appliance with randomized inputs for feeder load aggregation are proposed in this dissertation. The models for controllable loads (i.e. HVAC, water heater, clothes dryer and EV) are dynamic, and thus can fulfill the task of demand response simulations and analysis. The demand aggregation will reveal realistic diversities among different buildings and distribution circuits.

2.3.2. EV Penetration

1) Impact of EV Penetration into the Distribution Network with DR

In FERC's National Action Plan on Demand Response, FERC has identified the study of how plug-in hybrid electric vehicles interact with demand response programs as one of the research gaps.

Most of the research on EVs' penetration into the power system is based on fixed charge profiles which are not controllable. Though there have been different assumptions such as evening charge or off-peak charge, EV charge time is still in lack of flexibility. EV charge time and charge rate should be flexible for a realistic study.

There is the need to perform analysis of EV penetration into the distribution network and the interaction with existing loads. In one possible scenario, EV can be considered as one of the household loads and included in the appliance list that can perform demand response.

2) EV V2G control

Many Research on V2G for EV fleet are considering EV batteries as a simple energy storage system (ESS) from which energy can be drawn according to signals such as price or demand limit. However, there are many factors will affect the V2G performance such as battery life concerns and consumers' driving patterns.

In a more realistic way, EV is a specific load which can feed back to the smart grid. The fleet control has to take into consideration EV owners' preferences, the driving patterns, and battery SOC.

2.3.3. Demand Response Strategies

Incentive-based DR has been used for a long time in different forms, which provides utilities with some demand reduction when there is a demand limit. According to the literature search, the traditional incentive-based DR may either be arbitrary (e.g. direct load control, ancillary services, etc.) or not in real-time response (e.g. emergency demand response program, demand bidding, etc.). Without full knowledge of each customer's power consumption situation, the traditional incentive-based DR cannot guarantee the demand reduction amount. At the same time, some of the incentive-based DR cannot respect consumers' convenience. Even the comfort factor is taken into account during the strategy design, the privacy and different consumer preferences are still left out of the consideration with the incentive-based DR.

On the other hand, in the smart grid environment, price-based DR has been fostered to support customers to respond to the given price signal. Price-based demand response is a bottom-up approach, in which consumers' convenience and privacy are respected. However, with this mechanism, the DR results are highly dependent on consumers' reaction, which brings utilities more uncertainty on the load shape change. For Time-of-use rate (TOU) and critical peak pricing (CPP), there is also the problem of new peak demand creation after the "peak period".

Some previous work only focuses on demand response strategies for the commercial and industrial consumers. In fact, the demand for electricity required by residential consumers should not be simply neglected because they constitute a large share of the total electricity consumption.

There is definitely a need to develop a demand response strategy to keep the advantages from both price-based and incentive-base DR and eliminates their disadvantages. The strategy should provide utilities with trustworthy control results (i.e. load shape change according to demand limit) while respect consumers' convenience and privacy. The DR strategy should be suitable for both commercial and residential sectors. Furthermore, there is the need for better understanding of DR impacts on consumers' comfort level and reasonable DR potential, which have not been addressed in the previous works.

2.3.4. System Analysis and DR Evaluation

According to the literature search, there has been some work on system analysis with demand response. However, most of them are for large area power grid. The analysis does not reveal DR impacts on a distribution network, which is of more concern to the end users.

Demand response potential evaluation has been performed in a general way described in Section 2.2.3. The consumer comfort has been taken into consideration in the analysis of DR impacts and strategy design. However, there hasn't been much concern on non-thermal dynamic loads such as clothes dryer and EVs, which should be consider as important as the thermal comfort. Moreover, to emphasize the consumer side and foster the participation, DR potential evaluation based on consumers' convenience level is needed in the distribution network.

3. Modeling of Residential and Commercial Loads

This chapter describes the load modeling methodology at both appliance level and distribution circuit level for residential and commercial buildings. The load models are demand-response enabled thus can be controlled by DR signals. The work in this chapter sets the basis for the following DR operation and analysis.

3.1. Load Categorization

In general, a distribution network is referred to as all distribution-level components located downstream of a distribution substation.

Hourly load curves of an average household or commercial building are available from the RELOAD database [154] which is used by the Electricity Module of the National Energy Modeling System (NEMS) [155]. The hourly load curve data are available for twelve months (January to December), and three-day types (typical weekday, typical weekend and typical peak day).

Based on the RELOAD database, residential loads can be classified by the following nine load categories:

- Space cooling
- Space heating
- Water heating
- Clothes drying
- Cooking
- Refrigeration
- Freezer
- Lighting
- Others

For commercial buildings, the load types vary according to the building types and activities [156]. Major commercial building loads include:

- Space cooling
- Space heating
- Water heating
- Lighting
- Others

For the purpose of this study, all residential and commercial loads are classified into two categories: controllable and critical [112]. Controllable loads are defined as the loads that can be controlled without a noticeable impact on consumers' life styles. The other category contains loads that are either very important (critical loads) or loads that cannot be controlled.

- For residential houses, space cooling/heating, water heater and clothes dryer loads are controllable; and all other loads are considered critical or cannot be controlled.
- For commercial buildings, the space cooling load in summer and space heating load in winter are considered controllable; and all other loads are considered critical or cannot be controlled.

In this study, detailed load models and validation are developed for the controllable loads. Data from the RELOAD database are used to construct the critical load profiles for both residential and commercial load categories.

3.2. Space Cooling and Space Heating (HVAC) Load

3.2.1. Model Development

A central air conditioning (AC) system with a thermostat works in an "on-off" way and the AC will simply run at its rated power when turned on. In general, the thermostat control is set such that the room temperature (T) will fluctuate around the thermostat set point (T_s) within the dead band of $\pm\Delta T$.

For space heating, when the room temperature is lower than $Ts\text{-}\Delta T$, the heater will start working (at rated power, as mentioned above) and the room temperature will gradually increase. The heat produced is to warms up the room as well as compensates for the heat loss. When the room temperature reaches the upper bound at $T_s+\Delta T$, the heater will be turned off. Since the outdoor temperature T_{out} is lower than the room temperature (T), the room temperature will start to decrease due to the heat loss. While the temperature is within the range of $T_s\text{-}\Delta T \leq T \leq T_s\text{-}\Delta T$, the heater will keep its status until the room temperature reaches either boundary.

Similarly for the space cooling, when the room temperature is higher than $T_s+\Delta T$, the AC will start working at its rated power and the room temperature will gradually decrease. The AC cools down the room as well as compensates for the heat gained from the outdoors. When the room temperature reaches the lower bound at $T_s\text{-}\Delta T$, the AC will turn off. Since the outdoor temperature Tout is higher than the room temperature (T), the room temperature will start to increase due to the heat gain. While the room temperature is within the range of $T_s\text{-}\Delta T \leq T \leq T_s\text{-}\Delta T$, the heater will keep its status until the room temperature reaches either boundary.

Fig. 3-1 illustrates the block diagram of the HVAC load model. This model can be used for both residential and commercial space cooling/heating load.

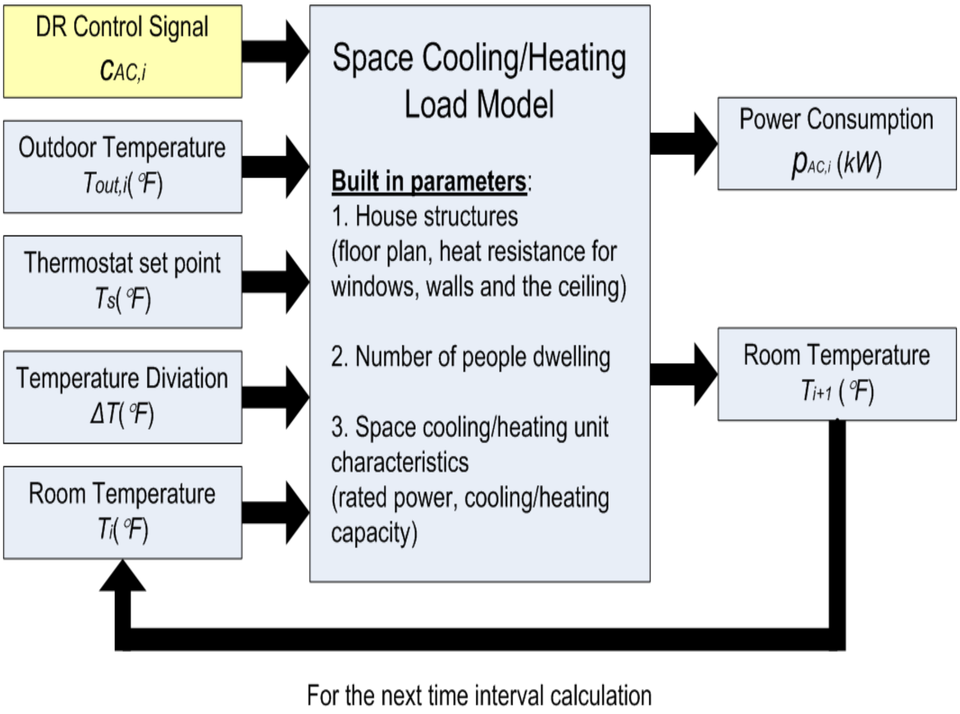


Fig. 3-1 HVAC Load Model Block Diagram.

Inputs to the model are the DR control signal ($c_{AC,i}$), time series outdoor temperature data (T_{out}), thermostat set point (T_s), allowable temperature deviation or dead band (ΔT) and time series room temperature data (T_i). The model outputs are the time series electric power consumption ($p_{AC,i}$) in kilowatts of the space cooling/space heating unit, and the room temperature (T_{i+1}) at the next time step. The room temperature output is used as an input to the load model at the next time step. The model needs additional house parameters, including house structures, number of people dwelling and the electrical characteristics of the space cooling/space heating unit.

1) Calculation of the electric power demand in each time slot:

$$p_{AC,i} = P_{AC} \cdot w_{AC,i} \qquad \text{Eq. 3-1}$$

Where,

P_{AC} : rated power of the space cooling/space heating system (kW);

$w_{AC,i}$: status of the space cooling/space heating unit in time slot i, 0=OFF, 1=ON.

For space cooling, the unit is ON when the room temperature increases above the set point, plus the threshold. The unit is OFF when the room temperature decreases below a certain value. The status of the unit remains the same if the room temperature is within the acceptable band. This relationship is presented in Eq.3-2.

$$w_{AC,i} = \begin{cases} 0, & T_i < \left(T_s + c_{AC,i}\right) - \Delta T \\ 1, & T_i > \left(T_s + c_{AC,i}\right) + \Delta T \\ w_{AC,i-1} & T_s - \Delta T \le T_i - c_{AC,i} \le T_s + \Delta T \end{cases} \qquad \text{Eq. 3-2}$$

For space heating, the operation is similar to above.

$$w_{AC,i} = \begin{cases} 0, & T_i > \left(T_s + c_{AC,i}\right) - \Delta T \\ 1, & T_i < \left(T_s + c_{AC,i}\right) + \Delta T \\ w_{AC,i-1} & T_s - \Delta T \le T_i - c_{AC,i} \le T_s + \Delta T \end{cases} \qquad \text{Eq. 3-3}$$

Where

$c_{AC,i}$: DR control signal for the space cooling/space heating unit in time slot *i* (℉)

The electric power demand also depends on the DR control signal ($c_{AC,i}$) received from an external source, such as an in-home controller, or a utility. For space cooling/space heating, the DR control signal will rewrite the temperature set point and change the space cooling/space heating load profile. This DR control signal, if received from an in-home controller, can be configured to take into account the priority of all end-use loads in a house, and customer comfort levels.

2) Determination of room temperature:

For each time step *i*, the room temperature is calculated as:

$$T_{i+1} = T_i - \Delta t \cdot \frac{G_i}{\Delta c} + \Delta t \cdot \frac{C_{HVAC}}{\Delta c} \cdot w_{AC,i} \quad \left(T_0 = T_s\right) \qquad \text{Eq. 3-4}$$

Where,

T_i : room temperature in time slot *i* (℉);

Δt : length of time slot *i* (*hour*);

G_i : heat gain rate of the house during time slot *i*, positive for heat gain and negative for heat loss (*Btu/h*);

C_{HVAC} : cooling/heating capacity, positive for heating and negative for cooling (*Btu/h*);

Δc : energy needed to change the temperature of the air in the room by 1℉ (*Btu/℉*).

3) Calculation of other parameters (G_i and Δc).

For each time slot *i*, the heat gain rate of the house (G_i) is calculated as:

$$G_i = \left(\frac{A_{wall}}{R_{wall}} + \frac{A_{ceiling}}{R_{ceiling}} + \frac{A_{window}}{R_{window}}\right) \cdot (T_{out,i} - T_i) + SHGC \times A_{window\_south} \times H_{solar} \times \frac{3.412 Btu/Wh}{10.76 ft^2/m^2} \qquad \text{Eq. 3-5}$$

Where, A_{wall}, $A_{ceiling}$, and A_{window} represent the area of the wall, ceiling, and window of the house, in ft^2. R_{wall}, $R_{ceiling}$, and R_{window} represent the heat resistance of the wall, ceiling, and window, in $℉ \cdot ft^2 \cdot h/Btu$ * [157].

$T_{out,i}$	:	outdoor temperature in time slot *i (℉)*;
$SHGC$	:	solar heat gain coefficient of windows [158];
H_{solar}	:	the solar radiation heat power *(Wh/m^2)*.

To change the house temperature by 1 ℉, the energy required (*Btu/℉*) is calculated as:

$$\Delta c = C_{air} \cdot V_{house} \qquad \text{Eq. 3-6}$$

Where,

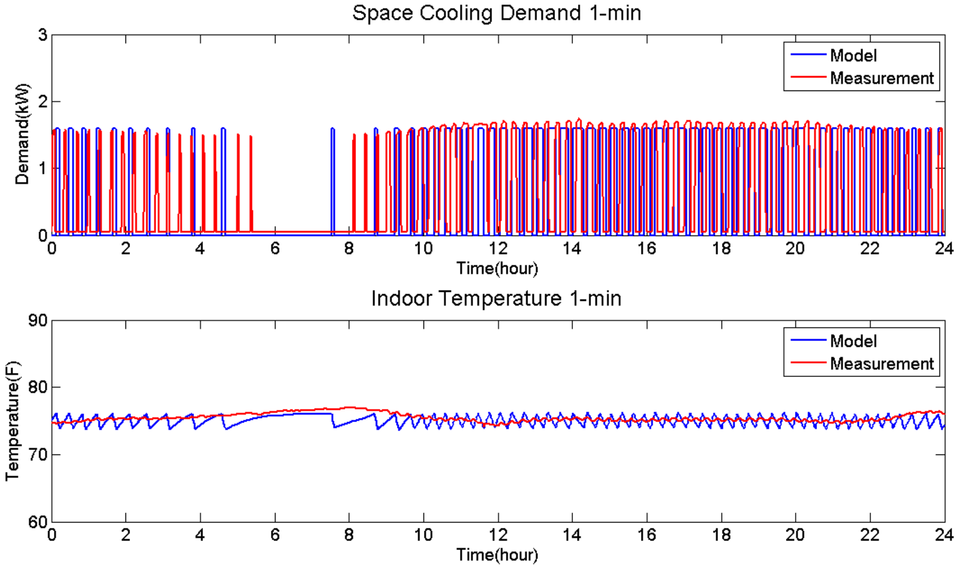
C_{air}	:	specific heat capacity of air for a typical room condition *(1.012J/gK or 0.0195 Btu/ft^3 ℉)*;
V_{house}	:	the volume of the house (ft^3).

3.2.2. Model Validation

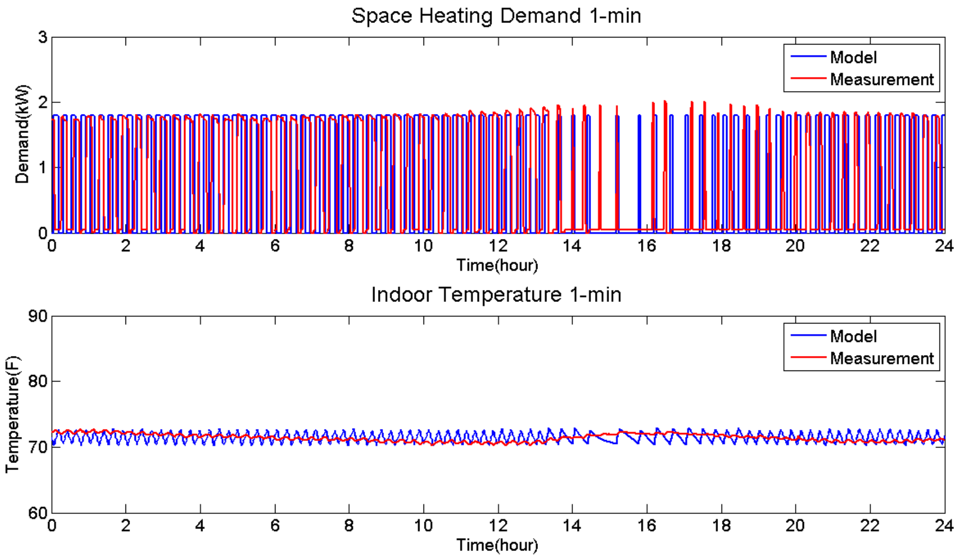
To validate the developed model, the HVAC model is run with the inputs (outdoor temperature, thermostat set point, dead band, house structure parameters, and HVAC unit size) from a real house in Charlottesville, VA. Using the same inputs, the model outputs (power consumption and indoor temperature) are compared with the actual measurements. This comparison is illustrated below for two 24-hour periods, one in the month of August for space cooling demand; and the other for the month of January for space heating demand.

Fig. 3-2 indicates similarities between the actual power consumption and the model output. Any discrepancies may result from the assumptions associated with the house structure parameters. In addition, the temperature measurements from the real house are smooth, while the temperature output from the model fluctuates around the dead band. This is because the actual temperatures were measured at several locations around the house, and averaged to obtain the room temperatures as shown.

* Insulation is rated in terms of thermal resistance, called R-value, which indicates the resistance to heat flow. The higher the R-value is, the greater the insulating effectiveness will be. The R-value of thermal insulation depends on the type of material, its thickness, and its density. In calculating the R-value of a multi-layered installation, the R-values of the individual layers are added. R-values have unit of *℉ ·ft2·h/Btu*.



a) Space Cooling Comparison



(b) Space Heating Comparison

Fig. 3-2 Space Cooling/Space Heating Model Validation – Comparison of Load Profile (*kW*) and Indoor Temperature (℉).

3.2.3. Aggregation of Space Cooling/Heating Load

According to section 3.2.1, the input parameters for a space cooling/space heating model are divided into three categories: temperatures, building structures and the space cooling/space heating unit characteristics. These are parameters needed to be randomized for different homes in the same distribution circuit.

The temperature category includes outdoor and indoor temperature set points. The outdoor temperatures are acquired from the National Climatic Data Center (NCDC) [159], which should be the same for all houses in the same neighborhood. For the indoor temperature set points, a uniform random function is used to determine the variation in temperature set points among different houses in the same distribution circuit.

The lower and upper limits for the temperature set points are determined based on data from ASHRAE [160].

The building structure category includes the floor plan of the buildings, areas of walls, ceilings and windows as well as the R-values for each of them. Similar to the indoor temperature, a uniform random function is used to determine the variation in R-values and areas of wall, window, ceiling and floor among different houses in the same distribution circuit. The lower and upper limits for these values are acquired from a survey of the service area. Such data for residential houses are obtained from the American Housing Survey [161].

The space cooling/heating characteristic category includes the cooling/heating capacities and power consumptions, which is usually known as the unit sizing. Usually, the sizing is based on the building floor plans, activities, occupants and environment. The unit sizing is calculated according to ASHRAE [162].

After getting all three sets of random functions for these input parameters, the demand aggregation for HVAC is quantified by running the space cooling/heating model $N+M$ times with different parameters. (N is the number of residential houses in the distribution network and M is the number of commercial buildings.)

3.3. Water Heating Load

3.3.1. Model Development

Water heating is the third largest energy expense in a normal residential house. It typically accounts for about 12% of your utility bill [163]. Note that as commercial water heating load is considered as “critical”, this DR-enabled water heating load model is for residential only.

For a traditional water heater with a tank for hot water storage, suppose the hot water outlet setting point is T_f, with a ΔT_w lower tolerance. It is reasonable to assume that the cold water inlet flow rate is equal to the hot water outlet flow rate. When the mixed water temperature drops below the lower bound, i.e. $T_{outlet}<T_f-\Delta Tw$, the heating coils will start working at its rated power until the outlet hot water temperature reaches the upper bound, i.e. T_f. If the outlet water temperature is kept within the range of the dead band, i.e. $T_f-\Delta Tw\leq T_{outlet}\leq T_f$, the heating coils will keep their status. The stand-by loss of the tank L_s also needs to be taken into consideration for a traditional water heater. Fig. 3-3 shows the water heater model block diagram.

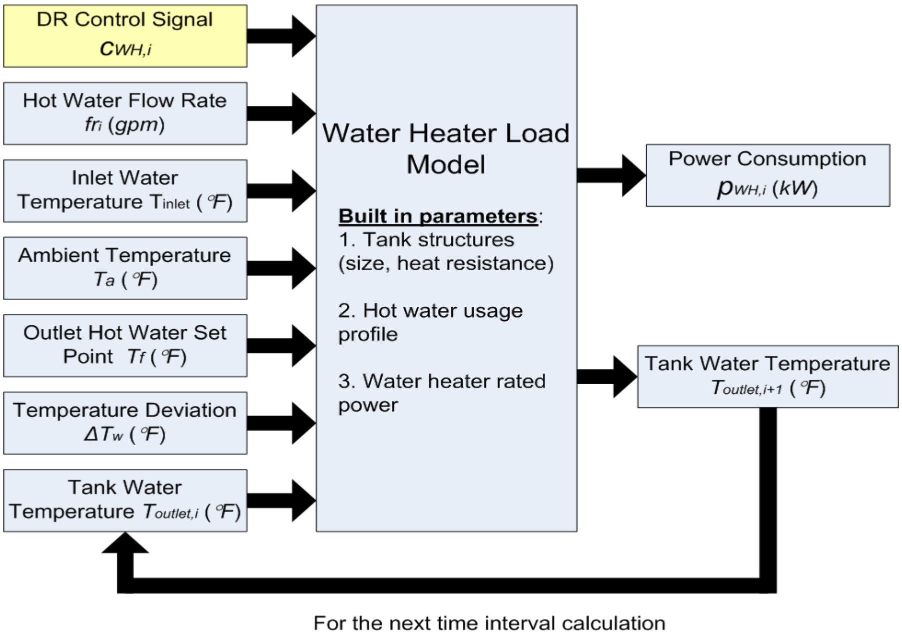


Fig. 3-3 Water Heater Load Model Block Diagram

For each time step *i*, the demand for electricity of the water heating unit ($p_{WH,i}$) is calculated as:

$$p_{WH,i} = w_{WH,i} \cdot P_{WH} \cdot \eta_{WH} \cdot c_{WH,i} \qquad \text{Eq. 3-7}$$

Where,

P_{WH} : rated power of the water heater *(kW)*;

η_{WH} : efficiency factor;

$w_{WH,i}$: status of the water heater in time slot *i*, 0=OFF, 1=ON;

$c_{WH,i}$: DR control signal for water heater (°F).

The water heater status ($w_{WH,i}$) is determined according to the following rules: when the water temperature in the hot water tank goes above the set point, it does not operate. When the water temperature drops below a lower bound, the heating coils start working again at its rated power until the outlet hot water temperature reaches the upper bound.

$$w_{WH,i} = \begin{cases} 0, & T_{outlet,i} > T_f \\ 1, & T_{outlet,i} < T_f - \Delta T_w \\ w_{WH,i-1}, & T_f - \Delta T_w \le T_{outlet,i} \le T_f \end{cases} \qquad \text{Eq. 3-8}$$

Where,

T_f : hot water temperature set point (°F);

ΔT_w : lower tolerance (°F);

$T_{outlet,i}$: mixed water temperature in the tank (°F);

The water temperature in the tank is calculated as:

$$T_{outlet,i+1} = \frac{T_{outlet,i}\left(V_{tank} - fr_i \cdot \Delta t\right)}{V_{tank}} + \frac{T_{inlet} \cdot fr_i \cdot \Delta t}{V_{tank}} + \frac{1gal}{8.34lb} \cdot \left[\frac{p_{WH,i} \cdot 3412BTU}{kWh} - \frac{A_{tank} \cdot \left(T_{outlet,i} - T_a\right)}{R_{tank}}\right] \cdot \frac{\Delta t}{60\frac{\min}{h}} \cdot \frac{1}{V_{tank}} \qquad \text{Eq. 3-9}$$

Where,

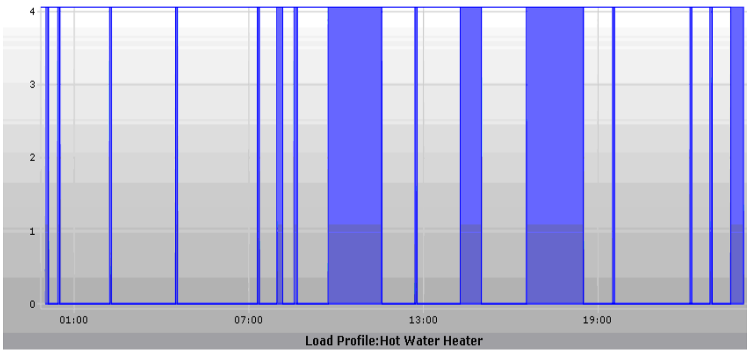
T_{inlet} : temperature of inlet water *(℉)*;
T_a : room temperature *(℉)*;
fr_i : hot water flow rate in time slot *i (gpm)*;
A_{tank} : surface area of the tank *(ft^2)*;
V_{tank} : volume of the tank *(gallons)*;
R_{tank} : heat resistance of the tank *(℉·ft^2·h/Btu)*;
Δt : duration of each time slot (*minutes*).

The electric power demand also depends on the DR control signal ($c_{WH,i}$) received from an external source, such as an in-home controller, or a utility. The DR control signal of 0 will shut off the unit, and the DR control signal of 1 will turn the unit on.

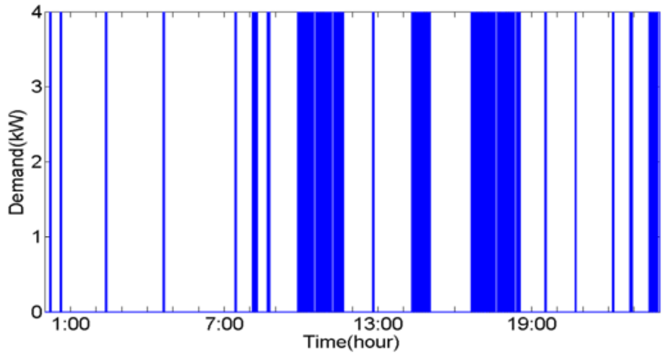
3.3.2. Model Validation

To validate the developed water heater model, there is a need to find out a house's water heater temperature set point, tank size and rated power. With the same input, the same water heater load profile is expected when compared to the measured load curve. Fig. 3-4 shows the comparisons of load profiles between the TED demo water heater power consumption data (a) and modeled water heater load profile (b).

Note that the water heater data is incomplete so there has to be some assumptions. Therefore the modeled load profile cannot be exactly the same as the measurements. The pictures are only to show that they are similar, so it is thereby reasonable to use the model for simulations and analysis.



(a) TED Demo Water Heater Power Consumption Data



(b) Modeled Water Heater Load Profile

Fig. 3-4 Water Heater Model Validation – Load Profile Comparison

3.3.3. Aggregation of Water Heating Load

The input parameters for the water heater model are divided into three categories: temperature profiles, water heater characteristics and hot water usages.

The temperature profile includes tank ambient temperatures, inlet water temperatures and hot water temperature set points. Tank ambient temperature is assumed to be the same as the room temperature, which can be acquired from the space cooling/space heating model. Inlet water temperature is assumed to be the same as the ground temperature, which can be acquired from Soil Climate Analysis Network (SCAN) [164]. For the hot water temperature set points, a uniform random function is used to determine the variation in temperature set points among different houses in the same distribution circuit.

The lower and upper limits for the hot water temperature set points are determined based on data from [163], which specifies typical residential hot water temperature set points between 110 ℉ and 120 ℉.

The water heater characteristics include the R-values, tank sizes and rated power. Similar to the hot water temperature, a uniform random function is used to determine the variation in R-values, water heater tank sizes and rated power among different houses in the same distribution circuit. The typical ranges for these values are acquired from [163,165].

For hot water usage, the hourly fraction data from California's Hourly Water Heating Calculations [166] are taken as a reference. At the same time, hot water usage is categorized into different types in percentage of the daily household hot water usage [167]. Therefore for each type of hot water usage, the water consumption duration in a minute is the hot water demand in gallon divided by the flow rate in gallon per minute (*gpm*). The Monte Carlo method is used to decide when the hot water is consumed based on the hot water hourly usage fraction shown in Fig. 3-5 for different residential houses.

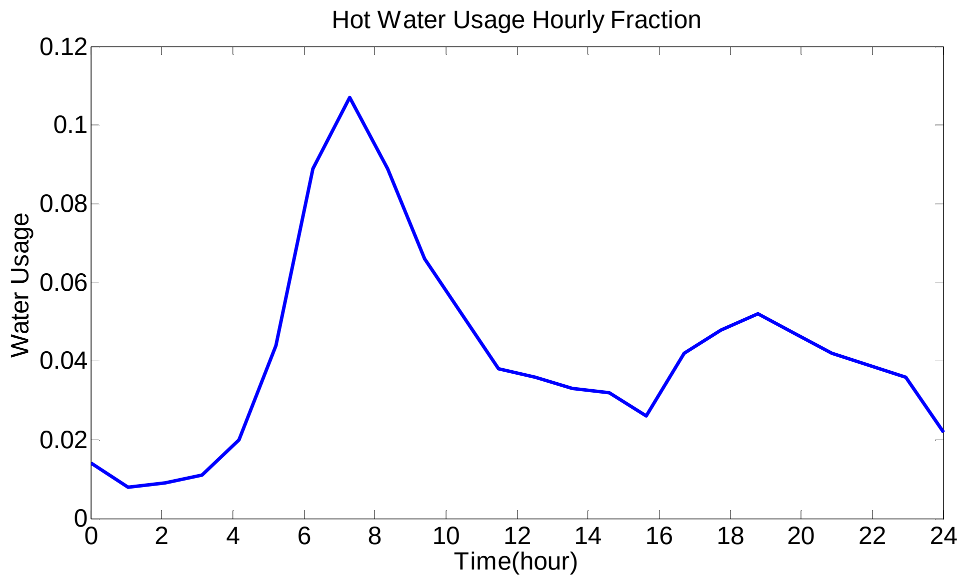


Fig. 3-5 Hot Water Usage Hourly Fraction

3.4. Clothes-drying Load

3.4.1. Model Development

The clothes-drying load model is designed for the residential sector only. The power consumption of a typical clothes dryer is from the motor and the heating coils. The power demand of the motor part is usually in the range of several hundred watts, but that of the heating coils can be several kilowatts. Fig. 3-6 shows the clothes-drying load model block diagram.

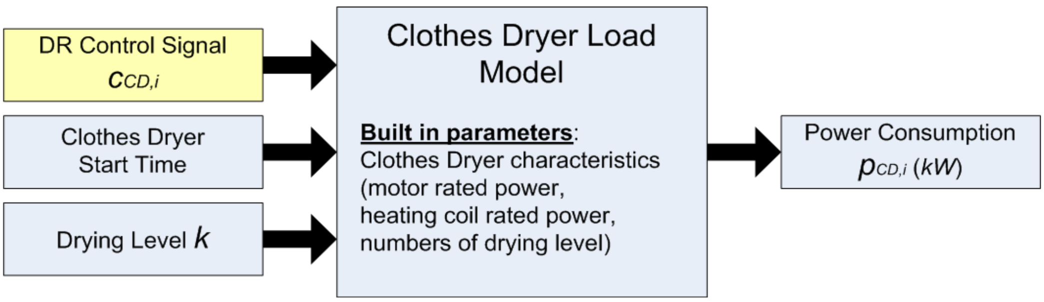


Fig. 3-6 Clothes Dryer Load Model Block Diagram

For each time slot *i*, the demand for electricity of the clothes-drying unit ($p_{CD,i}$) is calculated as:

$$p_{CD,i} = \frac{k \cdot P_h}{M} \cdot w_{CD,i} \cdot c_{CD,i} + P_m \cdot w_{CD,i} \quad (k = 1, \cdots, M) \qquad \text{Eq. 3-10}$$

Where,

P_h : rated power of clothes-dryer heating coil *(kW)*;

k : drying level *(k=1,…,M)*;

M	:	total number of drying levels;
P_m	:	power consumption of the dryer's motor *(kW)*;
$w_{CD,i}$	:	status of the clothes-dryer's heating coils in time slot i, 0=OFF, 1=ON;
$c_{CD,i}$	:	DR control signal for clothes dryer in time slot i, 0=OFF, 1=ON.

The electric power demand also depends on the DR control signal ($c_{CD,i}$) received from an external source, such as an in-home controller, or a utility. For the clothes dryer load, when a DR control signal is received, only the heating coil will be controlled (ON/OFF) but the motor part will not be controlled. This implies that the clothes dryer will be spinning during the control period, thus consuming only a fraction of the overall load (several *kW*).

3.4.2. Model Validation

For validation purpose, there is a need to find out a house's clothes dryer rated power and when it is being used. With the same input of power and time, the same clothes dryer load profile is expected compared to the measured load curve. Fig. 3-7 shows the comparisons of load profiles between the model and data from a real house in Virginia.

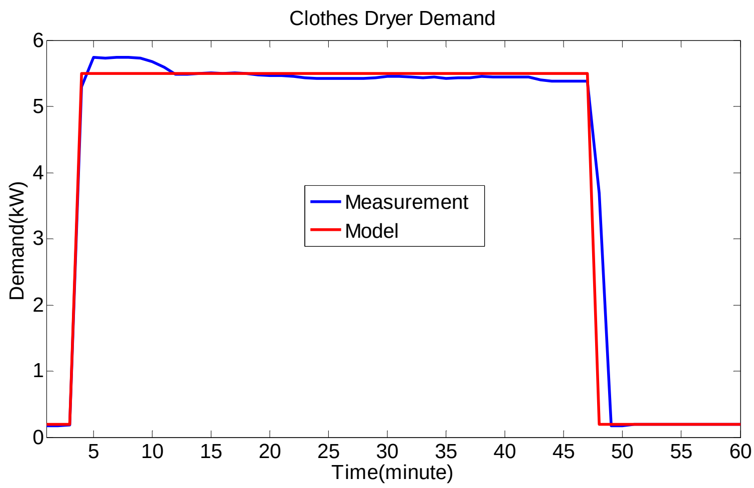


Fig. 3-7 Clothes Dryer Model Validation – Load Profile Comparison

The close match between the actual and modeled power consumption characteristics of a clothes dryer validates the usefulness of the simulation model.

3.4.3. Aggregation of Clothes-drying Load

The clothes dryer load profile is developed based on a probability distribution function that is similar to the dryer power consumption profile obtained from the measurement of a home in Florida [168]. The dryer running time generally starts from late morning to midnight, with the mean in the evening. After finding out the dryers' running time, the demand aggregation of clothes dryers is acquired by running the developed model to obtain power consumption of all dryers in the distribution circuit.

3.5. Critical Loads

3.5.1. Residential Critical Load Models

The aggregated load profile of critical loads is created based on the historical data of the industry-accepted database, i.e. RELOAD database. As critical loads will be kept as they are during the demand response periods, the average model will work for the distribution network. According to the categories in Section 3.1, “cooking”, “lighting”, “refrigerator”, “freezer” and “others” are considered as critical loads for residential customers.

Assuming that there are N residential houses in the distribution network, the critical load profile in a house can be derived based on the following equation:

$$L_{c\_r} = N \times \sum_{type=1}^{5} f_{type} \times \frac{L_{ar\_type}}{8760} \qquad \text{Eq. 3-11}$$

Where,

L_{c_r} : the critical load in one hour *(kW)*;

f_{type} : hourly fraction of annual residential load for load type;

L_{ar_type} : the average annual household load for load type i, which can be found from EIA monthly electricity sales data [169].

3.5.2. Commercial Critical Load Models

All loads besides space cooling and space heating are critical loads for commercial customers. Since different commercial buildings may have different load types, (e.g. an office building has “space cooling”, “space heating”, “ventilation”, “lighting”, “water heater” and “others” while a fast food service building also has “cooking” load), critical loads are defined according to the building activities.

Assuming that there are M commercial buildings in the distribution network, the total critical load curve for a 24-hour period can be acquired from:

$$L_{c\_c} = M_1 \times \sum_{iB_1=1}^{C_1} f_{iB_1} \times \frac{L^i_{aB_1}}{8760} + M_2 \times \sum_{iB_2=1}^{C_2} f_{iB_2} \times \frac{L^i_{aB_2}}{8760} + \cdots + M_x \times \sum_{iB_x=1}^{C_x} f_{iB_x} \times \frac{L^i_{aB_x}}{8760} \qquad \text{Eq. 3-12}$$

In which:

$M_1 \cdots M_x$ are the numbers of each commercial building type which makes $M = M_1 + M_2 + \cdots + M_x$.

$f_{iB_1} \cdots f_{iB_x}$ are the hourly fractions of annual commercial loads for load type i in commercial building B_1~B_x.

$L^i_{aB_1} \cdots L^i_{aB_x}$ are the average annual commercial loads for load type i in commercial building B_1~B_x.

$C_1 \cdots C_x$ are the numbers of critical load types in commercial building B_1~B_x.

3.5.3. Aggregation of Critical Loads

As the critical loads come from average data, the aggregation of critical loads is obtained by multiplying the load profiles for one building by the number of each type of building.

4. Modeling of Electric Vehicles (EV)

To investigate the impacts of EVs penetration into the distribution network, it is important to get a thorough understanding of the EV fleet charging pattern. This section describes the EV modeling methodology and shows an example of EV fleet charge load profile.

4.1. Model Development for Electric Vehicles

To model EV charging profiles, three parameters are essential: the rated charging power, the plug-in time and the battery state-of-charge (SOC). Fig. 4-1 shows the clothes-drying load model block diagram.

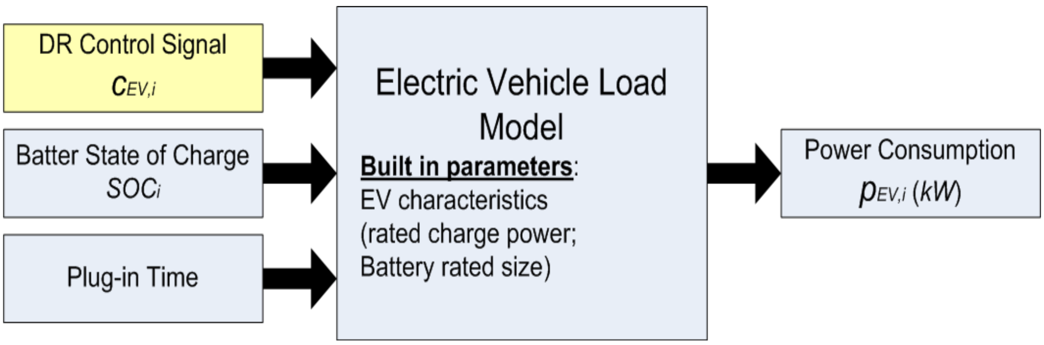


Fig. 4-1 Electric Vehicle Load Model Block Diagram

The calculation of the EV charging profile is described in Eq.4-1.

$$p_{EV,i} = P_{EV} \cdot S_{EV,i} \cdot w_{EV,i} \cdot c_{EV,i} \qquad \text{Eq. 4-1}$$

Where,

- $p_{EV,i}$: EV charge power in time slot i *(kW)*;
- P_{EV} : EV rated power *(kW)*;
- $S_{EV,i}$: EV connectivity status in time slot i, 0 if EV is not physically connected to the outlet and 1 if EV is connected;
- $w_{EV,i}$: Uncontrolled EV charging status in time slot i, which depends on the battery SOC as shown in Eq.4-2: 0 if EV is not being charged and 1 if EV is being charged;
- $c_{EV,i}$: DR control signal for EV in time slot i, 0=OFF, 1=ON.

$$w_{EV,i} = \begin{cases} 0, & SOC_i \geq SOC_{\max} \\ 1, & SOC_i < SOC_{\max} \end{cases} \qquad \text{Eq. 4-2}$$

The battery SOC at time slot i is a function of the SOC at the previous time slot, the energy used for driving and the battery rated capacity, which is determined by:

$$SOC_i = SOC_{i-1} + P_{EV} \cdot \Delta t / C_{batt}$$
$$SOC_0 = 1 - E_{dr} / C_{batt} \quad \text{Eq. 4-3}$$

Where,

SOC_0 : battery SOC when EV is plugged in;
Δt : length of time slot *i (minute)*;
E_{dr} : energy used for driving *(kWh)*;
C_{batt} : battery rated capacity *(kWh)*.

The EV power demand also depends on the DR control signal ($c_{EV,i}$) received from an external source, such as an in-home controller, or a utility. The DR control signal of 0 will stop the charging of an EV while the DR control signal of 1 will allow the EV to start charging. The EV will continue to be charged until it is fully charged. The developed EV model takes into account charging compensation time if the EV charging is interrupted by the DR signal.

4.2. Demand Aggregation of EV Fleet

To determine the EV fleet charge profile in a distribution circuit, three parameters (vehicle rated charging power, plug-in time and the battery SOC) have to be reasonably diversified.

For the EV rated charging power, Table 4-1 [170,171,172,173,174] shows the basic battery charge data of three popular EVs in the US market. The charge power presented in Table 4-1 is used to determine the charge power of the EV fleet with a reasonable mix of different EV makes and models. In this dissertation, the recommended charge rates are adopted for case studies.

The EV plug-in time is derived from the National Household Travel Survey [175]. The EV plug-in time is modeled using a normal distribution with a mean and a variance derived according to the data presented in [176].

Table 4-1 Popular EVs in the U.S. Market

Make & Model	Battery Size	Energy Available	All Electric Range	Charge Power
GM Chevy Volt	16kWh	8kWh	40 mi	1.9kW 3.3kW (Recommended)
Nissan LEAF	24kWh	19.2kWh	100 mi (LA4 mode)	1.8kW 3.3kW (Recommended) 49kW (fast)
Tesla Roadster	53kWh	37.1kWh	244 mi (Experiment)	1.8kW 9.6kW (Recommended) 16.8kW

EV driving patterns are used to determine the EV energy storage status, i.e. the battery

SOC. The daily driving distances for each EV in a distribution circuit is determined based on the data presented in Fig. 4-2 [175] using the Monte Carlo simulation. The battery SOC of each EV when plugged in is determined by Eq.4-3.

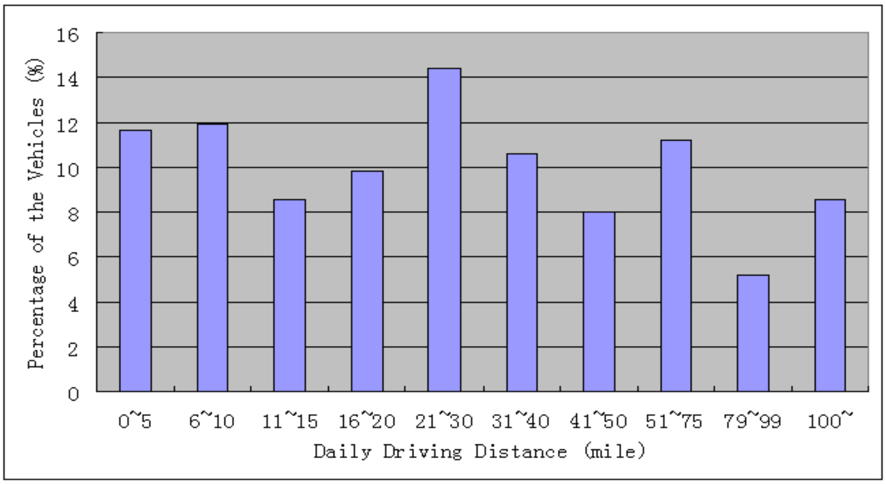


Fig. 4-2 American Driving Pattern Curve.

To illustrate the aggregation of the EV load at a distribution circuit level, Fig. 4-3 shows an example charging profile of a 100-EV fleet with the mix of 70% Chevy Volt, 20% Nissan LEAF and 10% Tesla Roadster. The EV fleet mix (70/20/10) is chosen as a representative mix to show a sample aggregation of different EV types. As the EV market share changes over time and new EV models enter the market, the EV fleet mix can change, but the methodology will stay the same. The recommended charging power rates in Table 4-1 are chosen for the simulation. The EVs are assumed to come back home and plugged in at different time according to a normal distribution with mean at 18:00 and 1 hour variance. The Monte Carlo simulation is used to determine the driving distance of each EV which derives the battery SOC.

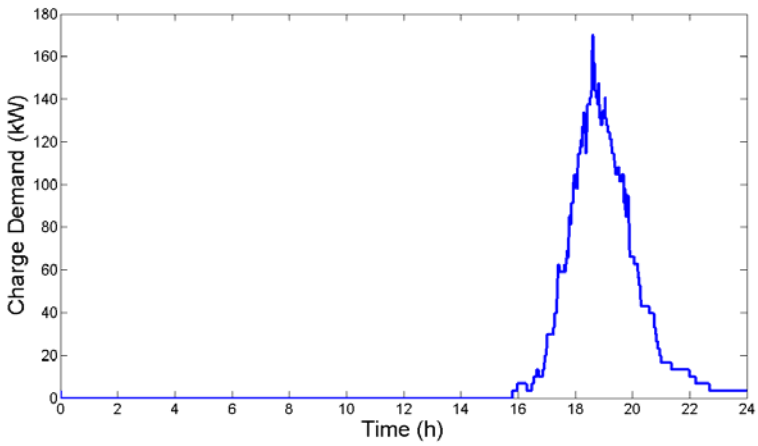


Fig. 4-3 Example EV Fleet Charging Profile for One Day

5. Design of Multi-layer Demand Response Strategy

5.1. Structure of the Multi-layer Demand Response

The multi-layer demand response (DR) strategy is designed from the top down. When there is a power system stress event happens, the utility announces the demand limit for the next time interval to all the substations in its service area. Then the substation will decide the allocation of the demand limit to each distribution circuit it servers. The proposed DR strategy is focusing at the distribution circuit level and lower. Therefore the demand limit is assumed to be given by the upper level command.

When a distribution circuit receives a demand limit, it will use the AHP to decide the priority for each consumer group served by the circuit. The demand limit for each consumer group is then decided accordingly. Next, each consumer group will distribute the demand limit to the home/building in its category. Finally, the DR control center in each home/building will manage the household or building demand below its assigned demand limit.

5.2. DR Strategy at the Distribution Circuit Level

When the utility issues a demand limit event, the task for this layer is to determine how much demand needs to be shed from each residential house or commercial building. This process is divided into two steps: a) demand limit allocation to each consumer group; and b) demand allocation to each building. Note that the demand limit event can be initiated based on the capacity contract with the utility.

5.2.1. Demand Limit Allocation to Each Consumer Group

In this dissertation, AHP is adopted to determine the demand reduction allocations among different consumer groups when there is a demand limit event. Since the demand side management here can be considered as a kind of resource allocation problem, the Expected Priority (EP) method described in [177] is proposed to address the problem.

To model the demand limitation allocation using an AHP, the goal, the criteria, and possible alternatives must be defined. The goal is the demand limit. The criteria are opinions from customers, experts and the utility. The alternatives are the consumer groups according to the principle building activities described in [156] as commercial and residential. Fig. 5-1 shows the AHP structure for demand limit allocation.

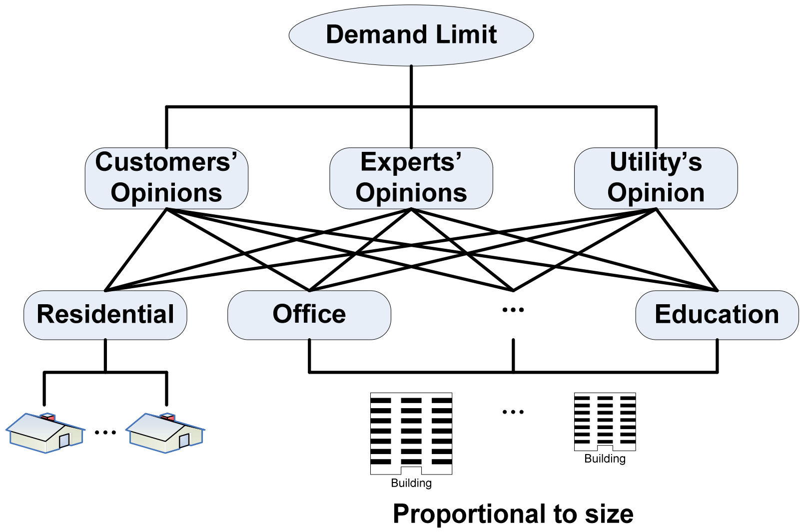


Fig. 5-1 AHP Structure for Demand Limit Allocation

Step 1: Survey customers, experts and the utility

Using AHP, the opinions from regular customers, experts and the utility are all taken into consideration. The pair-wise comparisons are conducted between each consumer group for different time periods.

The weight of customers' opinions, experts' and utility's are derived from pair-wise comparison according to Saaty's levels:

- 1, as equal;
- 3, as a little more important;
- 5, as more important;
- 7, as much more important; and
- 9, as extremely more important.
- 2,4,6,8 are intermediate values.

Using the Eigen value method, the weight for each criteria group's opinion are given by w_c, w_e, w_u respectively, in which: w_c is the weight of the opinions from consumer group, w_e is the weight of the opinions from the expert group and w_u is the weight of the opinion from the utility. $w_c + w_e + w_u = 1$.

Step 2: Create pair-wise comparisons

For the next layer, each criteria group gets to vote for the priority of each consumer group. Table 5-1 shows an example of a pair-wise comparison result during the daytime from one expert. As shown, during the daytime, office buildings are more important than residential buildings, and fast food service is a little more important than residential buildings while office buildings are a little more important than fast food service.

Table 5-1 Pair-wise Comparison

	Residential	Office	Public Assembly	School	Fast food
Residential	1	1/5	1/2	1/6	1/3
Office	5	1	4	1/2	2
Public Assembly	2	1/4	1	1/5	1/3
School	6	2	5	1	2
Fast Food	3	1/2	3	1/2	1

The corresponding judgment matrix (J) can be derived from Table 5-1 as:

$$J = \begin{bmatrix} 1 & 1/5 & 1/2 & 1/6 & 1/3 \\ 5 & 1 & 4 & 1/2 & 2 \\ 2 & 1/4 & 1 & 1/5 & 1/3 \\ 6 & 2 & 5 & 1 & 2 \\ 3 & 1/2 & 3 & 1/2 & 1 \end{bmatrix}$$

The judgment matrix can change according to the opinions from different customers, experts and the utility, as well as the number of customers/experts/utilities surveyed.

Step 3: Calculate Eigen Vector that represents the overall priority

The Eigen vector w, which makes $Jw = \lambda_{\max} w$, represents the final priority of the three consumer groups by the expert's opinion. Here $\lambda_{\max}$ is the maximum Eigen value. It is easy to calculate that:

$w = [0.1047, 0.6370, 0.2583]^T$, $\lambda_{\max} = 3.0385$.

The consistency index CI is calculated as:

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad \text{Eq. 5-1}$$

n is the order of judgment matrix J, i.e. here n = 3. Thus CI = 0.0192.

The consistency ratio (CR) is calculated as:

$$CR = \frac{CI}{RI} \qquad \text{Eq. 5-2}$$

In which RI can be looked up in Table 5-2 from Saaty's book, in which the upper row is the order of the random matrix, and the bottom row is the corresponding index of consistency for random judgments.

Table 5-2 Index of Consistency for Random Judgments

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Therefore here RI = 0.58, CR = 0.0331. CR > 0.1 indicates that the judgments are at the limit of consistency. As CR is much less than 0.1, the judgment is consistent.

Step 4: Calculate demand allocation for each customer group in each time slot

Assuming that we have *n* customers, *m* experts and 1 utility. Each customer gets to vote on the consumer group in each time slot for the whole day, comparing the priority by Saaty's levels. Thus for n customer we get n vectors to represent the customers' opinions on supply allocation in each time slot.

The demand allocation in time slot *i* according to customers' opinions will be:

$$V_c = \frac{w_c}{n}\sum_{k=1}^{n} w_k^i \qquad \text{Eq. 5-3}$$

w_k^i is the kth customer's opinion vector for time slot *i*.
V_c is the final value of the consumer group opinion.

Similarly, the demand limit allocation in time slot *i* according to experts' opinions will be:

$$V_e = \frac{w_e}{m}\sum_{j=1}^{m} w_j^i \qquad \text{Eq. 5-4}$$

w_j^i is the jth expert's opinion vector for time slot *i*.
V_e is the final value of the expert group opinion.

The demand limit allocation in time slot *i* according to utility's opinions will be:

$$V_u = w_u w^i \qquad \text{Eq. 5-5}$$

w^i is the utility's opinion vector for time slot i.
V_u is the final value of the utility's opinion.

To sum up, the final decision for the demand limit allocation for each consumer group in time slot *i* will be:

$$\max \sum_{l=1}^{l}\left(V_c + V_e + V_u\right)\times x_l^i, \qquad \text{Subject to:} \sum_{l=1}^{l} x_l^i \le D_l^i \qquad \text{Eq. 5-6}$$

In which x_l^i is the lth building demand limit share in time slot *i*, D_l^i is the total demand limit for time slot *i*.

5.2.2. Demand Limit Allocation for Each Building

After the demand limit for each consumer group has been decided, the demand limit has to be assigned to each residential house and commercial building.

- Residential customers:

For residential houses, the demand limit is determined by demand deduction from the sorted consumption queue. Fig. 5-2 shows the methodology to conduct the demand limit decision. First the neighborhood area network control center will sort all reported demand (*kW*). Then the demand limit for each house (red line) is set at the point that the total household demand to be served (shadow area) is less than or equal to the residential allocation of the demand limit.

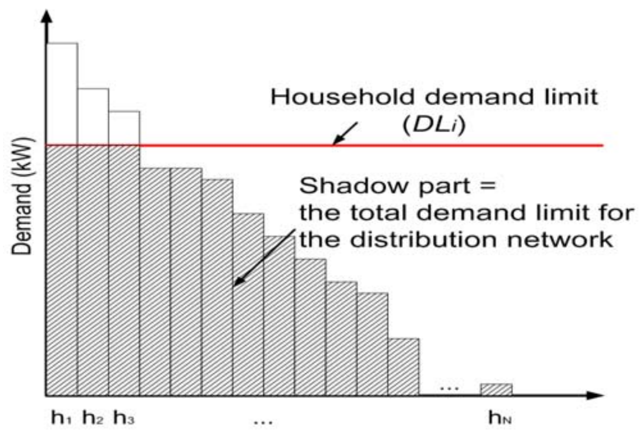


Fig. 5-2 Example of Sorted Consumption Queue and Demand Limit for Each House

DL_i can be determined by solving the optimization problem as shown in Eq.5-7.

$$\max\left(DL_i\right) \qquad \text{Eq. 5-7}$$

Subject to:

$$\sum_{m=1}^{N} D_{m,i} \le DL_{total,i}$$

$$D_{m,i} = \begin{cases} L_{m,i}, & L_{m,i} < DL_i \\ DL_i, & L_{m,i} \ge DL_i \end{cases} \quad m = 1, 2, ..., N$$

In which:

$L_{m,i}$ is the expected household power consumption in time slot i;

$D_{m,i}$ is the demand limit in time slot i;
$DL_{total,i}$ is the available supply for the residential sector in time slot i.

- Commercial customers:

For commercial buildings, the supply allocation will be determined according to the building size.

5.3. DR Strategy in at Home/Building Level

Inside each residential house, there will be a home area network (HAN) control center to manage the total household demand by controlling the controllable smart appliances. Similarly, the building area network (BAN) is the demand management network in a commercial building. Each smart appliance will have an interface to receive the control signal from the HAN/BAN center and to report its own status. Right now, many communication standards are applied to build HAN/BAN, such as Zigbee, 802.11, Bluetooth and so on. The common sense is that the network has to be wireless, fast and secure. However, the bandwidth doesn't have to be high since the data exchange shouldn't be too much. (TED, Google, … are producing the control center or information gathering center)

The household load has been divided into two categories according to Section 3.1: critical and controllable. The critical loads will only report their status while controllable loads can be controlled by the HAN/BAN control center according to the assigned demand limit. The DR strategy for a residential house is that when there is a demand limit, the control center will check if the household demand in the next time interval will be over the assigned limit. If yes, the control center will deny demand requests from some non-critical smart appliances according to customer pre-set preferences.

In this dissertation, the residential HVAC load, the water heater load and the clothes-drying load are considered controllable while all the other loads are considered critical. If the HAN control center sees that the total household is exceeding the demand limit, demand response actions will be taken.

The demand response in the HAN/BAN is performed as follows:

Step 1. Set the load priority. e.g. water heater is of the highest priority, HVAC is the second and clothes dryer is of the lowest priority.

Step 2. Set the convenience preference. e.g. clothes-drying must be finished by midnight. Room temperature should not be higher than 81°F.

Step 3. Perform demand response based on load priority and preferences. When the HAN/BAN control center sees the preferences are being violated, the corresponding loads' priorities will be temporarily raised to the highest.

For HVACs and water heaters, this can be done by tracking the temperatures. If the temperatures are going out of the range, keep the HVACs or water heaters on to remain in the comfort range. For clothes dryers, the heating coils' off time should be kept in a certain range so that the heat loss can be neglected. If a clothes dryer is turned off to save capacity for other loads due to DR but reaching the maximum "off-time", then the heating coil will be forced on to keep the heat in the dryer. For an EV, the battery state of charge (SOC) is monitored to make sure the charging can be finished by a given time without requiring a charge rate that is higher than the outlet rating. If an EV stops charging for a long time which is pushing to its margin, the controller will raise the EV's priority to make it start charging. At this time, some other loads which are not reaching their preference limit may be shut down to save the capacity.

If a house has an EV, the EV is then considered to be one of the controllable household loads. Therefore the control strategy will be the same as layer five for end use, which is described in Section 5.1. As a result, the EV will be on the preference list and controlled based on the demand deduction requirements as well as its priority. The difference for the EV is that this special controllable load can do better than other controllable loads that can only simply shut down or cycle. It can reduce the charging power or provide a V2G service if other appliances are really in need.

For commercial buildings, the only non-critical load is the space heating in winter and space cooling in summer. Therefore the control strategy is to change the temperature set point to reduce the total building demand.

The smart appliances will have two-way communication with the HAN/BAN control center. Each smart appliance has an IC built in to report the status and to receive the control signal. Recently, some home electronic companies such as General Electric have already started to produce smart appliances with an IP-based remote control signal receiver [178].

6. DR Potential Evaluation

As consumer acceptance is one of the key factors in order for demand response to succeed, it is very important to evaluate the DR impacts on consumers' daily life. Therefore comfort indices are introduced in this dissertation to measure consumer comfort levels. The consumer comfort indices are defined based on the severity, scale and duration of convenience violations for each controllable appliance.

6.1. Severity Indices

The severity indices are used to measure how severely the consumer comfort levels are violated. The indices are based on the maximum percentage deviation from the original settings.

6.1.1. Severity Indices for HVACs

For HVACs, the severity index $I_{se,HVAC}$ is defined as the largest room temperature deviation in percentage taking into account all homes in a distribution circuit. $T_{i,HVAC}$ is the actual room temperature while $T_{s,HVAC}$ is the room temperature setting.

$$I_{se,HVAC} = \max\left(\left|\frac{T_{i,HVAC} - T_{s,HVAC}}{T_{s,HVAC}}\right| \times 100\%\right) \qquad \text{Eq. 6-1}$$

6.1.2. Severity Indices for Water Heaters

For water heaters, the severity index $I_{se,WH}$ is defined as the largest hot water temperature deviation in percentage taking into account all homes in a distribution circuit. $T_{i,WH}$ is the actual outlet hot water temperature while $T_{s,WH}$ is the hot water temperature setting.

$$I_{se,WH} = \max\left(\left|\frac{T_{i,WH} - T_{s,WH}}{T_{s,WH}}\right| \times 100\%\right) \qquad \text{Eq. 6-2}$$

6.1.3. Severity Indices for Clothes Dryers

For clothes dryers, the severity index $I_{se,CD}$ is defined as the longest clothes-drying time delay in percentage taking into account all homes in a distribution circuit. $t_{i,CD}$ is the actual clothes-drying time while $t_{s,CD}$ is the original setting for the clothes-drying time.

$$I_{se,CD} = \max\left(\frac{t_{i,CD} - t_{s,CD}}{t_{s,CD}} \times 100\%\right) \qquad \text{Eq. 6-3}$$

6.1.4. Severity Indices for Electric Vehicles

For electric vehicles, the severity index $I_{se,EV}$ is defined as the longest EV charging time delay in percentage taking into account all homes in a distribution circuit. $t_{i,EV}$ is the actual EV charging time while $t_{s,EV}$ is the original EV charging time without DR.

$$I_{se,EV} = \max\left(\frac{t_{i,EV} - t_{s,EV}}{t_{s,EV}} \times 100\%\right) \qquad \text{Eq. 6-4}$$

6.2. Scale Indices

The scale indices are used to measure the number consumers whose comfort levels are violated as a percentage of a total household in the distribution circuit of interest.

6.2.1. Scale Indices for HVACs

For HVACs, the scale index $I_{sc,HVAC}$ is defined as the maximum ratio, considering all time slots in the study period, of number of homes with room temperatures out of the comfort ranges in each time slot to the total number of homes with HVAC in a distribution circuit. See Eq.6-5, where n_{HVAC} is the number of homes with the room temperatures out of pre-set comfort ranges in each time slot. N is the total number of consumers in a distribution circuit and OR_{AC} is the ownership rate of HVACs.

$$I_{sc,HVAC} = \max\left(\frac{n_{HVAC}}{N \times OR_{AC}} \times 100\%\right) \qquad \text{Eq. 6-5}$$

6.2.2. Scale Indices for Water Heaters

For water heaters, the scale index $I_{sc,WH}$ is defined as the maximum ratio, considering all time slots in the study period, of the number of homes with hot water temperatures out of the comfort ranges in each time slot to the total number of homes in a distribution circuit. See Eq.6-6, where n_{WH} is the number of homes with the hot water temperature out of pre-set comfort ranges in each time slot. N is the total number of consumers in a distribution circuit and OR_{WH} is the ownership rate of water heaters.

$$I_{sc,WH} = \max\left(\frac{n_{WH}}{N \times OR_{WH}} \times 100\%\right) \qquad \text{Eq. 6-6}$$

6.2.3. Scale Indices for Clothes Dryers

For clothes dryers, the scale index $I_{sc,CD}$ is defined as the ratio of the number of homes with clothes-drying job delayed to the total number of homes with electric clothes dryers in a distribution circuit. See Eq.6-7, where n_{CD} is the number of homes with a clothes-drying job delayed charge delayed longer than a pre-set comfort level. N is the total number of consumers in a distribution circuit and OR_{CD} is the ownership rate of clothes dryers.

$$I_{sc,CD} = \frac{n_{CD}}{N \times OR_{CD}} \times 100\% \qquad \text{Eq. 6-7}$$

6.2.4. Scale Indices for Electric Vehicles

For EVs, the scale index $I_{sc,EV}$ is defined as the ratio of the number of homes with an EV charging delayed to the total number of homes with EVs in a distribution circuit. See Eq.6-8 where n_{EV} is the number of homes with EV charge delayed longer than a pre-set comfort level. N is the total number of consumers in a distribution circuit and OR_{EV} is the ownership rate of electric vehicles.

$$I_{sc,EV} = \frac{n_{EV}}{N \times OR_{EV}} \times 100\% \qquad \text{Eq. 6-8}$$

6.3. Duration Indices

The duration indices are to describe the length of the inconvenient period for HVAC and water heater. (As the severity indices for clothes dryer and EV are already measured by duration, this type of indices is not applicable to them.)

6.3.1. Duration Indices for HVACs

For HVACs, the duration index $I_{d,HVAC}$ is defined as the longest duration of room temperature violating the pre set comfort level. t_{HVAC} is the duration that the room temperature is out of the comfort range, in minutes.

$$I_{d,HVAC} = \max\left(t_{HVAC}\right) \qquad \text{Eq. 6-9}$$

6.3.2. Duration Indices for Water Heaters

For water heaters, the duration index $I_{d,WH}$ is defined as the longest duration of hot water temperature violating the pre set comfort level. t_{WH} is the duration that the hot water temperature is out of the comfort range, in minutes.

$$I_{d,WH} = \max\left(t_{WH}\right) \quad \text{Eq. 6-10}$$

7. Case Studies

This chapter presents the results of implementing the proposed demand response strategy at various EV penetration levels. This is carried out at both the distribution circuit level and the household level. The case studies as presented here only show examples of how the proposed planning tool can be used. The planning tool can be used for a much wider range of applications related to demand response studies. For example, impact of different DR control algorithms and different DR adoption levels on load shape changes can be investigated.

7.1. Case Study Design

7.1.1. Circuit Description

To study the impact of the multi-layer demand response strategy on a distribution circuit load profile, a distribution network in the Virginia Tech Electric Service (VTES) area in Blacksburg, VA is taken for the case study. Fig. 7-1 [179] shows the map of the selected area for case studies. The customers served in the area can be categorized into five customer groups: residential, office, public assembly, school and food service.

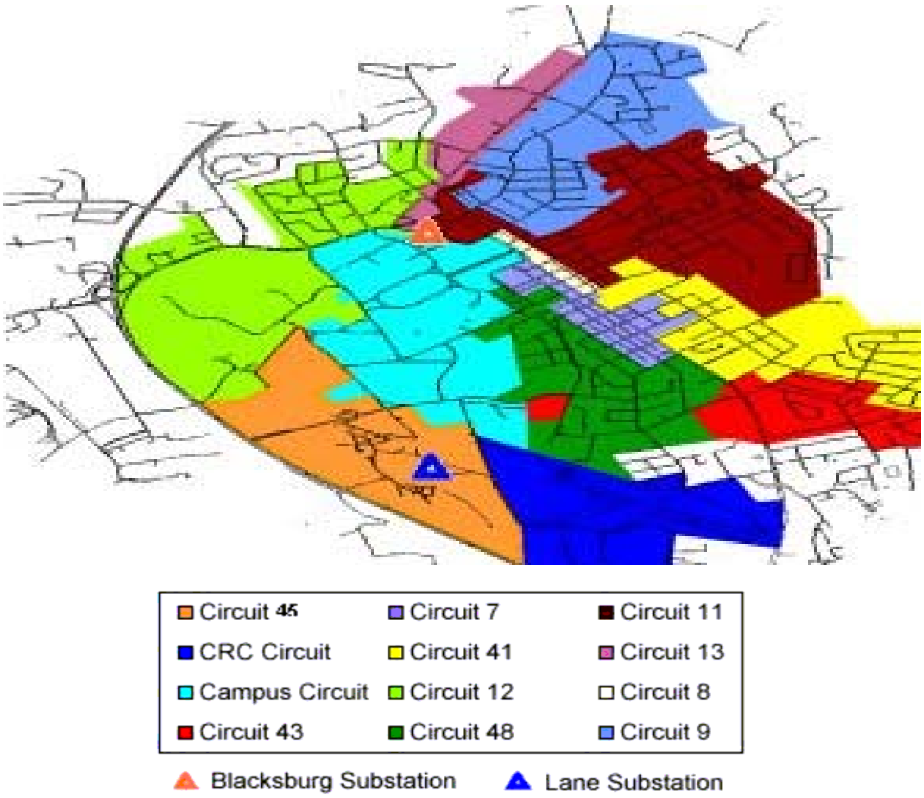


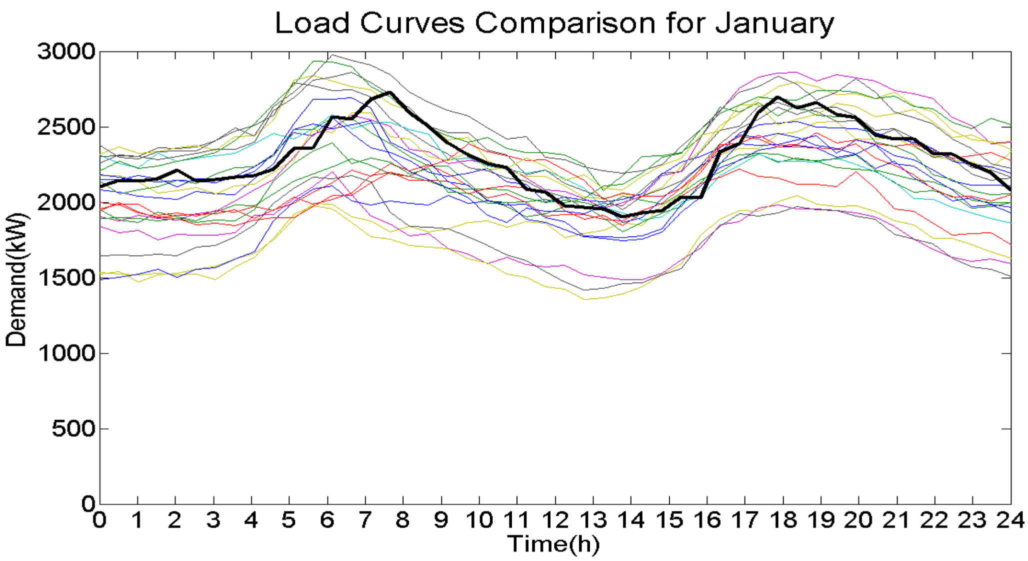
Fig. 7-1 Virginia Tech Electric Service (VTES) for Case Study

The area is served by VTES-owned generation and electricity bought from American Electric Power (AEP). In this case, the electricity transaction is not only based on energy but also based on power. In the wholesale electricity market, VTES and AEP may have a contract on the electric power consumption (demand limit) and the power overdrawn can cause a high demand charge to VTES. Therefore, when there is EV penetration into the distribution circuit, the total demand may go beyond the original agreed demand limit. (The demand limit in this case would be the purchasing power limit added up with the VTES-owned generation capacity.) On the other hand, if the EV fleet is large, the high consumption may even cause the system reliability problem such as frequency drop or voltage sag. Demand response is then used to keep the load within the demand limit to avoid the high demand charge and system stress conditions. Bonneville Power Administration (BPA) has a similar case in the Olympic Peninsula area, where the GridWise Demonstration Project I was deployed and the demand limit was set there to alleviate the distribution circuit congestion.

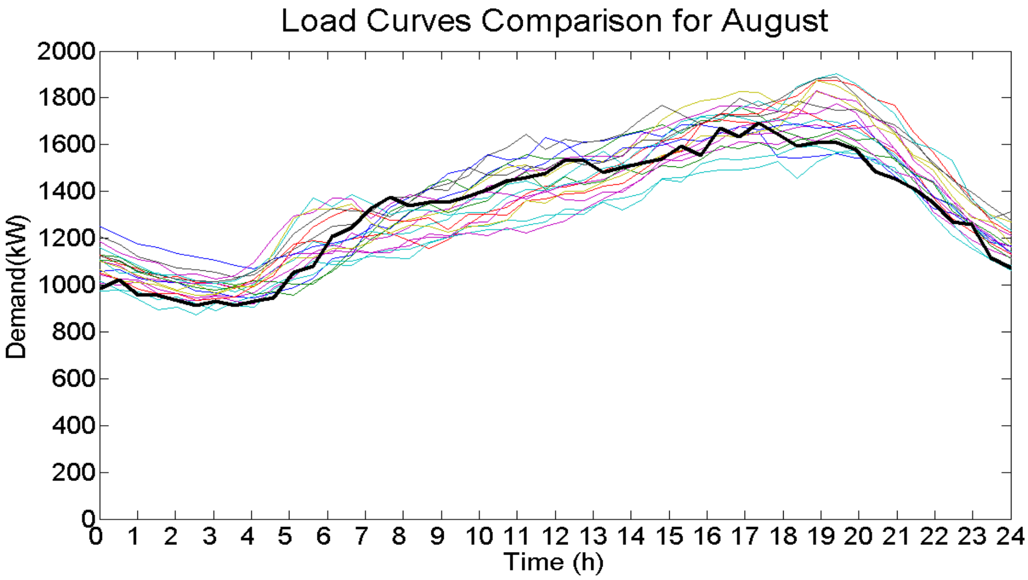
The presented case studies focus on a distribution circuit noted as Circuit 9 in the VTES service area. There are 34 laterals with 117 transformers serving 761 residential customers and 9 commercial customers in this circuit [180]. The circuit serves 523 regular houses, 138 townhouses, 100 units in 4 apartment complexes, 2 schools, 1 office building, 5 public assemblies (2 churches, 2 parks and 1 aquatic center), and 1 seven-eleven, counted as 1 food service.

7.1.2. Circuit Load Profiles

Fig. 7-2 shows the load profiles of Circuit 9 for (a) winter and (b) summer respectively. The thick black line represents the modeled weekday load curve (which is the simulation output from the load models developed in Chapter 3) while the multi-color fine lines are the measured data on different days of the month.



(a) Circuit Load Profile for Winter (Represented by January)



(b) Circuit Load Profile for Summer (Represented by August)

Fig. 7-2 Circuit 9 Demand for January and August Respectively

These charts show that the modeled load profiles represent measured load data quite well. Therefore it is adequate to use the circuit load model for further demand response studies.

7.1.3. EV Fleet Charge Profiles

In the case studies, three EV penetration levels are considered: 100 EVs, 200 EVs and 300 EVs. As discussed in Section 2.1.3.3 these three EV penetration levels represent 7%, 14% and 21% of the market share respectively. Fig. 7-3 shows the example charging profiles of three different sizes of EV fleets with the mix of 70% Chevy Volt, 20% Nissan LEAF and 10% Tesla Roadster. Each EV type has different charging rates according to Table 4-1. The recommended charging power rates are used to generate the simulation results. It is assumed that the EVs return back home and are plugged in at different times according to a normal probability distribution function with the mean at 18:00 and the variance of 1 hour, as discussed in Section 4.2. For weekends, it is assumed that the EV plug-in time follows a normal probability distribution function with the mean at 20:00 and the variance of 4 hours.

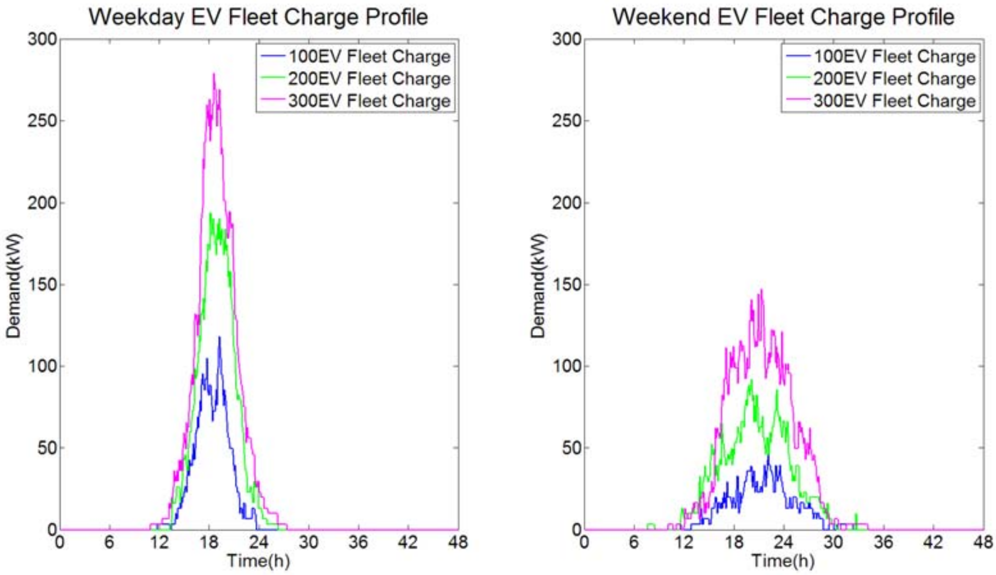


Fig. 7-3 EV Fleet Charging Profiles – Weekday and Weekend

Note that EVs can be charged anywhere with charging stations installed. As our focus is to deal with excessive load during peak hours for a residential distribution circuit, evening hours are of interest. Therefore we only consider the time period that is likely to be impacted by EV charging at home in the evening, which is the home-charge.

7.1.4. DR Target and Demand Limit for Each Consumer Group

In the following case studies, it is assumed that the original system is operated under normal condition. Therefore the main reason for the system stress condition comes from the EV fleet penetration. In this context, the demand response target is to make the EV penetration transparent to the system, which is to set the demand limit equal to the original peak demand. As the generation and transmission capacity may differ in different seasons due to maintenance schedules or weather conditions, the demand limits are set differently for summer and winter seasons, equal to the seasonal peak demands respectively. Note that the definition of summer is June to September while that of winter is October to April, according to Dominion Virginia Power's Time-of-Use Tariff [181].

Once the circuit of interest receives the demand limit from the substation, AHP will be used to decide the allocation for each customer group. The multi-layer DR structure for the test cases is shown in Fig. 7-4.

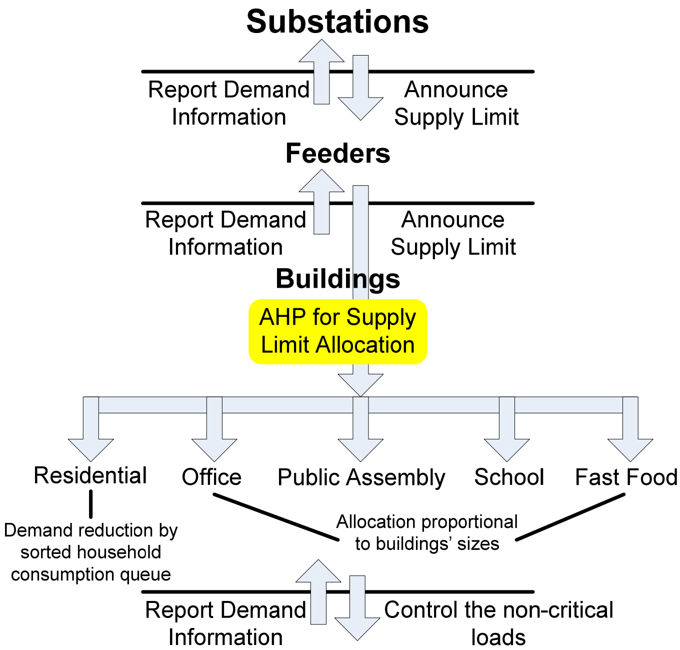


Fig. 7-4 Multi-layer DR Structure

Practically, an extensive survey is needed for the AHP opinion input. In this simulation, the pair-wise comparison opinions are given by random functions. The numbers in Table 7-1 represent the priority assigned by experts to buildings and functions they perform. The whole day is divided into two judgment categories: daytime and nighttime. The pair-wise opinions are generated for consumers, experts and the utility serving the area. Consistency ratios (CR) are checked for each group of opinions to remove the opinions that are not consistent. The final AHP results for summer and winter are shown in Table 7-1 and

Table 7-2 respectively.

Table 7-1 AHP Judgment Results for Winter

	Residential	**Office**	**Public Assembly**	**School**	**Fast Food**
Daytime (9 am ~5pm)	0.0737	0.4249	0.0312	0.3105	0.1244
Night-time (5pm~9am)	0.3920	0.1032	0.0827	0.1001	0.3220

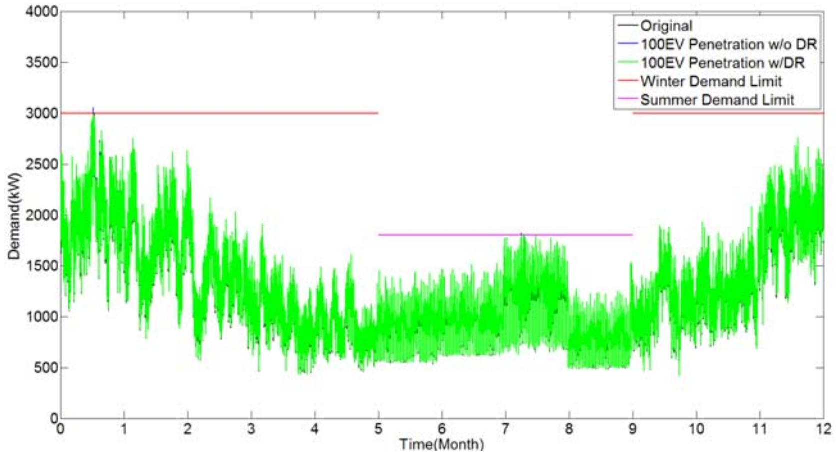
Table 7-2 AHP Judgment Results for Summer

	Residential	**Office**	**Public Assembly**	**School**	**Fast Food**
Daytime (9 am ~5pm)	0.0745	0.4126	0.0408	0.3052	0.1554
Night-time (5pm~9am)	0.3944	0.0931	0.0827	0.0912	0.3318

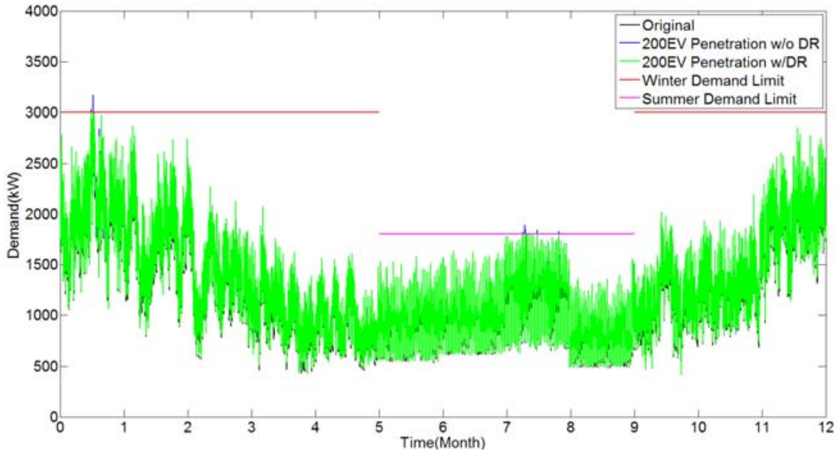
The AHP judgment results show that during the daytime, office and school buildings are more important, and thus likely to keep more of their load when there is a demand limit. Residential and fast food buildings are more important during the nighttime.

7.2. Demand Response Results at the Circuit Level for One Year

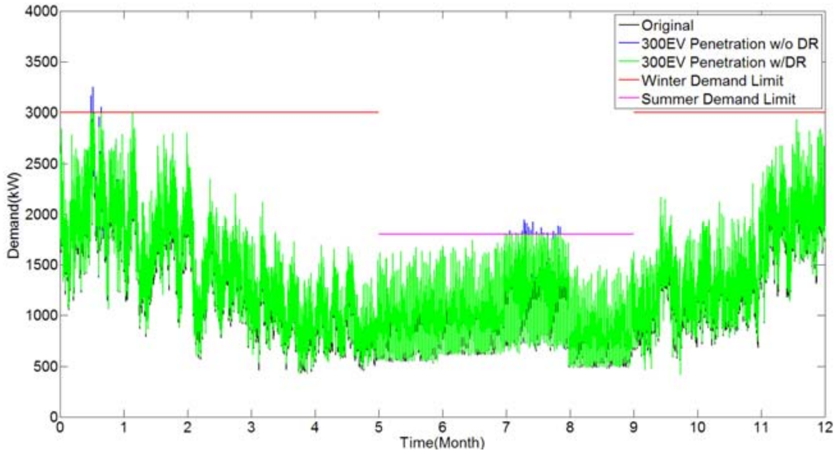
This section presents the DR results at a distribution circuit level for one year with different EV penetration levels, as shown in Fig. 7-5. The winter original peak demand is 3.0MW and the summer is 1.7MW. The demand limits for the two seasons are set at these levels.



(a) DR Results for 100 EV Penetration



(b) DR Results for 200 EV Penetration



(c) DR Results for 300 EV Penetration

Fig. 7-5 DR Results at the Distribution Circuit Level for One Year at Different EV Penetration Levels

As seen from Fig. 7-5, in order to keep the circuit load with EV penetration under the original peak demand, the DR will only affect a few peak days in January and August. Therefore, the following studies focus on these two months and the critical days that are being impacted by demand response.

7.3. DR Results by Sector for Critical Days

This section presents the demand response simulation results for the distribution circuit in summer and winter at different levels of EV penetration. The simulation results illustrate demand reduction and shifting for both residential and commercial buildings on the peak days to keep the circuit peak demand with EV penetration the same as that without the EV penetration.

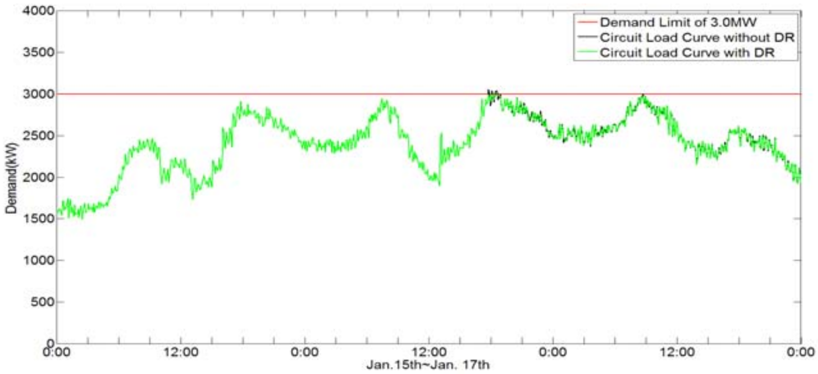
Simulation assumptions:

- Load priorities for household appliances are randomly set for the study purpose.
- The comfort zone of room temperature is randomized within the range of *(72~76)°F ±(1~2)°F*;
- The comfort zone of hot water temperature is randomized within the range of *(110~120)°F ±(5~10)°F*.
- The clothes-drying job cannot be interrupted for more than 40 minutes.
- No comfort range setting for EV charging.

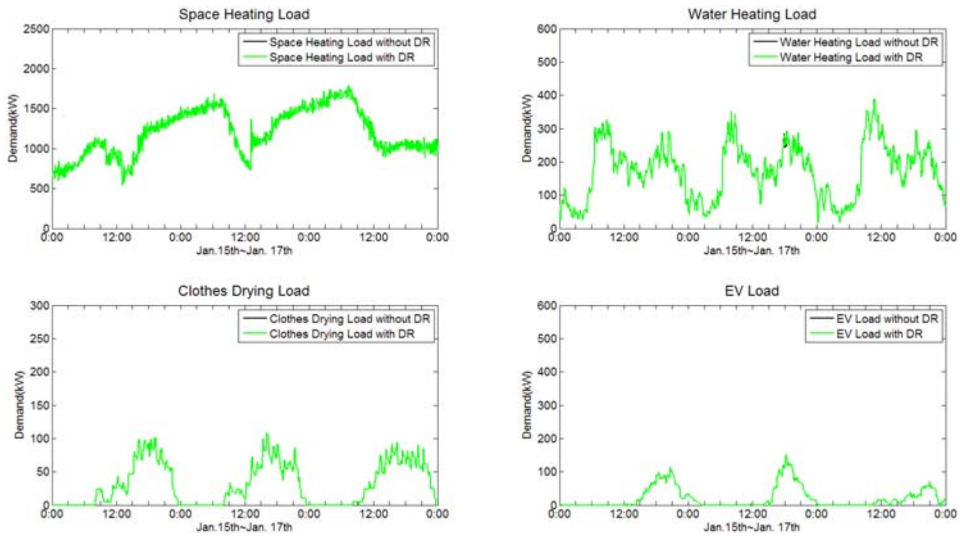
7.3.1. Winter Demand Response Results

1) 100 EV penetration

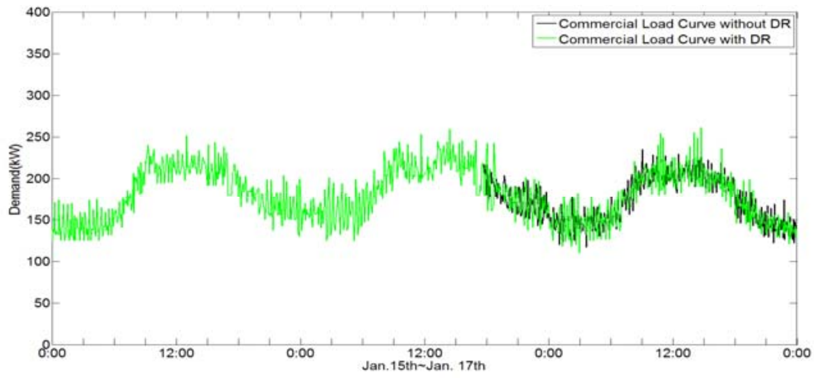
When there are 100 EVs plugged into the distribution circuit, the peak load is only a little higher than the original peak demand. The demand response can manage the circuit load profile below the original winter peak demand of 3.0MW. Fig. 7-6 (a) shows the circuit level 3-day load profile (Jan. 15^{th} ~ Jan. 17^{th}). (b) shows further details of the demand response results for the residential controllable loads and EVs for the same three days. (c) shows detailed demand response results for the commercial controllable load - space heating for the same three days.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



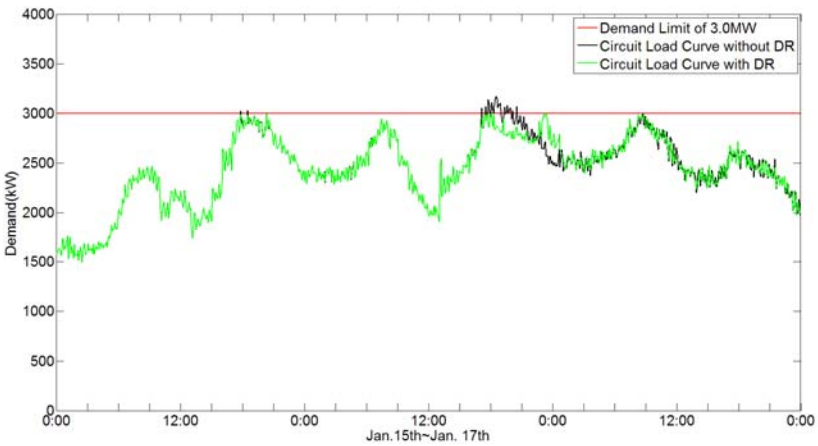
(c) Load Profiles of Commercial Space Heating

Fig. 7-6 Load Profiles w/wo Demand Response at a 100-EV Penetration Level – Winter Peak Days

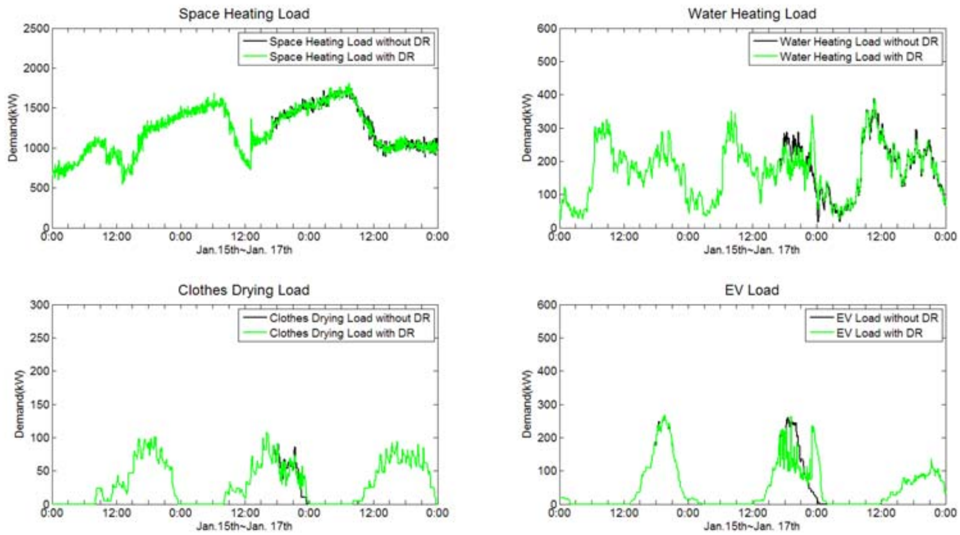
It can be seen from the load profiles that with 100 EVs plugged in, the load curves of residential appliances do not change much by the demand response to maintain the original peak demand. This means to make 100 EV penetration transparent to the distribution network, the demand response will only have a little impact on the residential consumers. Note that around noon of Jan.17th, the commercial load with DR is sometimes higher than without DR, which is a co-incidence due to the cold load pick-up after DR during the evening peak of the day before. As long as the total circuit load is below the original peak demand, there will be no control on it.

2) 200 EV penetration

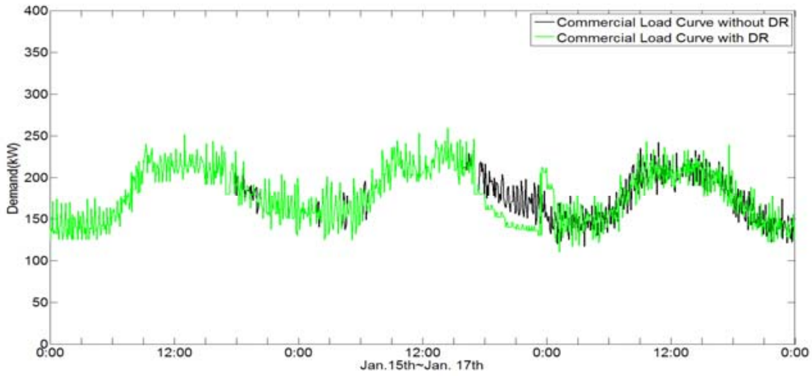
When there are 200 EVs plugged into the distribution circuit, the peak load appears higher than the original peak demand. See Jan. 15th and Jan. 16th in Fig. 7-7. Similar to Fig. 7-6, Fig. 7-7 (a) shows the circuit level 3-day load profile (Jan. 15th ~ Jan. 17th), (b) shows further details of the demand response results for the residential controllable loads and EVs for the same three days, and (c) shows detailed demand response results for the commercial controllable load - space heating for the same three days.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



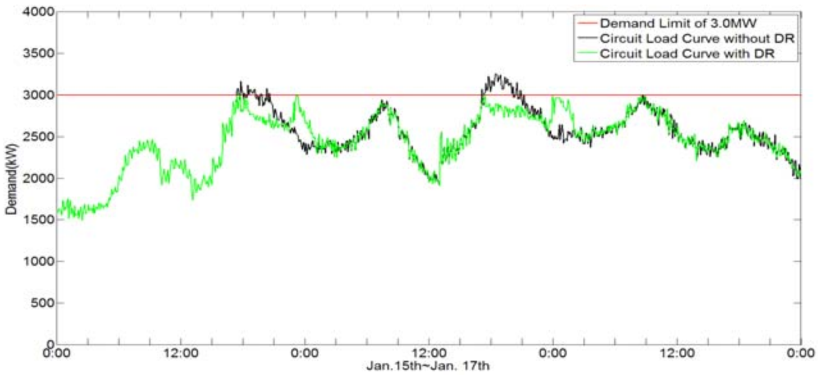
(c) Load Profiles of Commercial Space Heating

Fig. 7-7 Load Profiles w/wo Demand Response at a 200-EV Penetration Level – Winter Peak Days

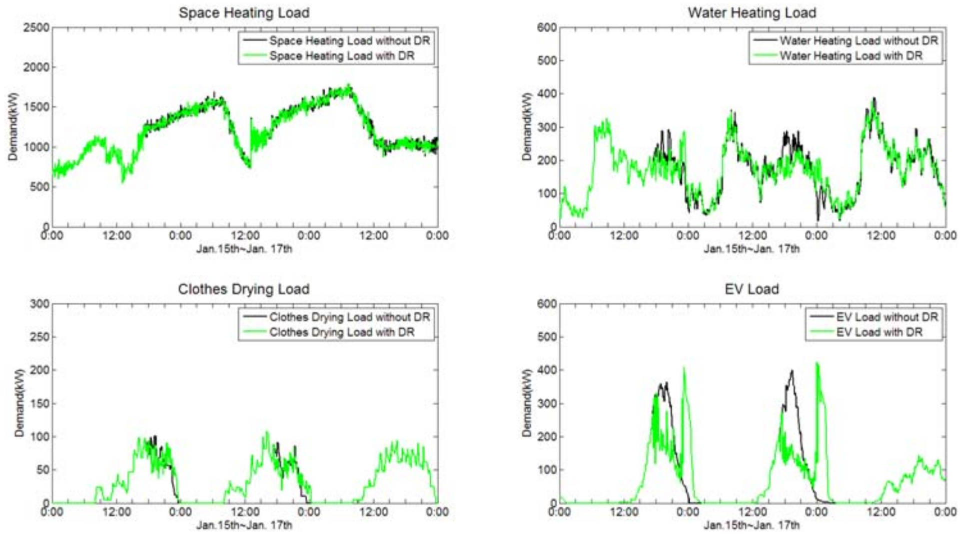
It can be seen from Fig. 7-7 that with 200 EVs plugged in, the load curves change more than the 100 EV penetration. The demand response has a higher impact on peak days. Since most commercial consumers are of low priority during the evening peak, they provide the majority of the demand reduction.

3) 300 EV penetration

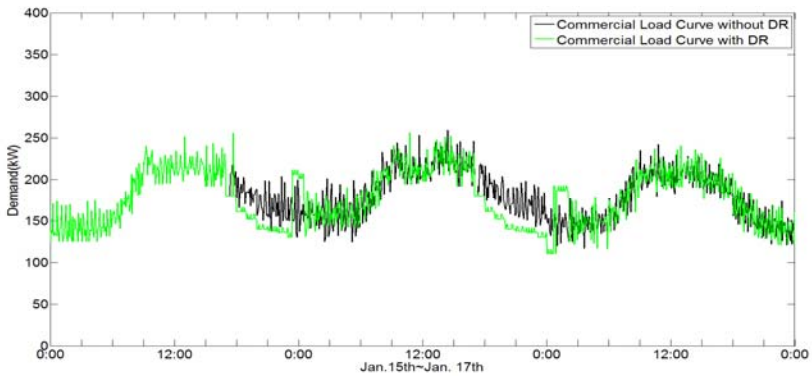
When there are 300 EVs plugged into the distribution circuit, the peak load appears to be much higher than the original peak demand. See Jan.15th and Jan. 16th in Fig. 7-8. To manage the circuit load profile below the original winter peak demand of 3.0MW, DR program has to shift or shed more loads.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



(c) Load Profiles of Commercial Space Heating

Fig. 7-8 Load Profiles w/wo Demand Response at a 300-EV Penetration Level – Winter Peak Days

It can be seen from the load profiles that with 300 EVs plugged in, the load curves change more than the 200 EV penetration. The demand response has a higher impact on peak days. Since most commercial consumers are of low priority during the evening peak, they provide the majority of the demand reduction. The residential load profiles before and after the DR show that the EV charging load is the one affected the most, followed by water heating and clothes-drying loads. This is due to the comfort zone setting assumptions mentioned at the beginning of Section 7.3. As the room temperature comfort zone is very sensitive, the space heating load cannot be controlled much. Even it is in DR status, the space heater will soon be turned on to make up the room temperature. Therefore the space heating load shows the least change.

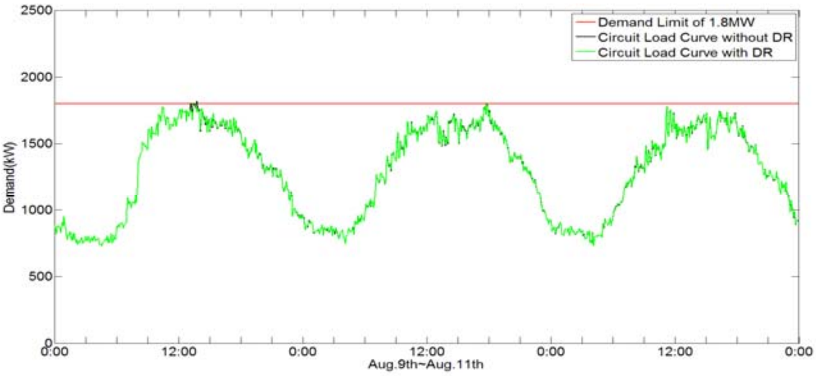
7.3.2. Summer Demand Response Results

As can be seen in Fig. 7-5, the daily peak demand values are closer to each other in summer load profiles than in the winter. Therefore there will be more “critical days” in summer than in winter when the EV fleet is plugged in. In this case study, there are 3 to 7 critical days in summer depending on the EV penetration level. The highest ones are picked for detailed study. The original peak demand of August is 1.7MW, which is set to be the demand limit, shown as a red line in the simulation results.

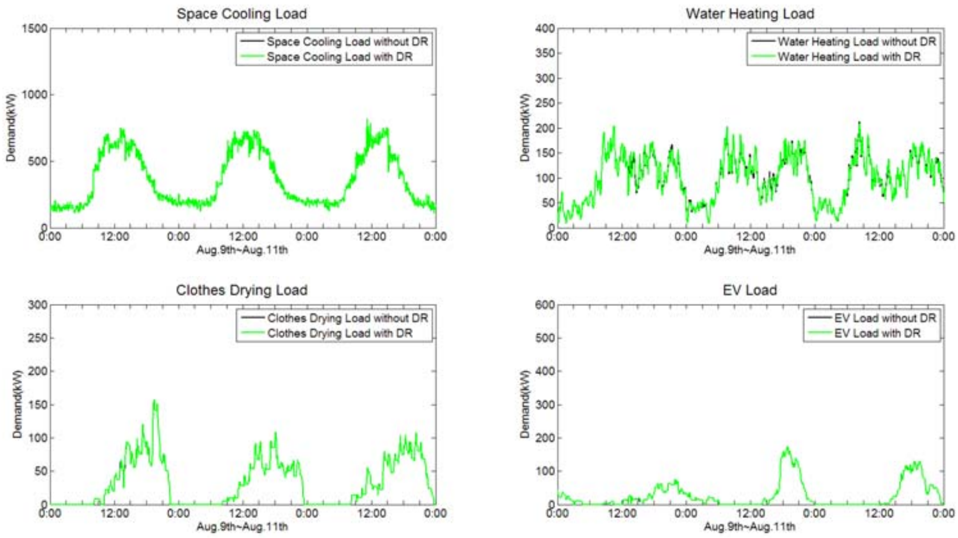
1) 100 EV penetration

(c) Load Profiles of Commercial Space Cooling

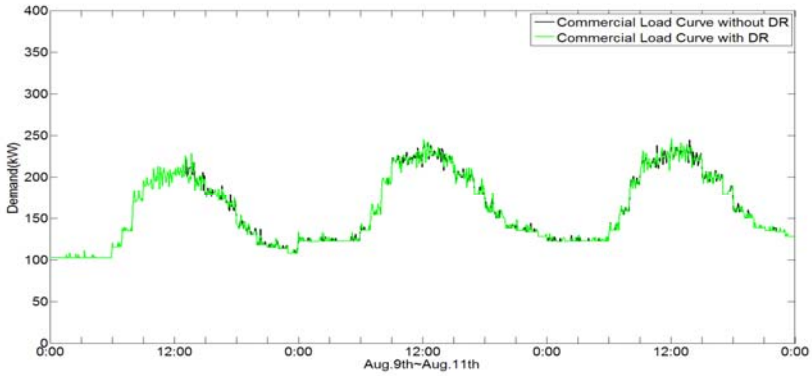
Fig. 7-9 (a) shows the circuit level 3-day load profile (Aug. 9th ~ Aug. 11th), (b) shows further details of the demand response results for the residential controllable loads and EVs for the same three days,and (c) shows detailed demand response results for the commercial controllable load - space cooling for the same three days.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



(c) Load Profiles of Commercial Space Cooling

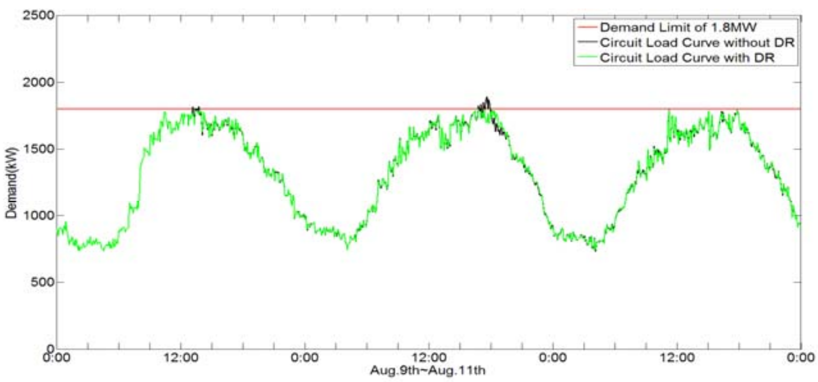
Fig. 7-9 Load Profiles w/wo Demand Response at a 100-EV Penetration Level – Summer Peak Days

It can be seen from the load profiles that with 100 EVs plugged in, the load curves do not change much, thus demand response will only have a little impact even on the peak day.

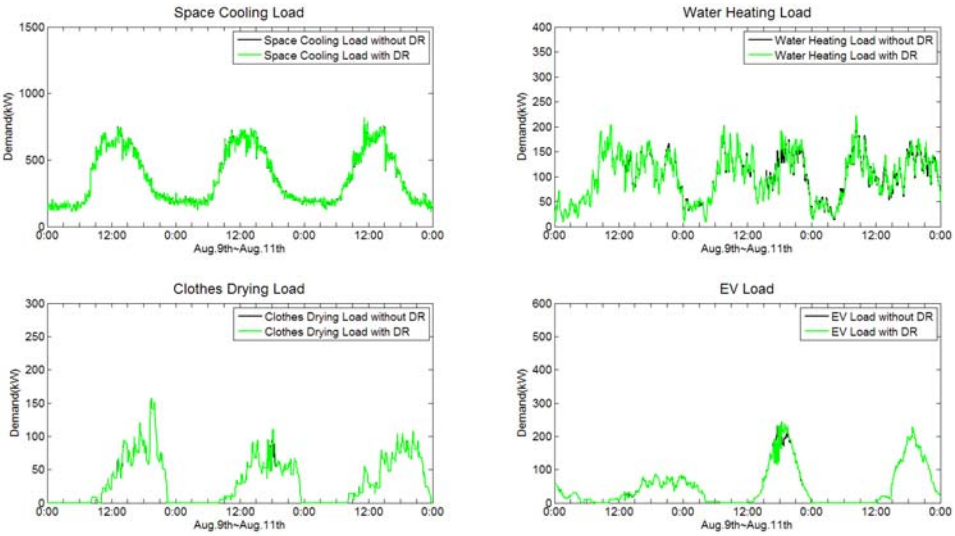
2) 200 EV penetration

(c) Load Profiles of Commercial Space Cooling

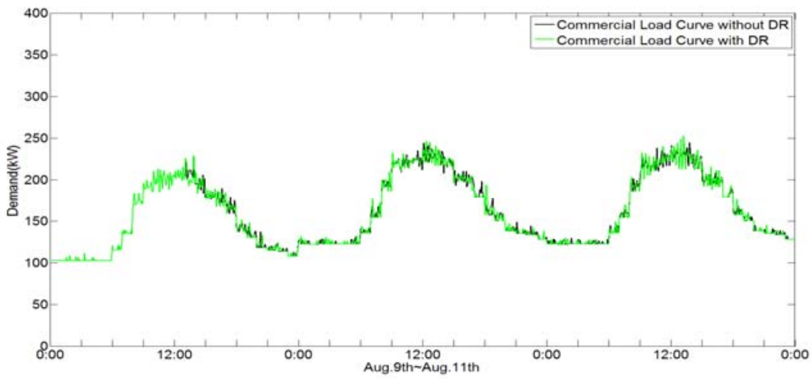
Fig. 7-10 (a) shows the circuit level 3-day load profile (Aug. 9th ~ Aug. 11th) with 200 EVs, (b) shows further details of the demand response results for the residential controllable loads and EVs for the same three days, and (c) shows detailed demand response results for the commercial controllable load - space cooling for the same three days.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



(c) Load Profiles of Commercial Space Cooling

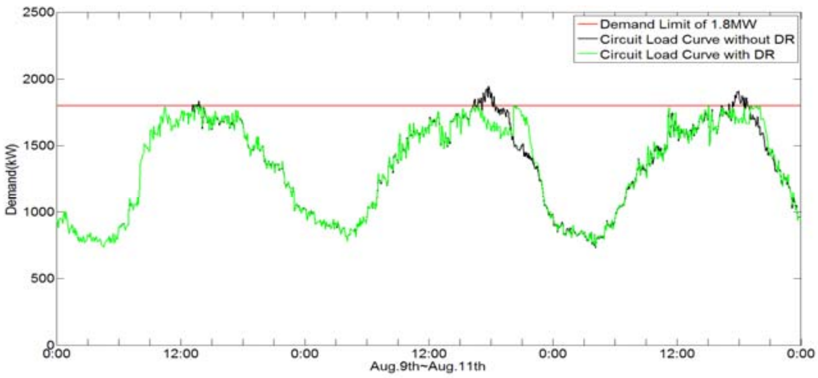
Fig. 7-10 Load Profiles w/wo Demand Response at a 200-EV Penetration Level – Summer Peak Days

It can be seen from the load profiles that with 200 EVs plugged in, the load curves change more than with the 100 EV penetration. The demand response has a higher impact on the peak days.

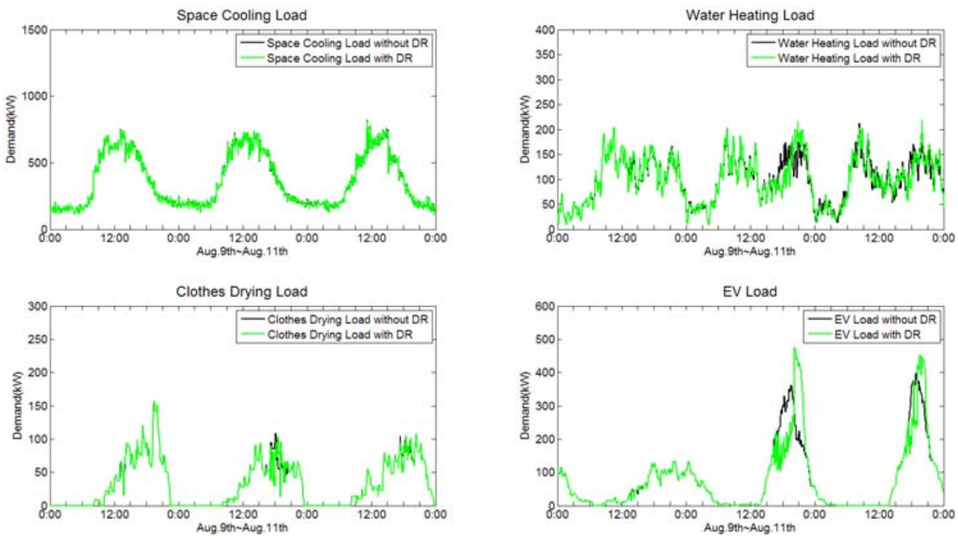
3) 300 EV penetration

(c) Load Profiles of Commercial Space Cooling

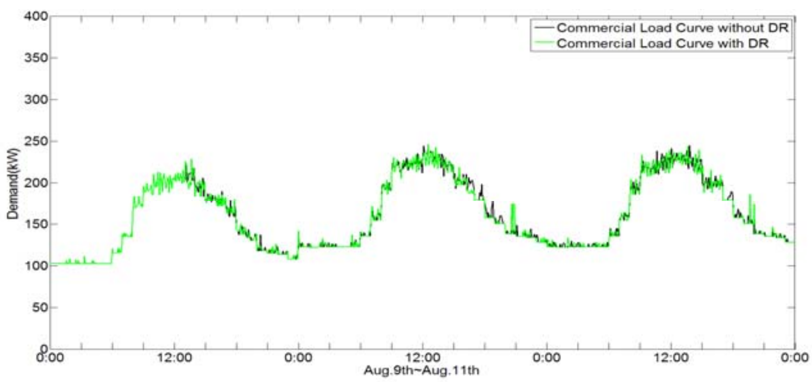
Fig. 7-11 (a) shows the circuit level 3-day load profile (Aug. 9th ~ Aug. 11th) with 300 EVs, (b) shows further details of the demand response results for the residential controllable loads and EVs for the same three days, and (c) shows detailed demand response results for the commercial controllable load - space heating for the same three days.



(a) Circuit Load Profiles



(b) Load Profiles of Residential Appliances and EVs



(c) Load Profiles of Commercial Space Cooling

Fig. 7-11 Load Profiles w/wo Demand Response at a 300-EV Penetration Level – Summer Peak Days

It can be seen from the load profiles that with 300 EVs plugged in, the load curves change more than that with 200 EVs. The demand response has a higher impact on the peak days. Similar to winter peak days, the residential load profiles before and after the DR show that the EV charging load is mostly affected, followed by water heating and clothes-drying loads due to the comfort zone settings. Note that there are spikes at around 9 pm after DR for water heaters, clothes dryers and EVs. This is because of the cold load pick-up (water heaters) and load shifting (clothes dryers and EVs). As long as the total circuit demand is below the limit (original peak demand without EV penetration), it is accepted in the DR program.

7.4. Example of Household Demand Response

As described in the methodology section, when a house receives the demand limit signal, it will check its total demand to see whether it is over the limit. If so, a demand response has to be performed to meet the requirements. The simulations described in this section are focused on the residential category, which has multiple appliances to control. Note that this section will only focus on the case of 300 EV penetrations, which is the most severe case in the presented study.

This section discusses the detailed demand response strategy implemented at a household level. For each critical day as discussed in Section 7.3, two houses with different sizes are shown as examples. For winter, the critical days are January 15th and January 16th. For summer, the critical days are August 10th and August 11th. To show the load management between appliances, the houses are chosen based on two criteria: a) it has to be equipped with all four controllable appliances, i.e. electric space heater, water heater, clothes dryer and EV; and b) all of the appliances are running on the critical days. The presented houses are randomly chosen to reflect DR in different houses with different sizes.

7.4.1. Winter Examples

1) January 15th

   a) House No. 108 (2400 ft^2)

Table 7-3 lists the priority and the rated power for each household appliance. The priorities are set to decide the load shedding sequence when there is a demand limit, 1 to 4 from highest to lowest. However, the preference setting will change the load priorities dynamically in order to keep the loads to operate within the convenience ranges.

Table 7-3 Load Priorities and Convenience Preference of House No.108 in Winter

	Space Heating	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	6 *kW*	4.5 *kW*	5.3 *kW*	3.3 *kW*
Comfort Setting	70 ℉±1 ℉	115 ℉±5 ℉	-	-

Fig. 7-12 shows the overall results of the household load profile from Jan. 15th at 18:00 to Jan. 16th at 3:00 before and after the demand response.

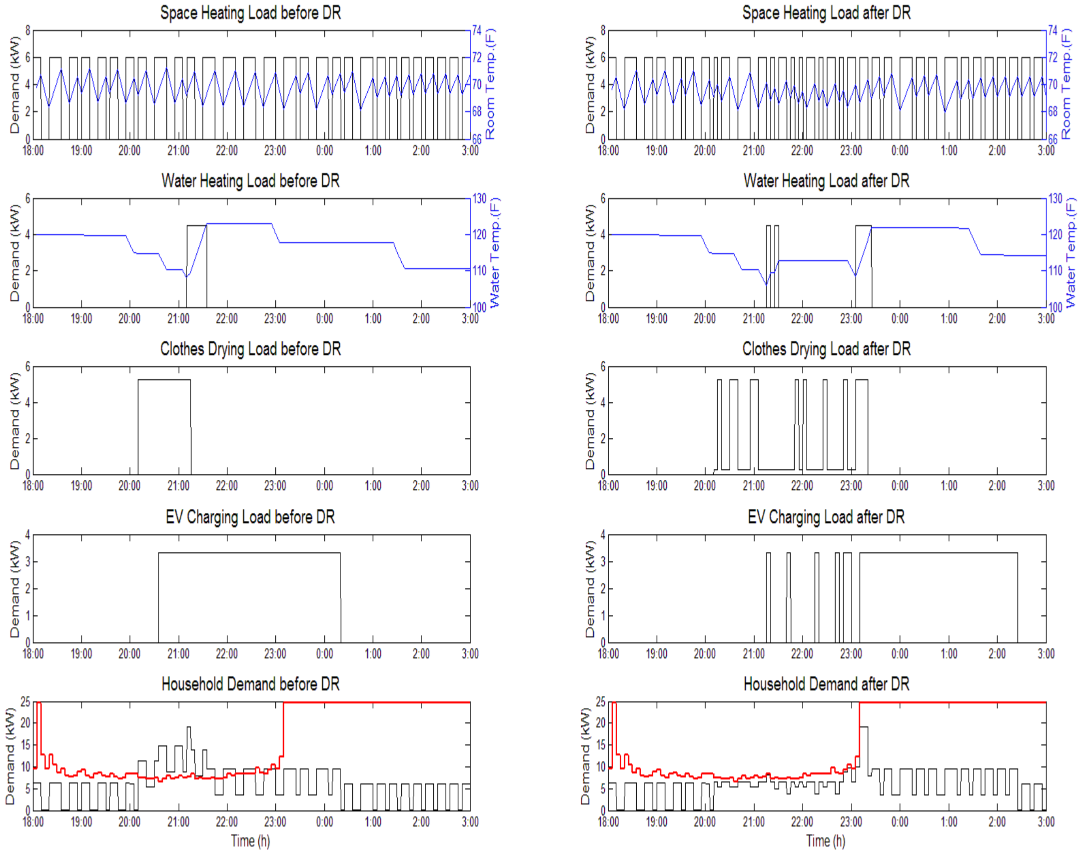


Fig. 7-12 No. 108 Household Load Profiles before and after DR during Jan. 15th 18:00~ Jan. 16th 3:00.

The red line in the picture indicates the demand limit assigned to the house. The household load will be managed below the assigned demand limit. When the redline hits the ceiling, it means there is no demand limit during that time period, thus no load control is needed.

It can be seen from the picture that the DR starts at 20:10, when the clothes dryer is turned on while the space heater is running. The demand limit at the time is 7.5kW, which is less than the total household demand. The heating coil of the clothes dryer has to stay off for five minutes to let the space heater recover the room temperature. Though the clothes-drying job is of a higher priority, the specified comfort levels must be met. After the room temperature rises into the specified comfort range, the space heater starts to cycle with the clothes dryer between 20:10 and 20:40 to keep the total household demand under the limit of 7.5kW. The EV is plugged in at 20:40 and the water heater is turned on at 21:10. The four appliances cycled according to their pre-set priorities and the comfort range till 23:10, when there is no demand limit for the house.

b) House No. 200 (1500 ft^2)

Table 7-4 lists the priority and rated power for each household appliance. The space heater and clothes dryer are of lower rated power since the house is of a smaller size than House No. 108.

Table 7-4 Load Priorities and Convenience Preference of House No.200 in Winter

	Space Heating	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	4 *kW*	4.5 *kW*	4.2 *kW*	3.3 *kW*
Comfort Setting	69 ℉±1 ℉	120 ℉±5 ℉	-	-

Fig. 7-13 shows the overall results of the household load profile from Jan. 15th at 18:00 to Jan. 16th at 3:00 before and after the demand response. Similarly, the red line in the picture indicates the demand limit assigned to the house, below which the household load should be managed. When the redline hits the ceiling, it means there is no demand limit during that time period, thus no load control is needed.

It can be seen from the picture that the DR starts at 20:30, when the EV is plugged in while the space heater is running. To keep the household demand under the limit of 7.2kW, the EV starts to cycle with space heater. Though the EV is of higher priority, it has to stop charging from time to time to allow the space heater to keep the room temperature within the preset comfort range. Similarly from 21:10 to 22:20, the clothes dryer is cycling with the space heater to keep the household demand under the limit of 8kW.

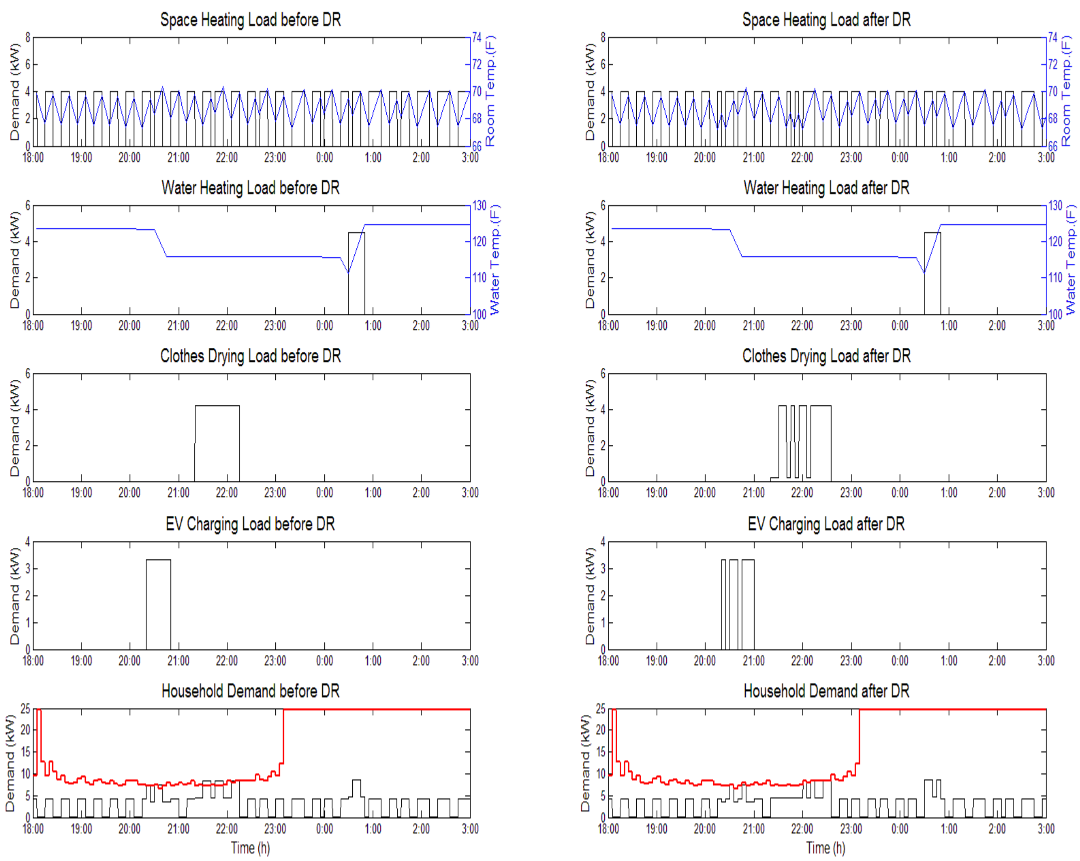


Fig. 7-13 No. 200 Household Load Profiles before and after DR during Jan. 15th 18:00~ Jan. 16th 3:00.

2) January 16th

a) House No. 68 (2000 ft^2)

Table 7-5 lists the priority and the rated power for each household appliance.

Table 7-5 Load Priorities and Convenience Preference of House No.68 in Winter

	Space Heating	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	5 kW	4.5 kW	4.2 kW	3.3 kW
Comfort Setting	68 ℉±2 ℉	115 ℉±5 ℉	-	-

Fig. 7-14 shows the overall results of the household load profile from Jan. 16th at 17:00 to Jan. 17th at 2:00 before and after the demand response.

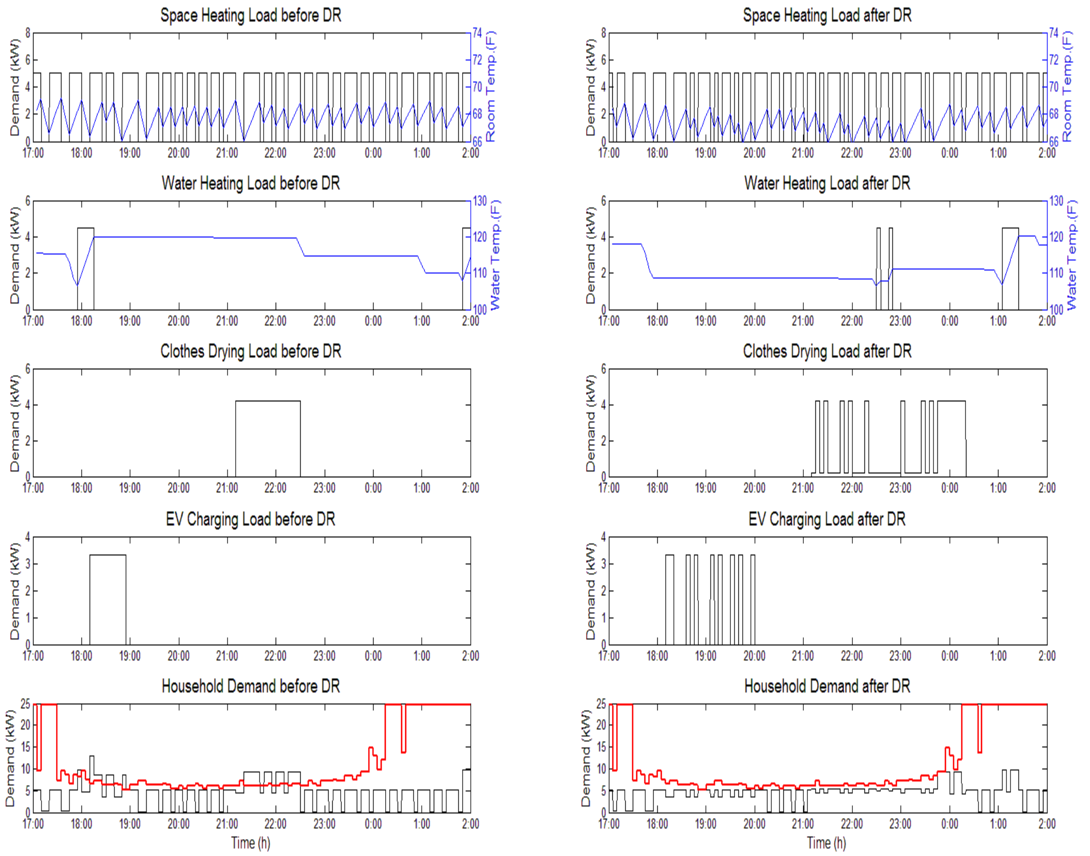


Fig. 7-14 No. 68 Household Load Profiles before and after DR during Jan. 16th 17:00~ Jan. 17th 2:00.

It can be seen from the picture that the DR starts at 17:55, when the space heater happens to run together with the water heater. To keep the household demand under the limit of 9kW, the water heater is stopped to allow the space heater to operate as the space heater has a higher priority. Then the EV is plugged in at 18:10, which has a lower priority than the space heater but a higher priority than the water heater. To keep the total household demand under the limit of 7.5kW at the time, the EV charging is stopped from time to time to keep the space heater running. After the EV is fully charged, the clothes dryer resumes its operation at 21:10, which is also stopped from time to time to keep the space heater running. The clothes-drying job is compensated after 23:00, when the household demand is naturally under the demand limits.

b) House No. 504 (1600 ft^2)

Table 7-6 lists the priority and rated power for each household appliance.

Table 7-6 Load Priorities and Convenience Preference of House No.504 in Winter

	Space Heating	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	4 *kW*	4 *kW*	4.2 *kW*	3.3 *kW*
Comfort Setting	70 ℉±1 ℉	115 ℉±5 ℉	-	-

Fig. 7-15 shows the overall results of the household load profile from Jan. 16th at 17:00 to Jan. 17th at 2:00 before and after the demand response.

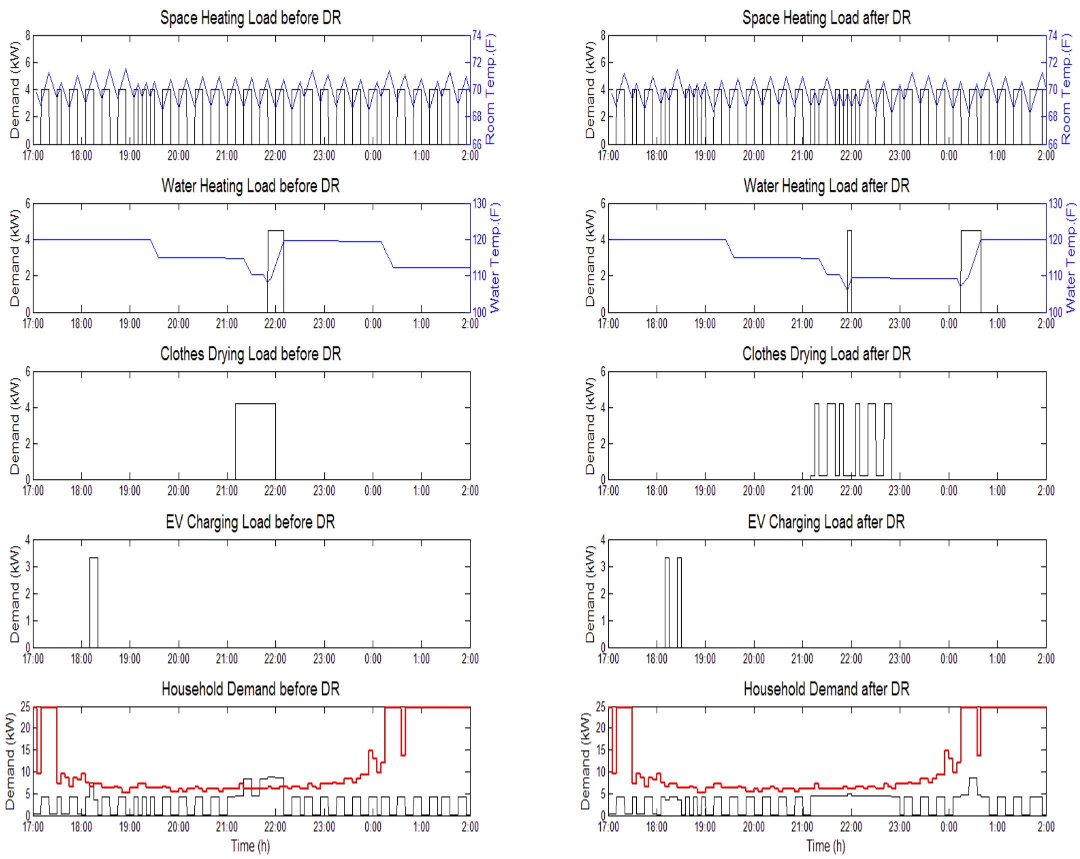


Fig. 7-15 No. 504 Household Load Profiles before and after DR during Jan. 16th 17:00~ Jan. 17th 2:00.

It can be seen from the picture that the DR starts at 18:10, when the space heater starts running while the EV is charging. To keep the household demand under the limit of 6.5kW, the EV charging is stopped to allow the space heater to operate since the latter has a higher priority. Then between 21:10 and 22:50, the space heater, the clothes dryer and the water heater are cycling to keep the total household demand under the chosen limits (varying between 6.2kW and 7.2kW). Note that though the water heater is of lower priority than the clothes dryer, it can still be turned on for some time to keep the hot water temperature within the comfort range.

7.4.2. Summer Examples

1) August 10th

a) House No. 16 (1500 ft^2)

Table 7-7 lists the priority and the rated power for each household appliance.

Table 7-7 Load Priorities and Convenience Preference of House No.16 in Summer

	Space Cooling	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	2 kW	4 kW	4.2 kW	3.3 kW
Comfort Setting	76 ℉±1 ℉	112 ℉±5 ℉	-	-

Fig. 7-16 shows the overall results of the household load profile from Aug. 10th at 16:00 to Aug. 11th at 1:00 before and after the demand response.

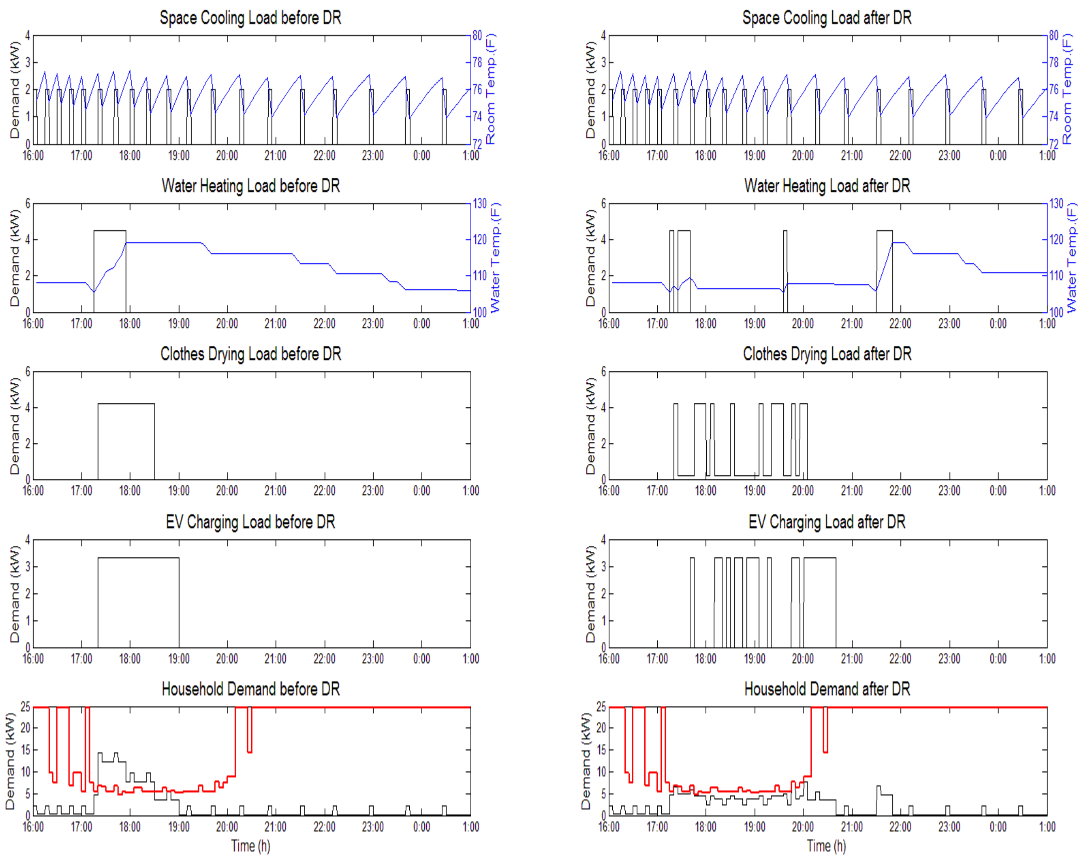


Fig. 7-16 No. 16 Household Load Profiles before and after DR during Aug. 10th 16:00~ Aug. 11th 1:00.

It can be seen from the picture that the DR starts at 17:20, when the clothes dryer and the EV start at the same time while the water heater is on. To keep the household demand under the limit of 6.7kW, the EV charging is stopped to allow the operation of the water heater and the clothes dryer since they are of higher priority. Then between 17:40 and 20:05, the clothes dryer and the water heater are cycling with each other to keep the total household demand under the limits (varying between 5.4kW and 6.9kW). The air conditioner (AC) is not affected since it has the highest priority.

b) House No. 360 (2200 ft^2)

Table 7-8 lists the priority and rated power for each household appliance. House No.360 is of a larger size therefore the household appliances are generally of higher rated powers.

Table 7-8 Load Priorities and Convenience Preference of House No. 360 in Summer

	Space Cooling	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	3kW	5 kW	5.4 kW	3.3 kW
Comfort Setting	73 ℉±1 ℉	113 ℉±5 ℉	-	-

Fig. 7-17 shows the overall results of the household load profile from Aug. 10th at 16:00 to Aug. 11th at 1:00 before and after the demand response.

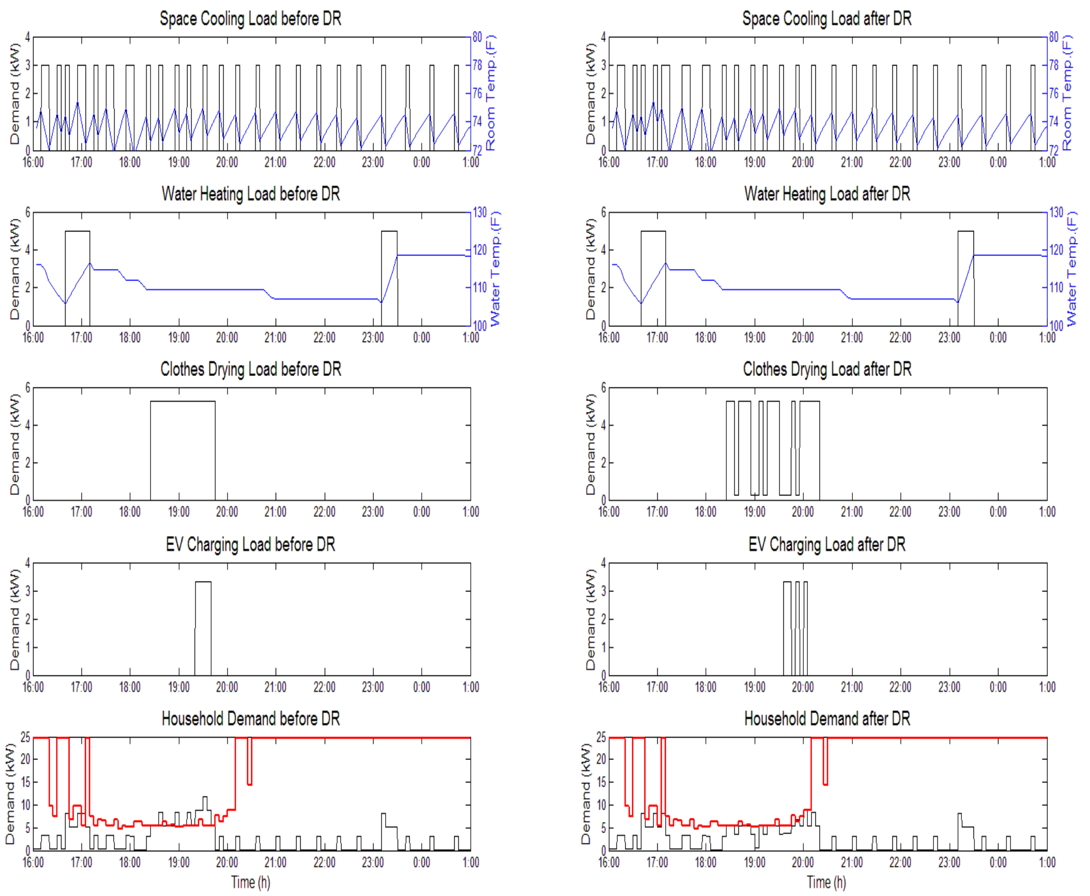


Fig. 7-17 No. 360 Household Load Profiles before and after DR during Aug. 10th 16:00~ Aug. 11th 1:00.

It can be seen from the picture that the DR starts at 17:00, when the water heater and the AC are running at the same time. To keep the household demand under the limit of 5.5kW, the air conditioner is turned off to keep the water heater running according to the priority settings. At 18:45, the AC is turned on while the clothes dryer is running. Then the heating coil of the clothes dryer is turned off to keep the AC on. From 19:20 to 20:05, the EV is cycling with the clothes dryer and the AC according to their priorities and comfort setting requirements.

2) August 11th

a) House No. 66 (2000 ft^2)

Table 7-9 lists the priority and the rated power for each household appliance.

Table 7-9 Load Priorities and Convenience Preference of House No. 66 in Summer

	Space Cooling	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	3 *kW*	4.5 *kW*	5.5 *kW*	3.3 *kW*
Comfort Setting	78 ℉±1 ℉	115 ℉±5 ℉	-	-

Fig. 7-18 shows the overall results of the household load profile from Aug. 11th at 16:00 to Aug. 12th at 1:00 before and after the demand response.

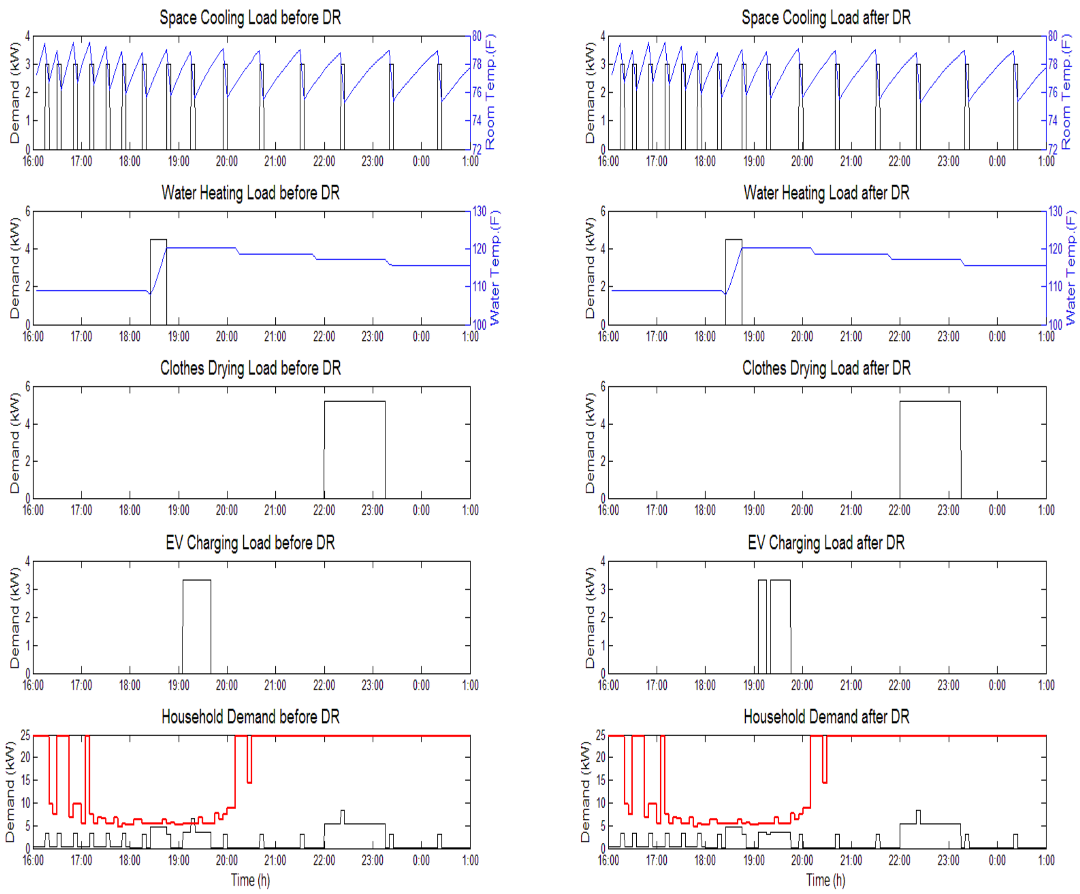


Fig. 7-18 No. 66 Household Load Profiles before and after DR during Aug. 11th 16:00~ Aug. 12th 1:00.

It can be seen from the picture that DR has only a little impact on the household demand, even though this is a house (2200 ft^2) with larger than average size (1800 ft^2). This is because the owner has a good habit of not using all appliances at the same time, especially during the peak hours. The DR control starts at 19:20, when the AC is turned on while the EV is charging. To keep the household demand under the limit of 5.5kW, the EV charging is interrupted to keep the AC on due to the priority settings.

b) House No. 574 (1800 ft^2)

Table 7-10 lists the priority and rated power for each household appliance.

Table 7-10 Load Priorities and Convenience Preference of House No. 574 in Summer

	Space Cooling	**Water Heating**	**Clothes-drying**	**EV Charging**
Rated Power	2 *kW*	4.5 *kW*	4 *kW*	3.3 *kW*
Comfort Setting	75 ℉±1 ℉	120 ℉±5 ℉	-	-

Fig. 7-19 shows the overall results of the household load profile from Aug. 11th at 16:00 to Aug. 12th at 1:00 before and after the demand response.

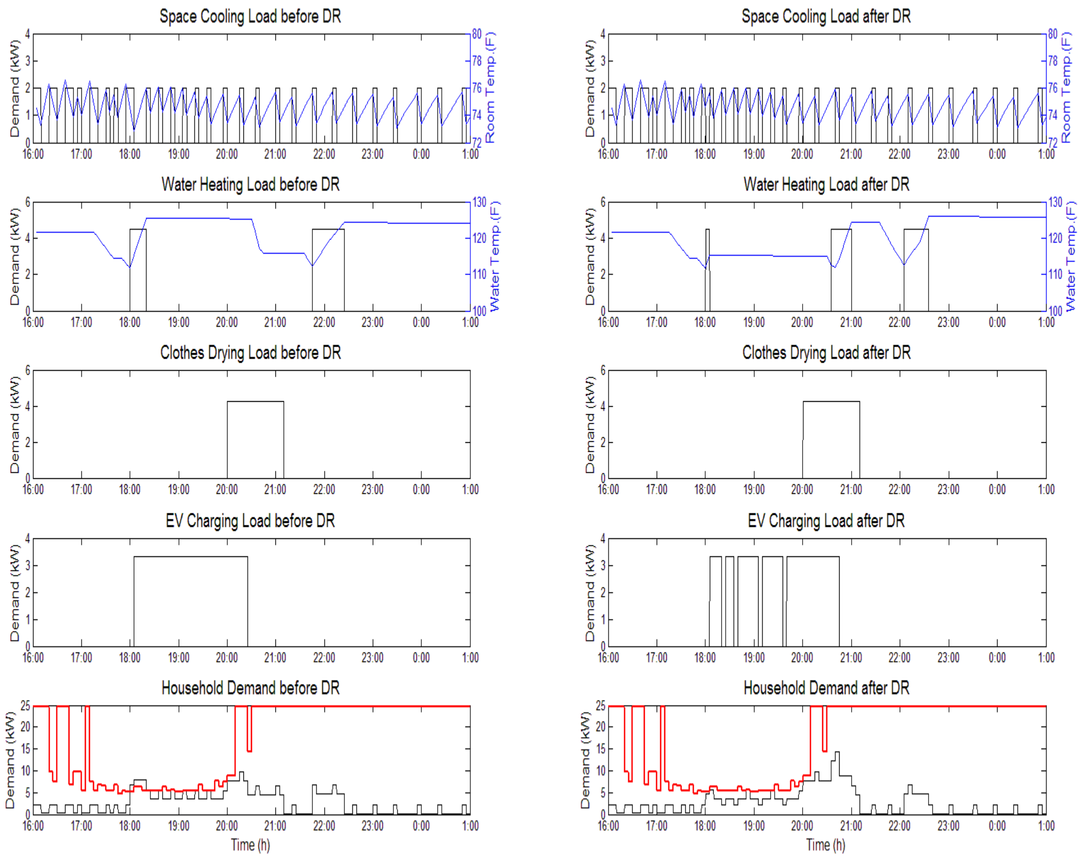


Fig. 7-19 No. 574 Household Load Profiles before and after DR during Aug. 11th 16:00~ Aug. 12th 1:00.

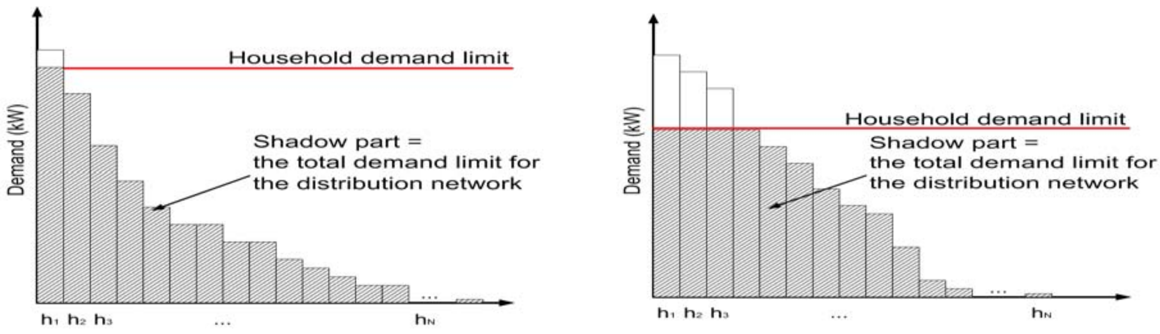
It can be seen from the picture that the DR starts at 18:00, when the water heater and the AC are running at the same time. To keep the household demand under the limit of

5.2kW, the AC is turned off to keep the water heater running even though the AC has a higher priority. This is because the water heater has to be on to keep the hot water temperature within the comfort range. At 18:05, the EV is plugged in. The water heater is turned off due to its low priority. From 18:05 to 19:40, the EV charging is interrupted from time to time to keep AC running due to the priority settings. After 19:40, the demand limit is no longer having impact on the appliances.

7.4.3. Findings from Household DR Results

It can be seen from both winter and summer household DR results that the proposed demand response strategy is able to manage the household load under the given demand limits. The following observations can be made from the household DR results:

1) In each time step, the demand limit is kept at the same level for each house to maintain consistency of the proposed DR program. However, as the time goes by, the demand limit will be changing along with the time. Generally speaking, during peak hours, the demand limit is low; during the non-peak hours, the demand limit is high or there may not be any demand limit. This can be explained by Fig. 7-20, which has also been described in Section 5.2.2. As the control target is to maintain the shadow area smaller than or equal to the original circuit demand limit, if most of the houses are of low demand, the household demand can be high and only very few houses need to be controlled, as shown in (a). On the other hand, if most of the houses are consuming much more electricity, the household demand limit is then lowered to keep the total circuit demand below the threshold, as shown in (b).



(a) High Household Demand Limit Case (b) Low Household Demand Limit Case

Fig. 7-20 Decision of Household Demand Limit Allocation

2) The impact of the DR on the household load profiles is not directly related to the house size. It is not always the case that houses with larger size and higher appliance power consumption will have to shift or reduce the load when there is demand limit. Mainly, the DR impacts are more related to the life style, i.e. whether the consumer has a habit of turning on many appliances at the same time.
3) As the room temperature is more sensitive to the control, to maintain the consumer comfort level, the HAN control center tends to keep space heating/cooling appliances on regardless of their original priories.

7.5. Impact of DR on Consumers' Convenience Indices

To evaluate the demand response potential, i.e. how much demand response can be accepted in the studied circuit, the consumer comfort indices are calculated and presented in this section according to the methodology presented in Chapter 6.

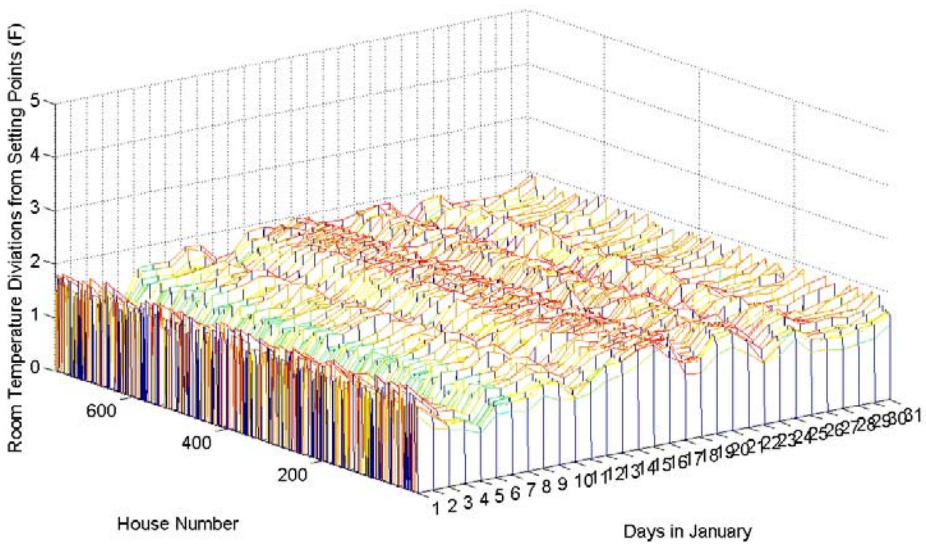
7.5.1. Residential Consumer Comfort Level

For residential consumers, the consumer comfort indices represent the room temperature, hot water temperature, clothes-drying time and EV charging time.

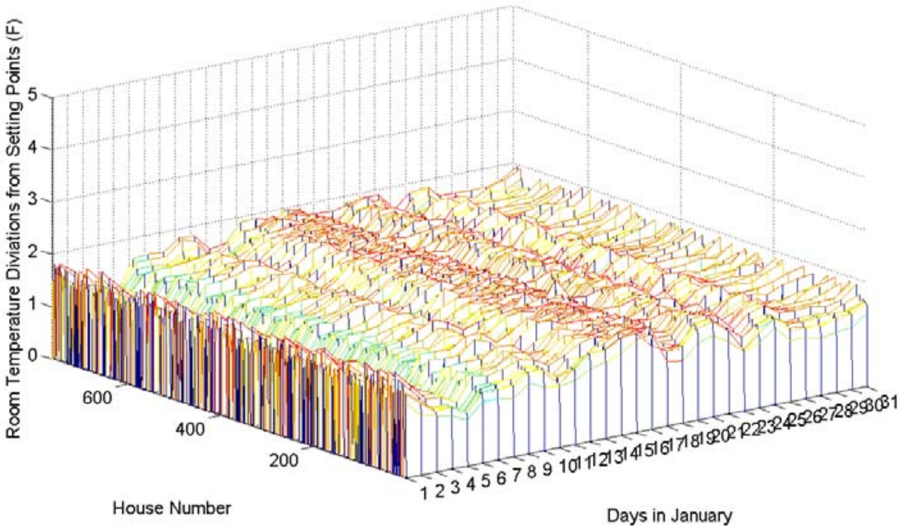
1) Winter

   a. Space Heating

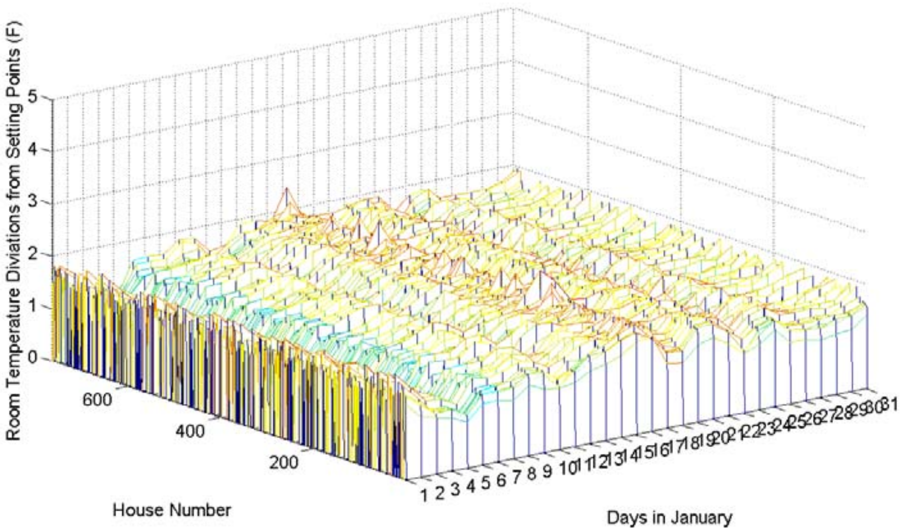
   Fig. 7-21 shows the space heating comfort indices – room temperature deviation from the set point, (a) is the base case, (b) shows 100 EV penetration, (c) shows 200 EV penetration, and (d) shows 300 EV penetration.



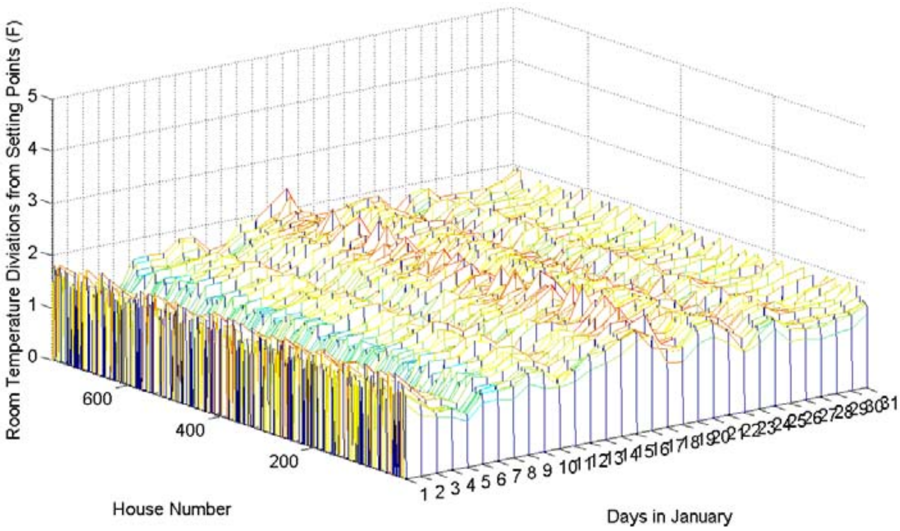
(a) Space Heating Comfort Level Base Case – no EV



(b) Space Heating Comfort Level – 100 EVs



(c) Space Heating Comfort Level – 200 EVs



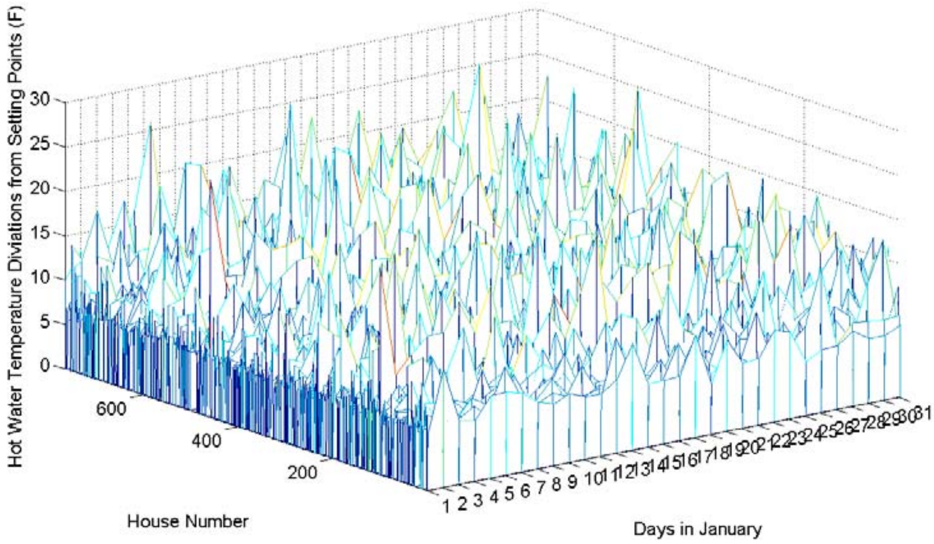
(d) Space Heating Comfort Level – 300 EVs

Fig. 7-21 Residential Space Heating Comfort Indices – January

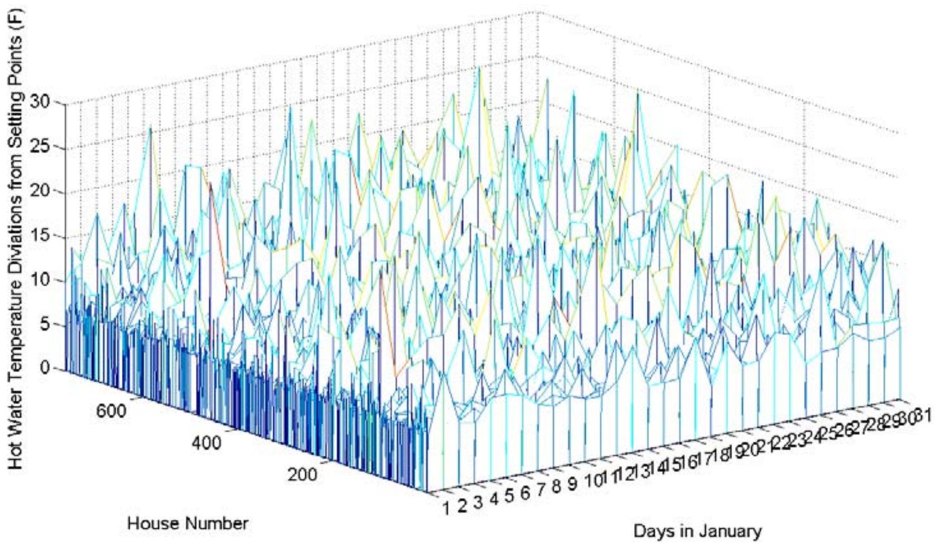
It can be seen from these figures that a larger EV fleet penetration does not incur more impact on the space heating comfort level, i.e. the room temperature deviation does not increase too much when there are more EVs plugged in to the distribution network. This is because the room temperature has a more strict comfort zone setting (only 1^oF to 2^oF deviation allowed), thus the DR strategy generally tries to keep the space heater on.

b. Water Heating

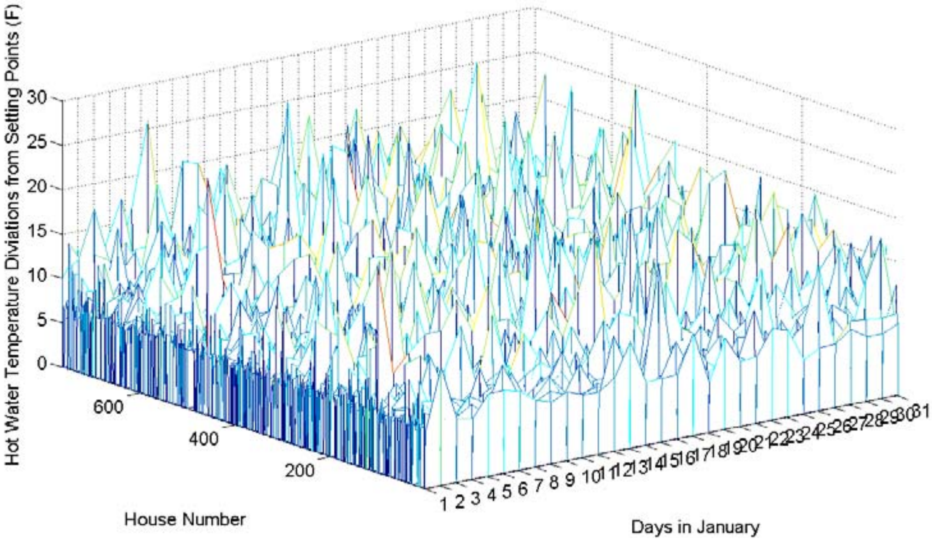
Fig. 7-22 shows the water heating comfort indices – hot water temperature deviation from the set point. (a) is the base case. (b) shows 100 EV penetration, (c) shows 200 EV penetration and (d) shows 300 EV penetration.



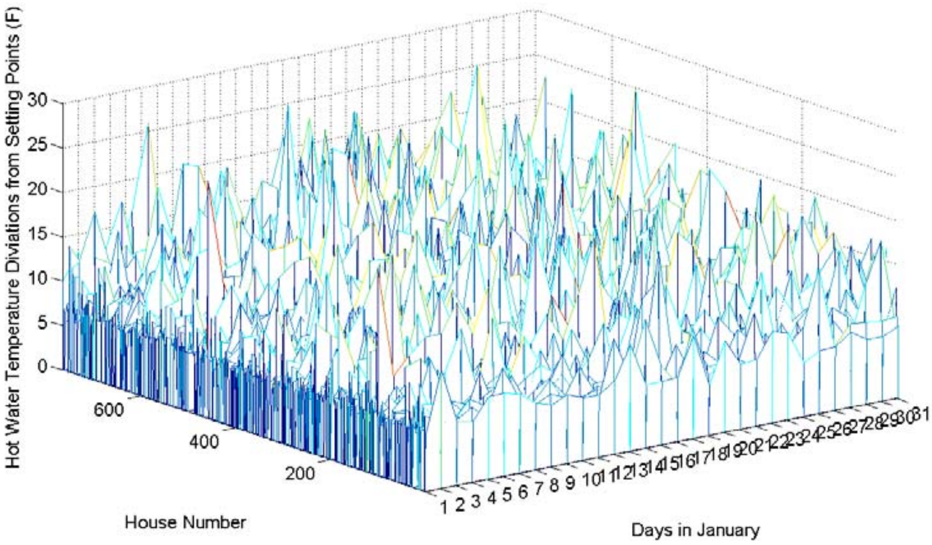
(a) Water Heating Comfort Level Base Case – no EV



(b) Water Heating Comfort Level – 100 EVs



(c) Water Heating Comfort Level – 200 EVs



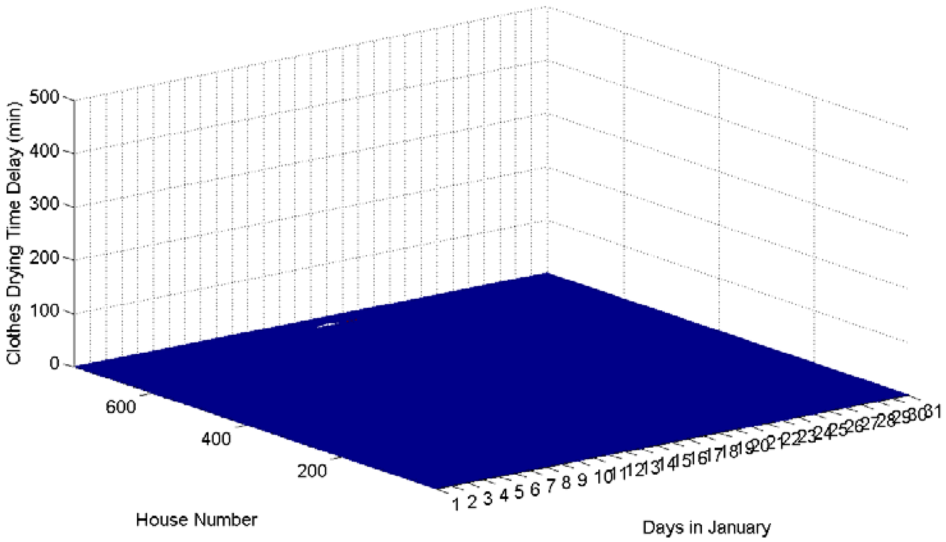
(d) Water Heating Comfort Level – 300 EVs

Fig. 7-22 Residential Water Heating Comfort Indices – January

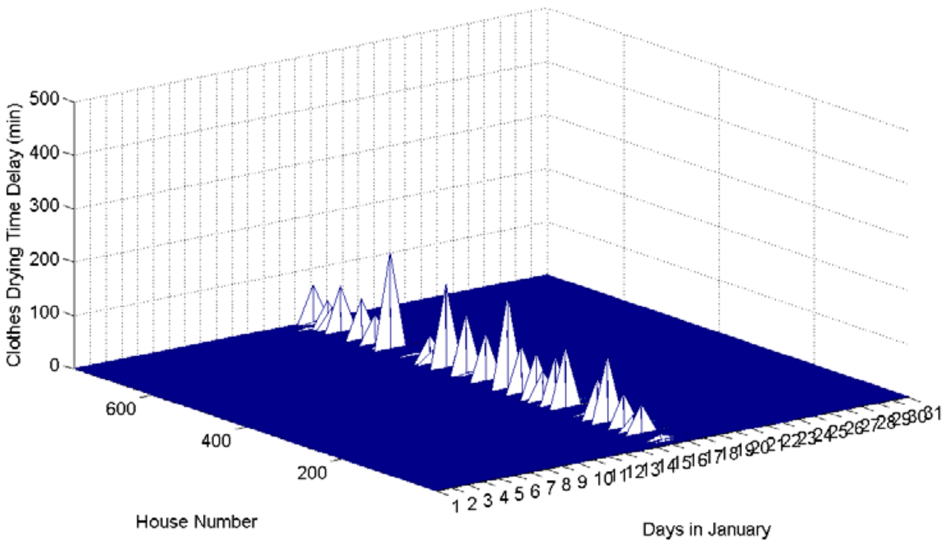
It can be seen from these figures that a larger EV fleet penetration does not incur more severe impact on the severity index (maximum temperature deviation) of the water heater comfort level. Instead, higher EV penetration level results in the increase of scale index (number of houses affected). This is because 1) water has a high specific heat capacity and does not easily lose energy when in stand-by mode. Therefore when the water heating demand is shifted to accommodate more EVs, it will not affect the hot water temperature too much. 2) Most water heater demand comes from the hot water usage compensation. i.e. to heat the inlet cold water. Therefore it is the high flow rate of the hot water usage that causes the most severe hot water temperature deviation, not demand response. Actually, no matter what priority is that of the water heater, during a high consumption hot water, the water heater will be kept on to maintain the consumer's comfort level. However, if the hot water flow rate is too high, the hot water temperature will keep on going down even the water heater is running.

c. Clothes-drying

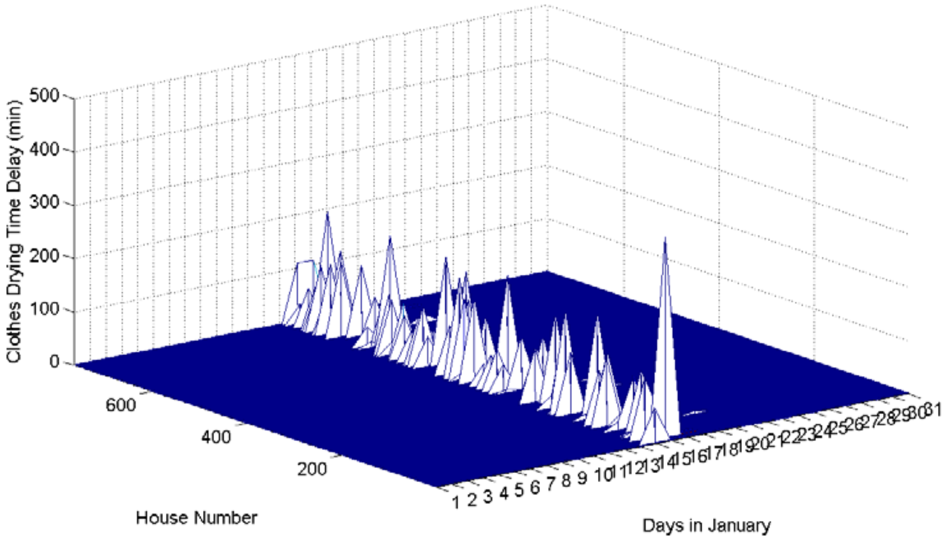
Fig. 7-23 shows the clothes-drying comfort indices – clothes-drying time delay, (a) shows 100 EV penetration, (b) shows 200 EV penetration and (c) shows 300 EV penetration.



(a) Clothes-drying Comfort Level – 100 EVs



(b) Clothes-drying Comfort Level – 200 EVs



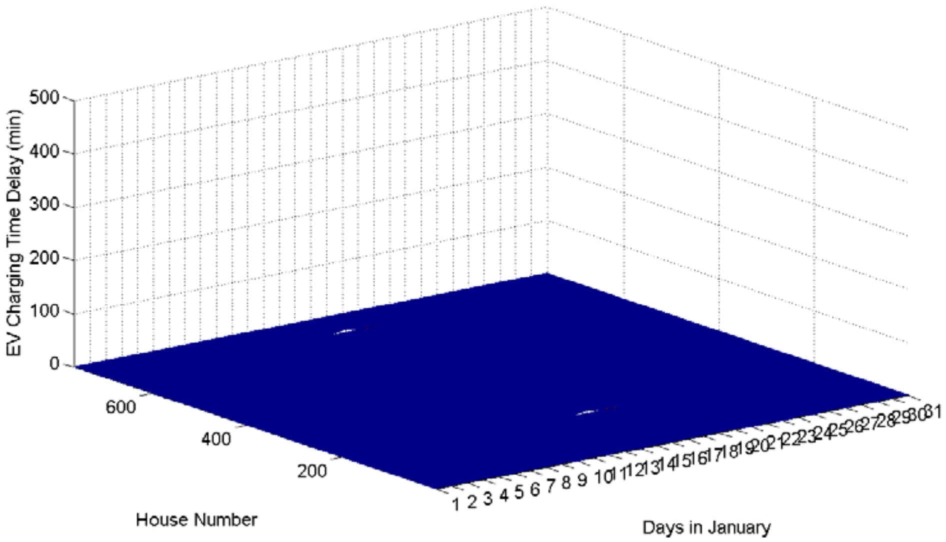
(c) Clothes-drying Comfort Level – 300 EVs

Fig. 7-23 Residential Clothes-drying Comfort Indices – January

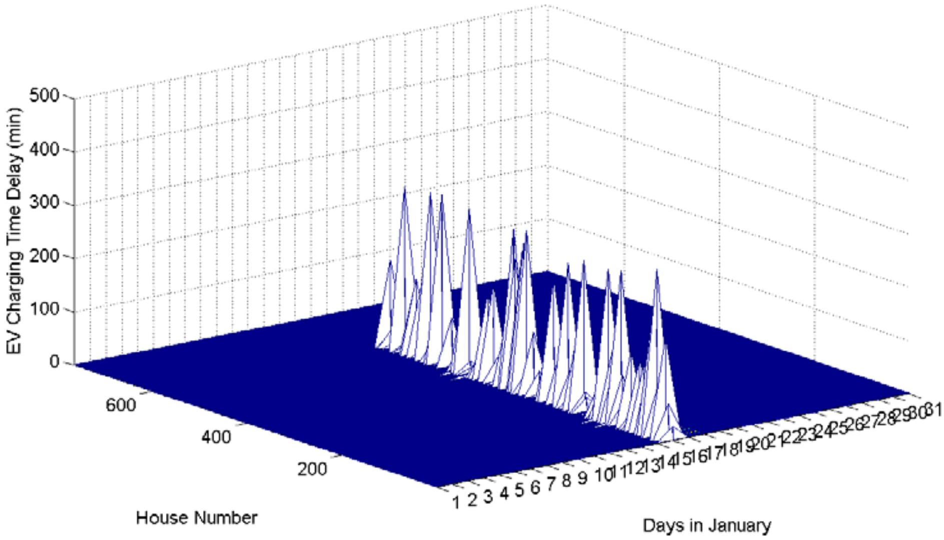
It can be seen from the pictures that the more EVs are plugged into the distribution network, the higher impact there is on the clothes-drying time delay, even though the priority settings are random. This is because the clothes dryer does not have a strict comfort zone setting so it will accept more control when the space heater and the water heater have to be on to keep the room temperature and the hot water temperature within the comfort range.

d. EV charging

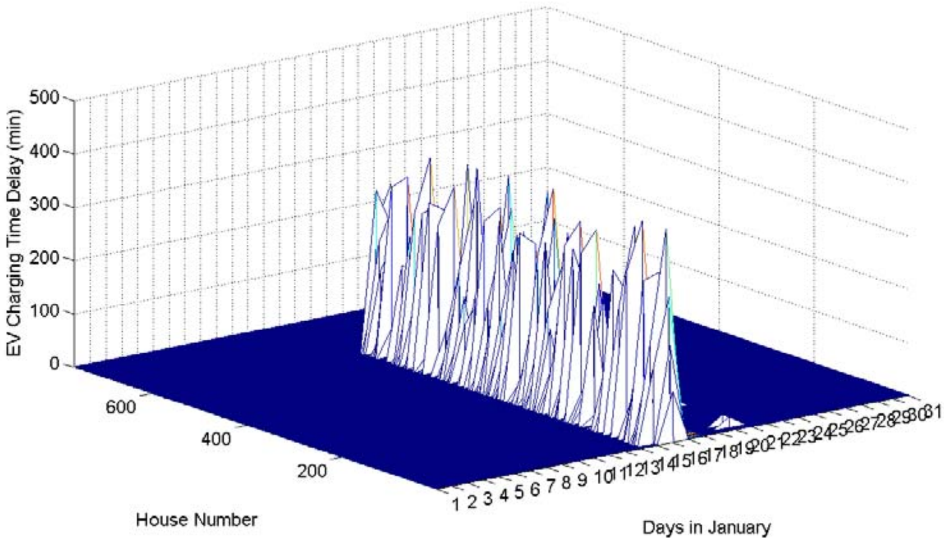
Fig. 7-24 shows the EV charging comfort indices – EV charging time delay. (a) shows 100 EV penetration, (b) shows 200 EV penetration and (c) shows 300 EV penetration.



(a) EV Charging Comfort Level – 100 EVs



(b) EV Charging Comfort Level – 200 EVs



(c) EV Charging Comfort Level – 300 EVs

Fig. 7-24 Residential EV Charging Comfort Indices – January

It can be seen from the pictures that the more EVs are plugged into the distribution network, the higher impact there is on the EV charging time delay, even though the priority settings are random. This is because the EVs do not have a strict comfort zone setting so the DR tends to control the EVs more.

It can be seen from the pictures that a higher EV penetration level will cause the DR to have higher impacts on the consumer comfort level in order to manage the household load under the household demand limit. Table 7-11 shows the circuit level residential consumer comfort indices for each appliance under different EV penetration levels in January.

Table 7-11 Residential Consumer Comfort Indices - January

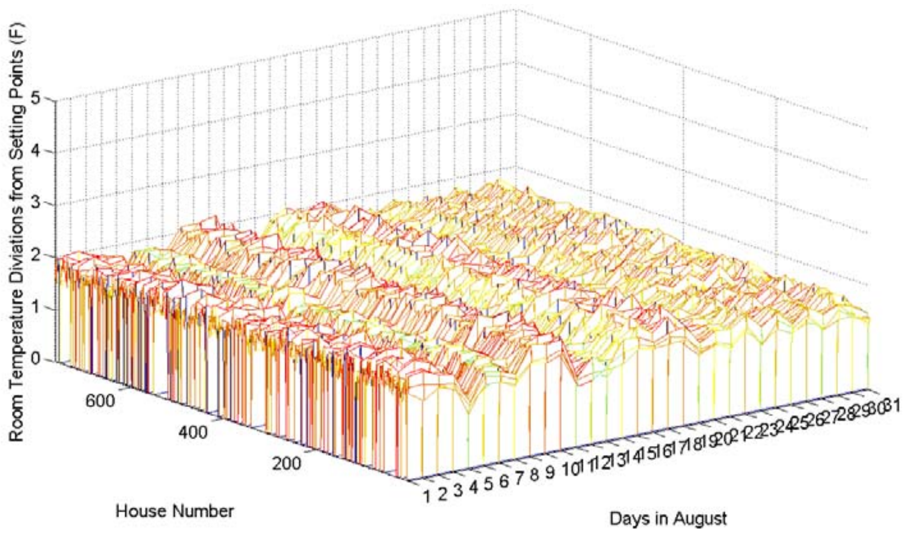
	Indices	**100 EVs**	**200 EVs**	**300 EVs**
Space Heating	Max. room temperature deviation (°F)	2.2	2.5	2.5
	Out of comfort zone duration (min)	55	60	55

	(deviation ≥2°F)			
	No. of affected houses (deviation ≥2°F)	7	62	84
Water Heating	Max. hot water temperature deviation (°F)	29.8	29.8	29.8
	Out of comfort zone duration (min) (deviation ≥20°F)	40	40	80
	No. of affected houses (deviation ≥20°F)	26	42	56
Clothes-drying	Max. clothes-drying time delay (min)	5	180	375
	No. of affected houses (delay > 60min)	0	16	26
EV Charging	Max. EV charging time delay (min)	5	315	400
	No. of affected houses (delay > 60min)	0	44	117

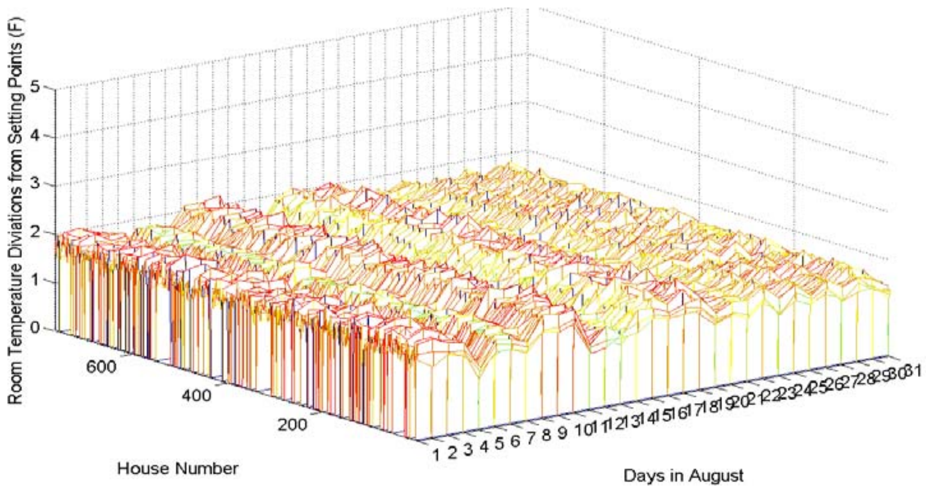
2) Summer

a. Space Cooling

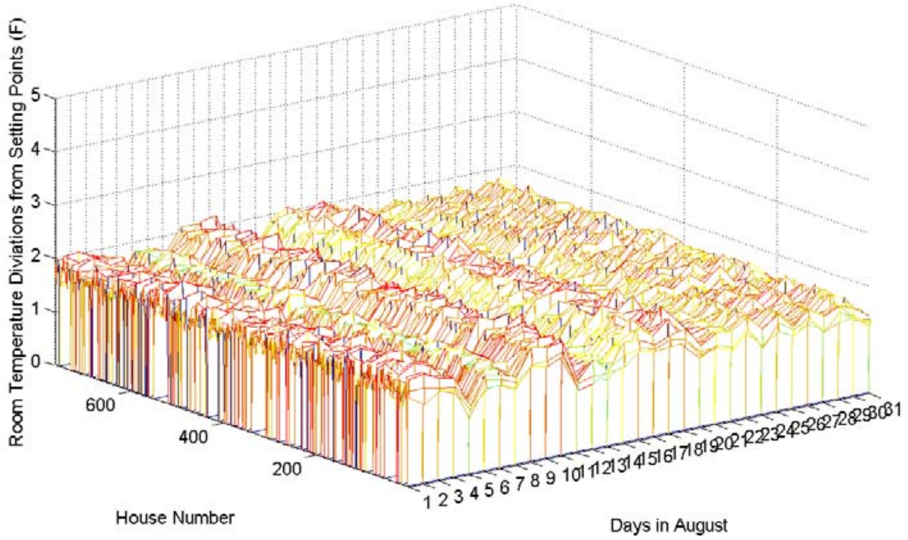
Fig. 7-25 Residential Space Cooling Comfort Level IndicesFig. 7-25 shows the space cooling comfort indices – room temperature deviation from the set point. (a) is the base case. (b) shows 100 EV penetration, (c) shows 200 EV penetration and (d) shows 300 EV penetration.



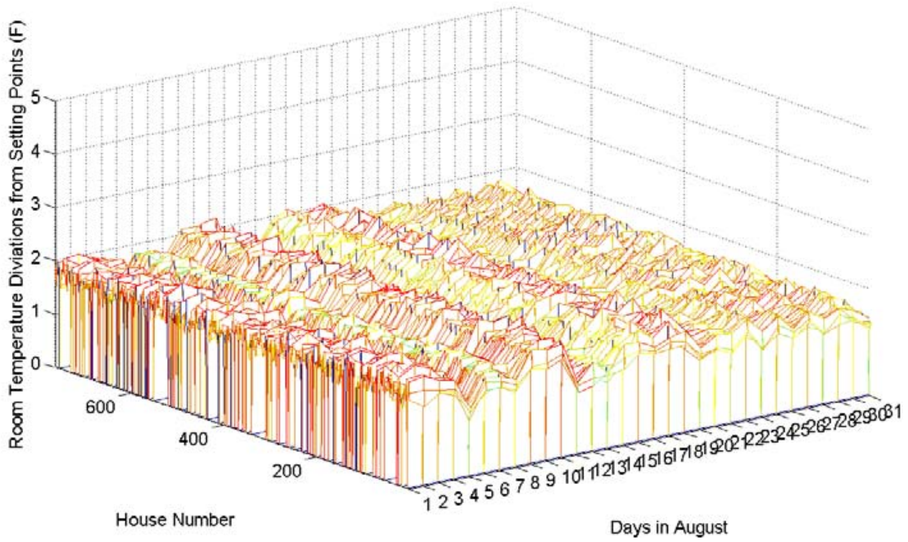
(a) Space Cooling Comfort Level Base Case – no EV



(b) Space Cooling Comfort Level – 100 EVs



(c) Space Cooling Comfort Level – 200 EVs



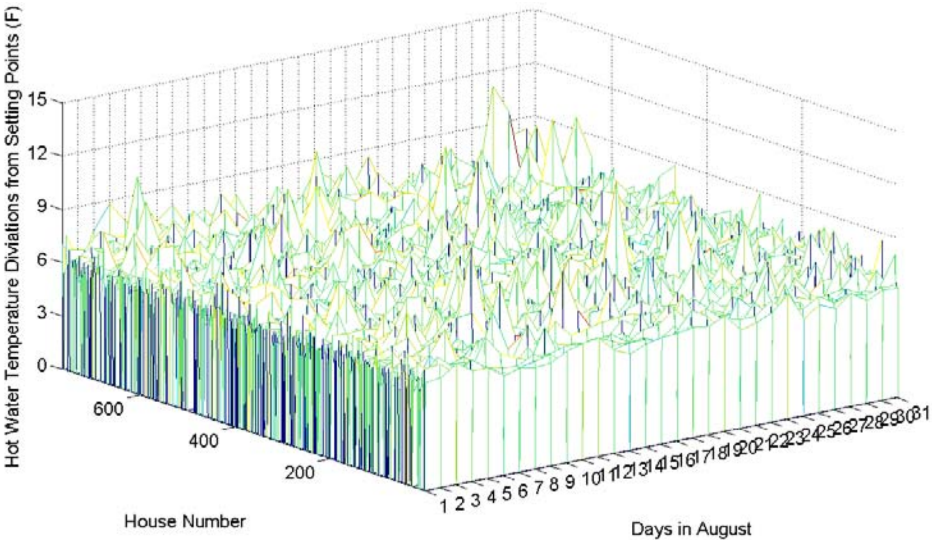
(d) Space Cooling Comfort Level – 300 EVs

Fig. 7-25 Residential Space Cooling Comfort Level Indices – August

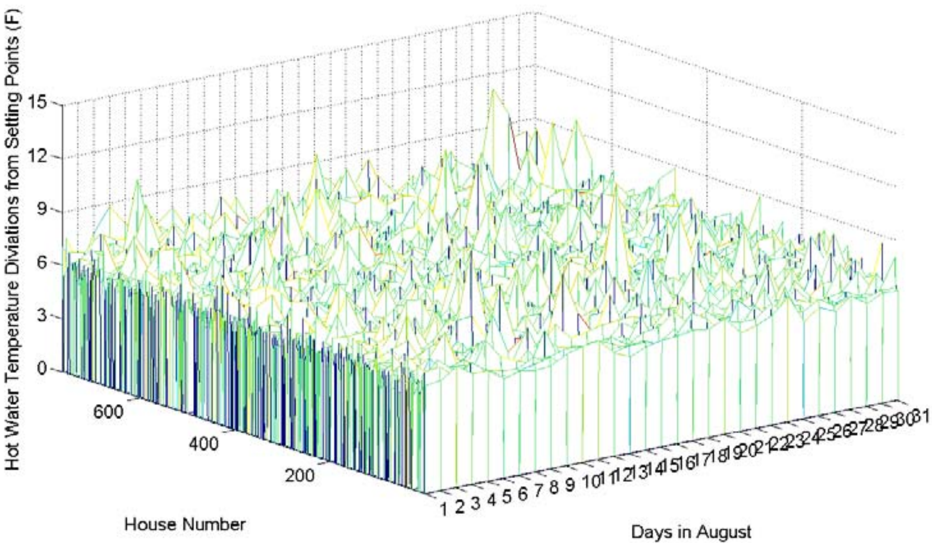
Similar to the situation in January, a larger EV fleet penetration does not incur more impact on the room temperature. This is because the room temperature has a more strict comfort zone setting (only 1^oF to 2^oF deviation allowed), thus the DR strategy generally tries to keep the space heater on.

b. Water Heating

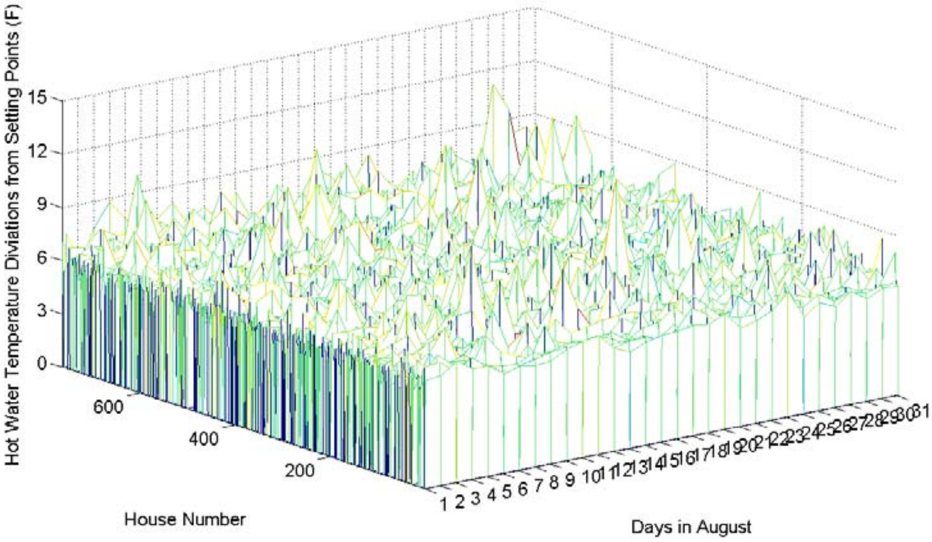
Fig. 7-26 shows the water heating comfort indices – hot water temperature deviation from the set point. (a) is the base case. (b) shows 100 EV penetration, (c) shows 200 EV penetration and (d) shows 300 EV penetration.



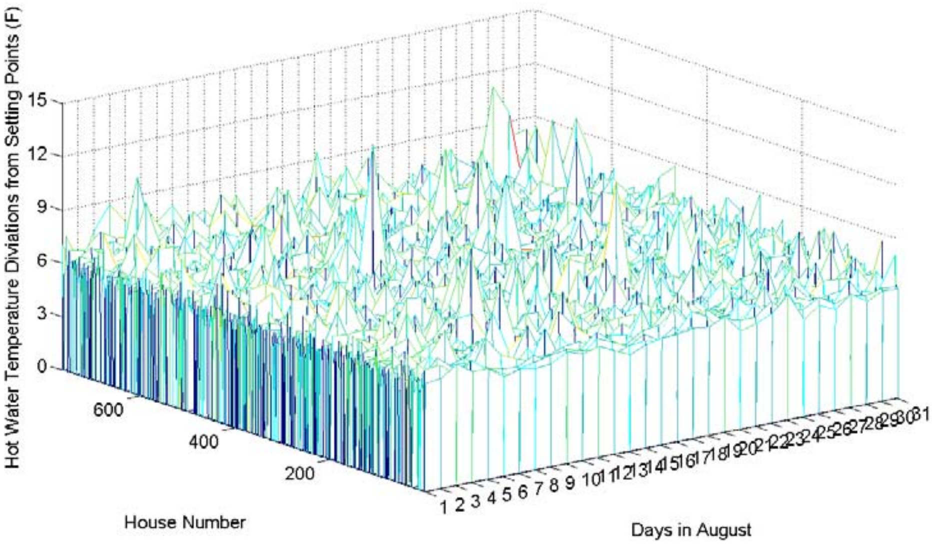
(a) Water Heating Comfort Level Base Case – no EV



(b) Water Heating Comfort Level – 100 EVs



(c) Water Heating Comfort Level – 200 EVs



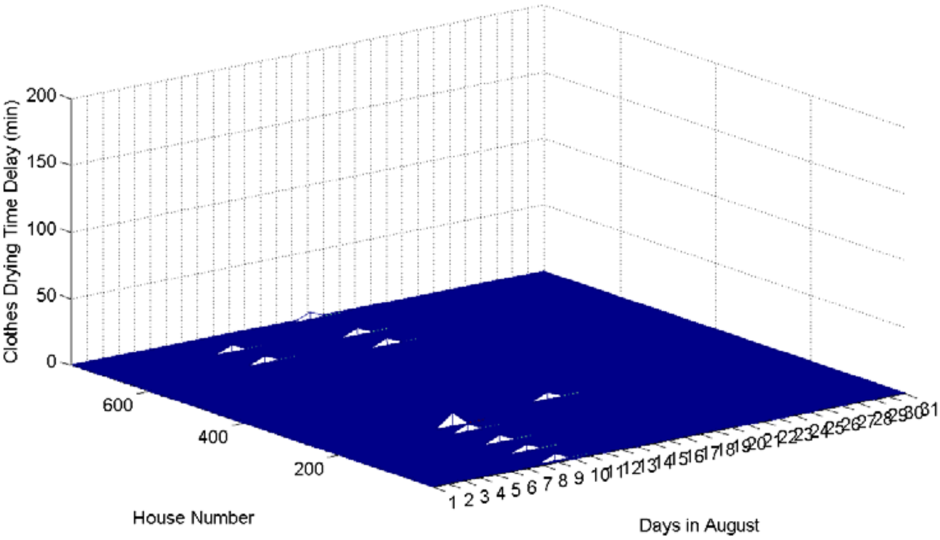
(d) Water Heating Comfort Level – 300 EVs

Fig. 7-26 Residential Water Heating Comfort Level Indices – August

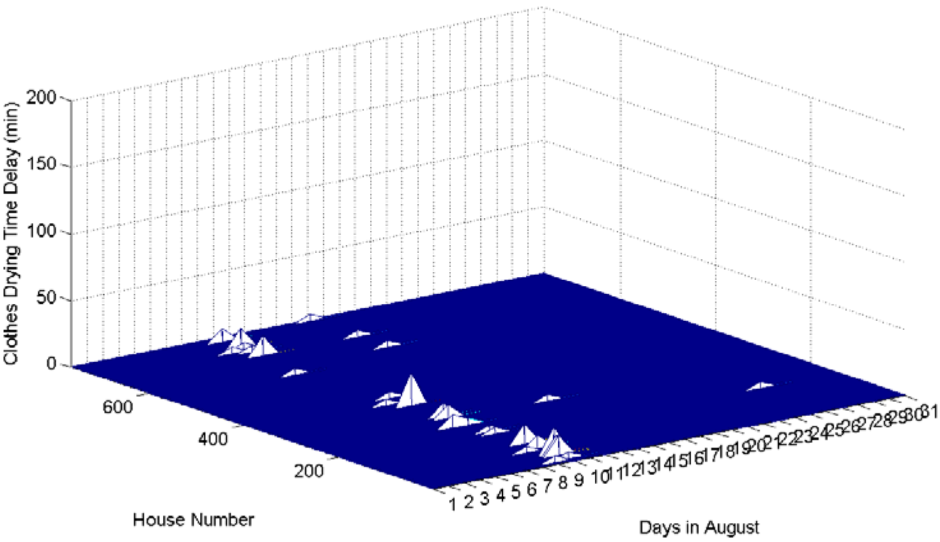
Similar to the situation in January, a larger EV fleet penetration does not incur more obvious impact on the hot water temperature deviation. The reasons have been discussed in the winter section. Actually, as the inlet water temperature is higher in summer than in winter, the hot water temperature gets even less impacted by the DR in August than in January.

c. Clothes-drying

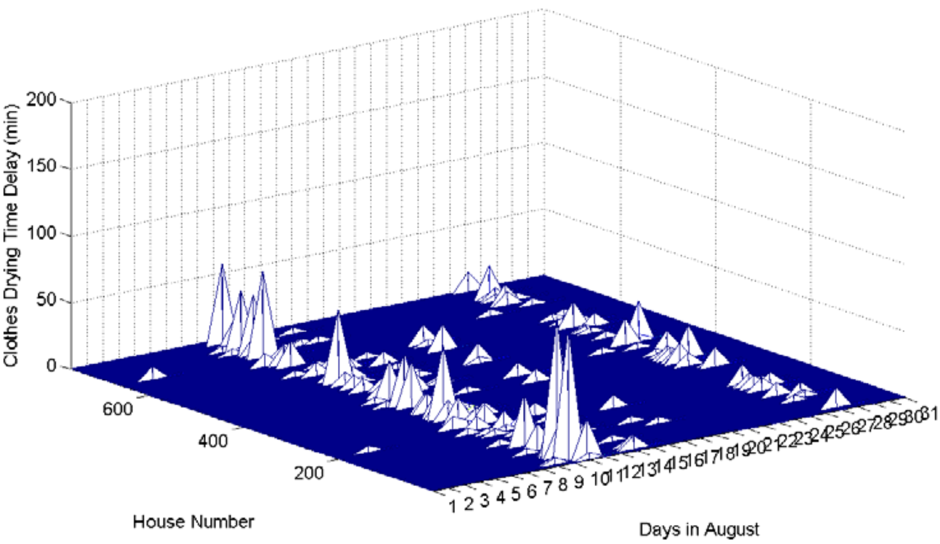
Fig. 7-27 shows the clothes-drying comfort indices – clothes-drying time delay, (a) shows 100 EV penetration, (b) shows 200 EV penetration and (c) shows 300 EV penetration.



(a) Clothes-drying Comfort Level – 100 EVs



(b) Clothes-drying Comfort Level – 200 EVs



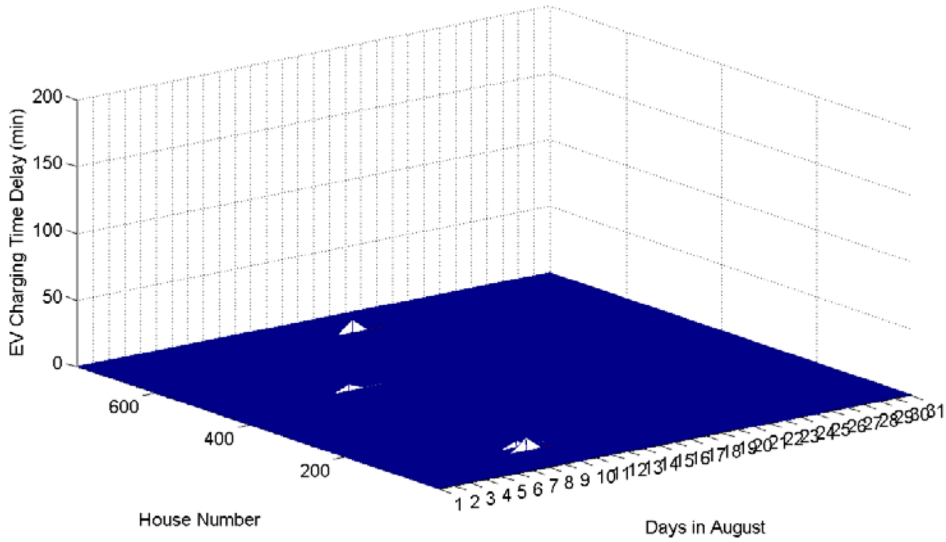
(c) Clothes-drying Comfort Level – 300 EVs

Fig. 7-27 Residential Clothes-drying Comfort Level Indices – August

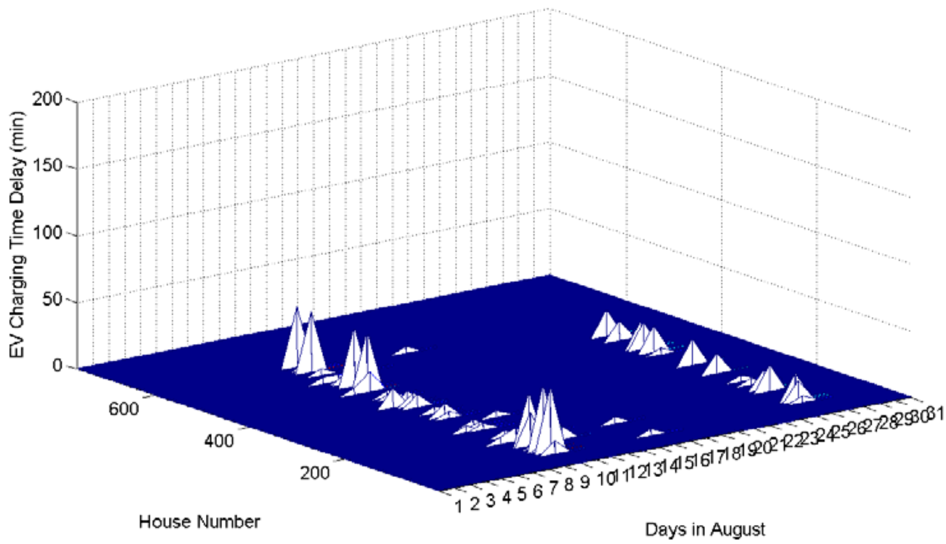
Similar to the situation in January, when there are more EVs plugged into the distribution network, the DR impact is higher on the clothes drying time delay, even though the priority settings are random. The difference between the two months is that the DR impact on the clothes-drying time delay in August is more scattered than that in January. This is because 1) there are more clothes-drying loads in August than in January; 2) the summer daily peaks are about the same height so more days are getting controlled in the DR program.

d. EV charging

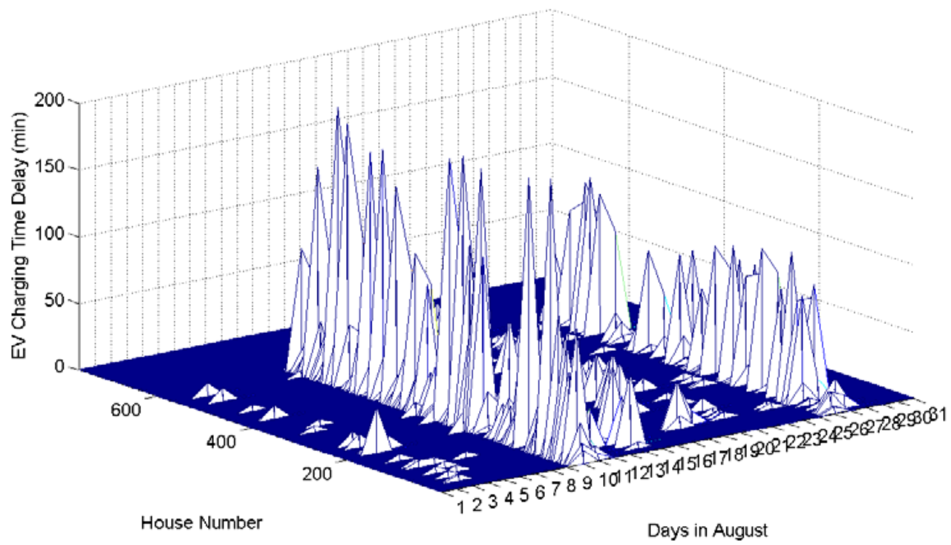
Fig. 7-28 shows the EV charging comfort indices – EV charging time delay. (a) shows 100 EV penetration, (b) shows 200 EV penetration and (c) shows 300 EV penetration.



(a) EV Charging Comfort Level – 100 EVs



(b) EV Charging Comfort Level – 200 EVs



(c) EV Charging Comfort Level – 300 EVs

Fig. 7-28 Residential EV Charging Comfort Level Indices – August

Similar to the situation in January, when there are more EVs plugged into the distribution network, the DR impact is higher on the EV charging time delay. The DR impact on the EV charging time delay in August is more scattered than that in January. This is because the summer daily peaks are about the same height so more days are getting controlled in the DR program.

It can be seen from the figures that a higher EV penetration level will cause the DR to have higher impacts on consumer comfort level in order to manage the household load under the household demand limit. Table 7-12 shows the circuit level residential consumer comfort indices for each appliance under different EV penetration levels in August.

Table 7-12 Residential Consumer Comfort Indices - August

	Indices	**100 EVs**	**200 EVs**	**300 EVs**
Space Cooling	Max. room temperature deviation (°F)	2.4	2.4	2.4
	Out of comfort zone duration (min) (deviation ≥2°F)	5	5	5
	No. of affected houses (deviation ≥2°F)	266	267	266
Water Heating	Max. hot water temperature deviation (°F)	12.5	12.5	14.2
	Out of comfort zone duration (min) (deviation ≥20°F)	0	0	0
	No. of affected houses (deviation ≥20°F)	0	0	0
Clothes-drying	Max. clothes-drying time delay (min)	10	25	105
	No. of affected houses (delay > 60min)	0	0	3
EV Charging	Max. EV charging time delay (min)	10	50	205
	No. of affected houses (delay > 60min)	0	0	26

7.5.2. Commercial Consumer Comfort Level

Table 7-13 and Table 7-14 show the commercial consumer comfort indices for winter (January) and summer (August) respectively. Note that when calculating the commercial consumer comfort indices, only the in-use time periods are taken into consideration, i.e. for office, school, public assembly, 9 a.m.~5 p.m., for fast food, 24 hours.

Table 7-13 Commercial Consumer Comfort Indices - January

	Indices	**100 EVs**	**200 EVs**	**300 EVs**
Space Heating	Max. room temperature deviation (°F)	2.2	2.2	2.2
	Out of comfort zone duration (min) (deviation ≥2°F)	5	5	5
	No. of affected buildings (deviation ≥2°F)	2	1	3

Table 7-14 Commercial Consumer Comfort Indices - August

	Indices	**100 EVs**	**200 EVs**	**300 EVs**
Space Cooling	Max. room temperature deviation (°F)	2.3	2.5	2.5
	Out of comfort zone duration (min) (deviation ≥2°F)	5	5	15
	No. of affected buildings (deviation ≥2°F)	4	6	8

7.6. Discussions and Findings

This section presents case studies of a distribution circuit at different EV penetration levels. The circuit mainly serves residential consumers. Thus, there is an obvious daily evening peak, which will be exacerbated by an EV home charge. Based on the simulations, the following discussions and findings can be made:

1) Circuit level one-year simulations

At a distribution circuit level, annual load curves differ a lot between summer and winter seasons. With the wide adoption of electric space heating, the winter peak demand is much higher than the summer peak demand. Therefore, the proposed demand response strategy targets different demand limit levels for these two seasons respectively.

At different EV penetration levels (100EVs~300EVs), the winter peak demand increases by 3%~9% (90kW~270kW) and the summer peak demand increases by 2.5%~7% (45kW~150kW). This is because the peak demand of the EV fleet charge happens closer to the winter peak period than summer, which adds more power consumption to the winter peak. However, since there are only several critical days in January and August being impacted by the demand response, the detailed daily load profiles are studied only for these critical days.

2) Circuit level critical-day simulations by sector

In the detailed daily simulations, it shows that the new peak demand due to EV penetration always occurs in the evening (the evening peak periods come about 1 or 2 hours earlier in summer than winter), during which period most commercial buildings are of lower priority (except food service) according to the judgment matrix from AHP. Therefore, the office, school and public assembly buildings assume more demand reduction and shift than residential and food service. Note that originally winter daily load curves have morning and evening peaks while summer daily load curves only have evening peaks. However, EV penetration only adds to the evening peaks. (See Chapter 4 for EV modeling.)

In the residential sector, DR results in more shifting of EV charging and clothes-drying loads than the shifting and reduction of thermal dynamic loads (space heating/cooling and water heating). This is because the thermal dynamic loads will be turned on from time to time in order to maintain the comfort levels, regardless of the priority settings. As clothes dryers and EVs do not have strict comfort zones, they are controlled more than HVACs and water heaters during DR operation. Further comparison between space heating/cooling and water heating shows that space heating/cooling load profiles change less than water heating load profiles since the room temperature has a more strict comfort range setting than the hot water temperature.

3) Household DR simulations for typical houses

The household DR simulation examples are selected from the worst-case scenario – the 300 EV penetration level. The results show that the proposed demand response strategy is able to manage the household load under the given demand limits for both summer and winter.

In each time step, the demand limit is kept at the same level for each house to maintain consistency of the proposed DR program. However, from time to time, the household demand limit will change. When the circuit demand is high, the household demand limit is low in order to keep the total power consumption of all houses under the circuit level demand limit.

The impact of the DR on the household load profiles is more related to the life style than to the house size. That is to say, a large house with high rated power appliances are not necessarily heavily impacted by participating in DR programs as long as they do not have the habit of turning on everything at the same time. A smaller house with lower-power consumption appliances may suffer more load shift and reduction due to a peak-time electricity usage pattern.

It is also confirmed here that as the room temperature is more sensitive than other indices, to maintain the consumer comfort level, the house control center tends to keep space heating/cooling appliances on regardless of their original priorities.

4) Studies on consumer comfort indices

The study of consumer comfort level shows an obvious impact - higher EV penetration level results in a higher DR impact. The results also confirm the findings from daily detailed simulations that EV and clothes dryers get more control than water heater and space heater/air conditioner. Since the load priorities are set randomly, this is mostly because the room temperature has a more strict comfort zone setting, while the water temperature comfort zone setting is less strict. The clothes drying and EV charging have more liberal comfort zone settings.

Moreover, it is interesting to notice that hot water comfort levels do not change too much with different EV penetration levels. This is because most water heating demand comes from the hot water usage, during which time the water heater will be kept on regardless of its priority to maintain the consumer comfort level. When there is no hot water consumption, the water heating loads can be easily shifted since water has a high specific heat capacity and does not easily lose energy when in stand-by mode. This may indicate that water heaters have a high potential to be a DR resource without having a noticeable impact on consumer comfort levels.

Simulation results in January and August indicate that the DR impact on residential consumers is more severe in winter than that in summer while the opposite effect is observed in commercial groups. This is because the winter evening peak coincides with the EV charging load peak, which means the increase in the winter peak load due to EV penetration is greater than that in summer. Therefore it is more difficult to keep the EV penetration transparent to the circuit in winter than in summer.

In winter, commercial buildings assume more load reduction/shift than residential houses. This is because the winter evening peak comes later (i.e. after 5pm) and after this time residential houses have higher priority. In terms of comfort indices, since the late evening period does not contribute to the comfort indices of most commercial building (except food service), simulation results indicate less impact on consumer comfort for commercial buildings in winter. On the other hand, the summer evening peak comes earlier, thus, the DR impact on the commercial buildings in the last working hour (4pm-5pm) has to be taken into consideration for comfort indices calculation. That is why DR impact on commercial buildings is more severe in summer than in winter.

8. Summary, Conclusions and Future Work

8.1. Summary

The objective of the dissertation is to propose a planning tool for electric utilities that can provide an insight into the implementation of demand response at an end-use level. The proposed planning tool comprises control algorithms and a simulation platform that are designed to intelligently manage end-use loads and make the EV penetration transparent to an electric power distribution network.

The dissertation reviews existing work on smart grid, load modeling, electric vehicle and demand response. A multi-layer demand response strategy is designed to manage the distribution circuit load at or below the original seasonal peak demand taking into account EV charging load. Analytic hierarchy process (AHP) is adopted to rank the priorities of different consumer groups by taking into account the opinions from different stakeholder groups.

Residential and commercial loads, as well as EVs, are modeled, aggregated and validated against available real-world measurements. Case studies are performed at different EV penetration levels. The demand response target is set to make the EV penetration transparent to the distribution network. Consumer comfort indices are calculated and presented for the peak winter month (January) and the peak summer month (August) respectively.

8.2. Conclusions

The share of electric vehicles is expected to grow in the U.S. personal automotive market. A large fleet of EV penetration will first be visible in distribution circuits. The study indicates that while the EV fleet charging increases the sale of the electric energy (kWh), the EV charging profile, if not coordinated with other loads, will inevitably increase the peak load demand (kW) in a distribution circuit. While additional electricity (kWh) sales are financially attractive to an electric utility, the growth in peak demand (kW) requires additional investment on their part in equipment and services.

Various demand side management programs have long been implemented to deal with power system stress conditions. However, traditional demand side management strategies cannot provide utilities with the assurance of load factor improvements. Moreover, it deprives consumers' convenience and comfort because the consumers do not have control over the use of their own loads. In this dissertation, a multi-layer DR strategy is proposed to enable a distribution circuit to accommodate higher levels of EV penetration without overloading the network. The proposed methodology is designed to maintain the existing demand limit with increased EV penetration. AHP is adopted to perform the demand limit allocation to different consumer groups, namely residential and commercial customers.

The proposed DR strategy includes an energy management tool within a home/building that allows customers to control their own loads based on their preference and comfort levels. Since, under this approach, the electric utility only sends the demand limit to each house and leaves all the household control decision to the consumer, the proposed DR strategy will respect the consumers' choices and protect their privacy.

Residential and commercial loads are modeled, aggregated and validated to study the proposed DR strategy. A distribution circuit in Blacksburg, VA is selected for the simulation. The DR results show that the proposed DR strategy can fulfill the task of maintaining the original peak demand with different EV penetration levels.

Furthermore, consumer comfort indices are defined, calculated and presented to provide a better understanding of the DR impact on the consumer's comfort level. It should be noted that maintaining the same distribution circuit-level peak load with higher EV penetration levels may negatively impact the consumer's convenience, resulting in more complaints. Therefore, utilities can use the proposed indices to estimate the capability of demand response programs developed here to accommodate EV fleet into a certain distribution circuit.

The end-use load models, the DR strategy and the consumer comfort indices serve as building blocks for the proposed planning tool. The presented case studies showcase examples of how the proposed DR strategy can be performed and what impact they have on distribution circuit load shape changes and consumer comfort. The planning tool can be used for a much wider range of applications related to demand response studies, such as DR potential analysis, impact of DR adoption levels and implementation of different DR algorithms. Utilities can use the tool to design proper incentives to encourage consumers to participate in DR programs; while consumers can use it to manage the usage of the electric appliances and understand the trade-offs to enroll in a DR program.

As the number of EVs increases, the load diversity will decrease resulting in distribution transformers to be overloaded. At that point, utilities may not be able to rely solely on demand response to shave the peak demand. Electric utilities can then explore other means such as the use of distributed generation or equipment upgrade to address high levels of EV penetrations.

8.3. Future Work

The proposed planning tool is a starting point that can enable additional demand response research and practical work. This dissertation points to several possible future work paths along the same line of demand response to alleviate power system stress conditions and to accommodate higher levels of EV penetration into a distribution network.

1) Planning tool improvement and potential applications

The load models built in the tool only take into consideration objective parameters such as the house structure, climate data and so on. Actually, human factors are also very important, especially for DR-enabled load models. The proposed load models have taken into account appliance ownership rates, the number of people in a building and randomized the usage data using Monte-Carlo simulations. The models can be potentially improved by taking into account the complexity of human activities in commercial buildings and residential houses. The improved load models will lead to a more refined demand response operation.

Given a constraint on comfort ranges, the consumer comfort indices designed in this planning tool have an implication for analyzing DR potentials in a distribution network. This may require a vast survey of consumer comfort range settings.

Other analysis such as impact of DR adoption levels on distribution network load shape changes can also be conducted by adjusting the planning tool accordingly.

2) EV cluster effect on distribution transformers

While 300 EVs may not cause a very high peak demand at the distribution level, it is likely that, at the local distribution transformer level, on the same street, the presence of several EV's can cause overloads as the spare capacity can quickly be exceeded. In order to avoid this capacity shortage, it may require all the HAN control centers in the neighborhood area to be able to communicate with each other to decide on a common load management plan. Such communication and control strategies may require cutting-edge technologies such as game theory, agent techniques and multi-way signal processing.

3) Flexible assignment of demand limit

The proposed DR strategy takes into consideration the fairness and effectiveness in assigning a proper demand limit to each building. Results show that it can maintain the circuit load under a certain demand limit. However, there may be the case that some houses have higher demand requests than the limit while some others are below it. As the household demand is discrete since each appliance has certain rated power, there may also be the case that a house has to shutdown a 4-kW appliance to keep the household demand under the given limit while it is only 1-kW higher than the limit. Therefore, along the lines of case no.1 mentioned above, research is needed in peer-communication, negotiation between neighbors with advanced methodology, agent techniques and communication technologies to better decide the assignment of demand limit to each house/building and give them more flexibility in using their appliances.

4) DR Incentive design

Even though, necessary steps are taken to maintain the consumers' comfort and convenience, it has to be admitted that DR will have an impact on the consumers' electricity usage pattern, and will inevitably cause some inconveniences. Therefore, utilities will need to properly design incentive programs to encourage consumers to participate in their DR programs. The study of consumer comfort indices in this dissertation may provide some hints to design a proper DR incentive. On the other hand, the proposed DR strategy can also be incorporated with price signals, which will require consumers to set a price threshold and demand limit by themselves.

5) Distributed generation integration

Last but not least, it can be seen from the simulations that with the increase in the number of EVs, more load control has to be performed, thus resulting in higher impacts on the consumers' comfort level. Therefore, at some point, DR resources may be exhausted and other alternatives have to be introduced to tackle the problem of system stress conditions. Distributed generation (DG) and community scale storage are some of the possible choices. This aspect introduces many potential research topics such as optimal sizing, operation and location. An EV can also become a DG when it provides Vehicle-to-Grid services.

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